Package 'yuima'

February 29, 2024

Type Package

Title The YUIMA Project Package for SDEs

Version 1.15.27

Depends R(>= 2.10.0), methods, zoo, stats4, utils, expm, cubature, mvtnorm

Imports Rcpp (>= 0.12.1), boot (>= 1.3-2), glassoFast, coda, calculus (>= 0.2.0), statmod,

Author YUIMA Project Team

Maintainer Stefano M. Iacus <siacus@iq.harvard.edu>

Description Simulation and Inference for SDEs and Other Stochastic Processes.

License GPL-2

URL https://yuimaproject.com

BugReports https://github.com/yuimaproject/yuima/issues

LinkingTo Rcpp, RcppArmadillo

NeedsCompilation yes

Repository CRAN

Date/Publication 2024-02-29 21:30:03 UTC

R topics documented:

`adaBayes` *Adaptive Bayes estimator for the parameters in sde model*

Description

The `adabayes.mcmc` class is a class of the **yuima** package that extends the `mle-class`.

Usage

```
adaBayes(yuima, start, prior, lower, upper, method = "mcmc", iteration = NULL,mcmc,
rate =1, rcpp = TRUE, algorithm = "randomwalk",center=NULL,sd=NULL,rho=NULL,
path = FALSE)
```

Arguments

`yuima`	a 'yuima' object.
`start`	initial suggestion for parameter values
`prior`	a list of prior distributions for the parameters specified by 'code'. Currently, dunif(z, min, max), dnorm(z, mean, sd), dbeta(z, shape1, shape2), dgamma(z, shape, rate) are available.
`lower`	a named list for specifying lower bounds of parameters
`upper`	a named list for specifying upper bounds of parameters
`method`	`"nomcmc"` requires package `cubature`
`iteration`	number of iteration of Markov chain Monte Carlo method
`mcmc`	number of iteration of Markov chain Monte Carlo method
`rate`	a thinning parameter. Only the first n^rate observation will be used for inference.
`rcpp`	Logical value. If `rcpp = TRUE` (default), Rcpp code will be performed. Otherwise, usual R code will be performed.
`algorithm`	If `algorithm = "randomwalk"` (default), the random-walk Metropolis algorithm will be performed. If `algorithm = "MpCN"`, the Mixed preconditioned Crank-Nicolson algorithm will be performed.

center	A list of parameters used to center MpCN algorithm.
sd	A list for specifying the standard deviation of proposal distributions.
path	Logical value when method = "mcmc". If path=TRUE, then the sample path for each variable will be included in the MCMC object in the output.
rho	A parameter used for MpCN algorithm.

Details

Calculate the Bayes estimator for stochastic processes by using the quasi-likelihood function. The calculation is performed by the Markov chain Monte Carlo method. Currently, the Random-walk Metropolis algorithm and the Mixed preconditioned Crank-Nicolson algorithm is implemented.

Slots

mcmc: is a list of MCMC objects for all estimated parameters.

accept_rate: is a list acceptance rates for diffusion and drift parts.

call: is an object of class language.

fullcoef: is an object of class list that contains estimated parameters.

vcov: is an object of class matrix.

coefficients: is an object of class vector that contains estimated parameters.

Note

algorithm = nomcmc is unstable.

Author(s)

Kengo Kamatani with YUIMA project Team

References

Yoshida, N. (2011). Polynomial type large deviation inequalities and quasi-likelihood analysis for stochastic differential equations. Annals of the Institute of Statistical Mathematics, 63(3), 431-479. Uchida, M., & Yoshida, N. (2014). Adaptive Bayes type estimators of ergodic diffusion processes from discrete observations. Statistical Inference for Stochastic Processes, 17(2), 181-219. Kamatani, K. (2017). Ergodicity of Markov chain Monte Carlo with reversible proposal. Journal of Applied Probability, 54(2).

Examples

```
## Not run:
set.seed(123)
b <- c("-theta1*x1+theta2*sin(x2)+50","-theta3*x2+theta4*cos(x1)+25")
a <- matrix(c("4+theta5","1","1","2+theta6"),2,2)
true = list(theta1 = 0.5, theta2 = 5,theta3 = 0.3,
            theta4 = 5, theta5 = 1, theta6 = 1)
lower = list(theta1=0.1,theta2=0.1,theta3=0,
             theta4=0.1,theta5=0.1,theta6=0.1)
```

```
upper = list(theta1=1,theta2=10,theta3=0.9,
             theta4=10,theta5=10,theta6=10)
start = list(theta1=runif(1),
             theta2=rnorm(1),
             theta3=rbeta(1,1,1),
             theta4=rnorm(1),
             theta5=rgamma(1,1,1),
             theta6=rexp(1))
yuimamodel <- setModel(drift=b,diffusion=a,state.variable=c("x1", "x2"),solve.variable=c("x1","x2"))
yuimasamp <- setSampling(Terminal=50,n=50*10)
yuima <- setYuima(model = yuimamodel, sampling = yuimasamp)
yuima <- simulate(yuima, xinit = c(100,80),
                  true.parameter = true,sampling = yuimasamp)
prior <-
  list(
    theta1=list(measure.type="code",df="dunif(z,0,1)"),
    theta2=list(measure.type="code",df="dnorm(z,0,1)"),
    theta3=list(measure.type="code",df="dbeta(z,1,1)"),
    theta4=list(measure.type="code",df="dgamma(z,1,1)"),
    theta5=list(measure.type="code",df="dnorm(z,0,1)"),
    theta6=list(measure.type="code",df="dnorm(z,0,1)")
  )
set.seed(123)
mle <- qmle(yuima, start = start, lower = lower, upper = upper, method = "L-BFGS-B",rcpp=TRUE)
print(mle@coef)
center<-list(theta1=0.5,theta2=5,theta3=0.3,theta4=4,theta5=3,theta6=3)
sd<-list(theta1=0.001,theta2=0.001,theta3=0.001,theta4=0.01,theta5=0.5,theta6=0.5)
bayes <- adaBayes(yuima, start=start, prior=prior,lower=lower,upper=upper,
                  method="mcmc",mcmc=1000,rate = 1, rcpp = TRUE,
                   algorithm = "randomwalk",center = center,sd=sd,
                   path=TRUE)
print(bayes@fullcoef)
print(bayes@accept_rate)
print(bayes@mcmc$theta1[1:10])

## End(Not run)
```

---

ae *Asymptotic Expansion*

Description

Asymptotic expansion of uni-dimensional and multi-dimensional diffusion processes.

Usage

```
ae(
  model,
  xinit,
  order = 1L,
```

```
  true.parameter = list(),
  sampling = NULL,
  eps.var = "eps",
  solver = "rk4",
  verbose = FALSE
)
```

Arguments

model	an object of yuima-class or yuima.model-class.
xinit	initial value vector of state variables.
order	integer. The asymptotic expansion order. Higher orders lead to better approximations but longer computational times.
true.parameter	named list of parameters.
sampling	a yuima.sampling-class object.
eps.var	character. The perturbation variable.
solver	the solver for ordinary differential equations. One of "rk4" (more accurate) or "euler" (faster).
verbose	logical. Print on progress? Default FALSE.

Details

If sampling is not provided, then model must be an object of yuima-class with non-empty sampling.

if eps.var does not appear in the model specification, then it is internally added in front of the diffusion matrix to apply the asymptotic expansion scheme.

Value

An object of yuima.ae-class

Author(s)

Emanuele Guidotti <emanuele.guidotti@unine.ch>

Examples

```
## Not run:
# model
gbm <- setModel(drift = 'mu*x', diffusion = 'sigma*x', solve.variable = 'x')

# settings
xinit <- 100
par <- list(mu = 0.01, sigma = 0.2)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)

# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 4, true.parameter = par, xinit = xinit)
```

```
# exact density
x <- seq(50, 200, by = 0.1)
exact <- dlnorm(x = x, meanlog = log(xinit)+(par$mu-0.5*par$sigma^2)*1, sdlog = par$sigma*sqrt(1))

# compare
plot(x, exact, type = 'l', ylab = "Density")
lines(x, aeDensity(x = x, ae = approx, order = 1), col = 2)
lines(x, aeDensity(x = x, ae = approx, order = 2), col = 3)
lines(x, aeDensity(x = x, ae = approx, order = 3), col = 4)
lines(x, aeDensity(x = x, ae = approx, order = 4), col = 5)

## End(Not run)
```

`aeCharacteristic` *Asymptotic Expansion - Characteristic Function*

Description

Asymptotic Expansion - Characteristic Function

Usage

```
aeCharacteristic(..., ae, eps = 1, order = NULL)
```

Arguments

`...`	named argument, data.frame, list, or environment specifying the grid to evaluate the characteristic function. See examples.
`ae`	an object of class `yuima.ae-class`.
`eps`	numeric. The intensity of the perturbation.
`order`	integer. The expansion order. If `NULL` (default), it uses the maximum order used in `ae`.

Value

Characteristic function evaluated on the given grid.

Examples

```
## Not run:
# model
gbm <- setModel(drift = 'mu*x', diffusion = 'sigma*x', solve.variable = 'x')

# settings
xinit <- 100
par <- list(mu = 0.01, sigma = 0.2)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)
```

```
# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 4, true.parameter = par, xinit = xinit)

# The following are all equivalent methods to specify the grid via ....
# Notice that the character 'u1' corresponds to the 'u.var' of the ae object.
approx@u.var

# 1) named argument
u1 <- seq(0, 1, by = 0.1)
psi <- aeCharacteristic(u1 = u1, ae = approx, order = 4)
# 2) data frame
df <- data.frame(u1 = seq(0, 1, by = 0.1))
psi <- aeCharacteristic(df, ae = approx, order = 4)
# 3) environment
env <- new.env()
env$u1 <- seq(0, 1, by = 0.1)
psi <- aeCharacteristic(env, ae = approx, order = 4)
# 4) list
lst <- list(u1 = seq(0, 1, by = 0.1))
psi <- aeCharacteristic(lst, ae = approx, order = 4)

## End(Not run)
```

`aeDensity` *Asymptotic Expansion - Density*

Description

Asymptotic Expansion - Density

Usage

```
aeDensity(..., ae, eps = 1, order = NULL)
```

Arguments

`...`	named argument, data.frame, list, or environment specifying the grid to evaluate the density. See examples.
`ae`	an object of class `yuima.ae-class`.
`eps`	numeric. The intensity of the perturbation.
`order`	integer. The expansion order. If `NULL` (default), it uses the maximum order used in `ae`.

Value

Probability density function evaluated on the given grid.

Examples

```
## Not run:
# model
gbm <- setModel(drift = 'mu*x', diffusion = 'sigma*x', solve.variable = 'x')

# settings
xinit <- 100
par <- list(mu = 0.01, sigma = 0.2)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)

# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 4, true.parameter = par, xinit = xinit)

# The following are all equivalent methods to specify the grid via ....
# Notice that the character 'x' corresponds to the solve.variable of the yuima model.

# 1) named argument
x <- seq(50, 200, by = 0.1)
density <- aeDensity(x = x, ae = approx, order = 4)
# 2) data frame
df <- data.frame(x = seq(50, 200, by = 0.1))
density <- aeDensity(df, ae = approx, order = 4)
# 3) environment
env <- new.env()
env$x <- seq(50, 200, by = 0.1)
density <- aeDensity(env, ae = approx, order = 4)
# 4) list
lst <- list(x = seq(50, 200, by = 0.1))
density <- aeDensity(lst, ae = approx, order = 4)

# exact density
exact <- dlnorm(x = x, meanlog = log(xinit)+(par$mu-0.5*par$sigma^2)*1, sdlog = par$sigma*sqrt(1))

# compare
plot(x = exact, y = density, xlab = "Exact", ylab = "Approximated")

## End(Not run)
```

---

aeExpectation *Asymptotic Expansion - Functionals*

Description

Compute the expected value of functionals.

Usage

```
aeExpectation(f, bounds, ae, eps = 1, order = NULL, ...)
```

Arguments

f	character. The functional.
bounds	named list of integration bounds in the form `list(x = c(xmin, xmax), y = c(ymin, ymax), ...)`
ae	an object of class yuima.ae-class.
eps	numeric. The intensity of the perturbation.
order	integer. The expansion order. If NULL (default), it uses the maximum order used in ae.
...	additional arguments passed to cubintegrate.

Value

return value of cubintegrate. The expectation of the functional provided.

Examples

```
## Not run:
# model
gbm <- setModel(drift = 'mu*x', diffusion = 'sigma*x', solve.variable = 'x')

# settings
xinit <- 100
par <- list(mu = 0.01, sigma = 0.2)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)

# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 4, true.parameter = par, xinit = xinit)

# compute the mean via integration
aeExpectation(f = 'x', bounds = list(x = c(0,1000)), ae = approx)

# compare with the mean computed by differentiation of the characteristic function
aeMean(approx)

## End(Not run)
```

---

aeKurtosis *Asymptotic Expansion - Kurtosis*

Description

Asymptotic Expansion - Kurtosis

Usage

```
aeKurtosis(ae, eps = 1, order = NULL)
```

Arguments

ae	an object of class yuima.ae-class.
eps	numeric. The intensity of the perturbation.
order	integer. The expansion order. If NULL (default), it uses the maximum order used in ae.

Value

numeric.

Examples

```
## Not run:
# model
gbm <- setModel(drift = 'mu*x', diffusion = 'sigma*x', solve.variable = 'x')

# settings
xinit <- 100
par <- list(mu = 0.01, sigma = 0.2)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)

# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 4, true.parameter = par, xinit = xinit)

# expansion order max
aeKurtosis(ae = approx)

# expansion order 1
aeKurtosis(ae = approx, order = 1)

## End(Not run)
```

---

aeMarginal *Asymptotic Expansion - Marginals*

Description

Asymptotic Expansion - Marginals

Usage

```
aeMarginal(ae, var)
```

Arguments

ae	an object of class yuima.ae-class.
var	variables of the marginal distribution to compute.

Value

An object of yuima.ae-class

Examples

```
## Not run:
# multidimensional model
gbm <- setModel(drift = c('mu*x1','mu*x2'),
                diffusion = matrix(c('sigma1*x1',0,0,'sigma2*x2'), nrow = 2),
                solve.variable = c('x1','x2'))

# settings
xinit <- c(100, 100)
par <- list(mu = 0.01, sigma1 = 0.2, sigma2 = 0.1)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)

# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 3, true.parameter = par, xinit = xinit)

# extract marginals
margin1 <- aeMarginal(ae = approx, var = "x1")
margin2 <- aeMarginal(ae = approx, var = "x2")

# compare with exact solution for marginal 1
x1 <- seq(50, 200, by = 0.1)
exact <- dlnorm(x = x1, meanlog = log(xinit[1])+(par$mu-0.5*par$sigma1^2), sdlog = par$sigma1)
plot(x1, exact, type = 'p', ylab = "Density")
lines(x1, aeDensity(x1 = x1, ae = margin1, order = 3), col = 2)

# compare with exact solution for marginal 2
x2 <- seq(50, 200, by = 0.1)
exact <- dlnorm(x = x2, meanlog = log(xinit[2])+(par$mu-0.5*par$sigma2^2), sdlog = par$sigma2)
plot(x2, exact, type = 'p', ylab = "Density")
lines(x2, aeDensity(x2 = x2, ae = margin2, order = 3), col = 2)


## End(Not run)
```

---

aeMean *Asymptotic Expansion - Mean*

Description

Asymptotic Expansion - Mean

Usage

```
aeMean(ae, eps = 1, order = NULL)
```

Arguments

ae	an object of class yuima.ae-class.
eps	numeric. The intensity of the perturbation.
order	integer. The expansion order. If NULL (default), it uses the maximum order used in ae.

Value

numeric.

Examples

```
## Not run:
# model
gbm <- setModel(drift = 'mu*x', diffusion = 'sigma*x', solve.variable = 'x')

# settings
xinit <- 100
par <- list(mu = 0.01, sigma = 0.2)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)

# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 4, true.parameter = par, xinit = xinit)

# expansion order max
aeMean(ae = approx)

# expansion order 1
aeMean(ae = approx, order = 1)

## End(Not run)
```

---

aeMoment *Asymptotic Expansion - Moments*

Description

Asymptotic Expansion - Moments

Usage

```
aeMoment(ae, m = 1, eps = 1, order = NULL)
```

Arguments

ae	an object of class yuima.ae-class.
m	integer. The moment order. In case of multidimensional processes, it is possible to compute cross-moments by providing a vector of the same length as the state variables.
eps	numeric. The intensity of the perturbation.
order	integer. The expansion order. If NULL (default), it uses the maximum order used in ae.

Value

numeric.

Examples

```
## Not run:
# model
gbm <- setModel(drift = 'mu*x', diffusion = 'sigma*x', solve.variable = 'x')

# settings
xinit <- 100
par <- list(mu = 0.01, sigma = 0.2)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)

# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 4, true.parameter = par, xinit = xinit)

# second moment, expansion order max
aeMoment(ae = approx, m = 2)

# second moment, expansion order 3
aeMoment(ae = approx, m = 2, order = 3)

# second moment, expansion order 2
aeMoment(ae = approx, m = 2, order = 2)

# second moment, expansion order 1
aeMoment(ae = approx, m = 2, order = 1)

## End(Not run)
```

---

aeSd *Asymptotic Expansion - Standard Deviation*

Description

Asymptotic Expansion - Standard Deviation

Usage

```
aeSd(ae, eps = 1, order = NULL)
```

Arguments

ae	an object of class yuima.ae-class.
eps	numeric. The intensity of the perturbation.
order	integer. The expansion order. If NULL (default), it uses the maximum order used in ae.

Value

numeric.

Examples

```
## Not run:
# model
gbm <- setModel(drift = 'mu*x', diffusion = 'sigma*x', solve.variable = 'x')

# settings
xinit <- 100
par <- list(mu = 0.01, sigma = 0.2)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)

# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 4, true.parameter = par, xinit = xinit)

# expansion order max
aeSd(ae = approx)

# expansion order 1
aeSd(ae = approx, order = 1)

## End(Not run)
```

---

aeSkewness *Asymptotic Expansion - Skewness*

Description

Asymptotic Expansion - Skewness

Usage

```
aeSkewness(ae, eps = 1, order = NULL)
```

Arguments

ae	an object of class yuima.ae-class.
eps	numeric. The intensity of the perturbation.
order	integer. The expansion order. If NULL (default), it uses the maximum order used in ae.

Value

numeric.

Examples

```
## Not run:
# model
gbm <- setModel(drift = 'mu*x', diffusion = 'sigma*x', solve.variable = 'x')

# settings
xinit <- 100
par <- list(mu = 0.01, sigma = 0.2)
sampling <- setSampling(Initial = 0, Terminal = 1, n = 1000)

# asymptotic expansion
approx <- ae(model = gbm, sampling = sampling, order = 4, true.parameter = par, xinit = xinit)

# expansion order max
aeSkewness(ae = approx)

# expansion order 1
aeSkewness(ae = approx, order = 1)

## End(Not run)
```

---

asymptotic_term *asymptotic expansion of the expected value of the functional*

Description

calculate the fisrt and second term of asymptotic expansion of the functional mean.

Usage

```
asymptotic_term(yuima, block=100, rho, g, expand.var="e")
```

Arguments

yuima	an yuima object containing model and functional.
block	the number of trapezoids for integrals.
rho	specify discounting factor in mean integral.
g	arbitrary measurable function for mean integral.
expand.var	default expand.var="e".

Details

Calculate the first and second term of asymptotic expansion of the expected value of the functional associated with a sde. The returned value d0 + epsilon * d1 is approximation of the expected value.

Value

terms	list of 1st and 2nd asymptotic terms, terms$d0 and terms$d1.

Note

we need to fix this routine.

Author(s)

YUIMA Project Team

Examples

```
## Not run:
# to the Black-Scholes economy:
# dXt^e = Xt^e * dt + e * Xt^e * dWt
diff.matrix <- "x*e"
model <- setModel(drift = "x", diffusion = diff.matrix)
# call option is evaluated by averating
# max{ (1/T)*int_0^T Xt^e dt, 0}, the first argument is the functional of interest:
Terminal <- 1
xinit <- c(1)
f <- list( c(expression(x/Terminal)), c(expression(0)))
F <- 0
division <- 1000
e <- .3
yuima <- setYuima(model = model, sampling = setSampling(Terminal=Terminal, n=division))
yuima <- setFunctional( yuima, f=f,F=F, xinit=xinit,e=e)

# asymptotic expansion
rho <- expression(0)
F0 <- F0(yuima)
get_ge <- function(x,epsilon,K,F0){
  tmp <- (F0 - K) + (epsilon * x)
  tmp[(epsilon * x) < (K-F0)] <- 0
  return( tmp )
}
```

```
g <- function(x) get_ge(x,epsilon=e,K=1,F0=F0)
set.seed(123)
asymp <- asymptotic_term(yuima, block=10, rho,g)
asymp
sum(asymp$d0 + e * asymp$d1)


### An example of multivariate case: Heston model
## a <- 1;C <- 1;d <- 10;R<-.1
## diff.matrix <- matrix( c("x1*sqrt(x2)*e", "e*R*sqrt(x2)",0,"sqrt(x2*(1-R^2))*e"), 2,2)
## model <- setModel(drift = c("a*x1","C*(10-x2)"),
## diffusion = diff.matrix,solve.variable=c("x1","x2"),state.variable=c("x1","x2"))
## call option is evaluated by averating
## max{ (1/T)*int_0^T Xt^e dt, 0}, the first argument is the functional of interest:
##
## Terminal <- 1
## xinit <- c(1,1)
##
## f <- list( c(expression(0), expression(0)),
## c(expression(0), expression(0)) , c(expression(0), expression(0))  )
## F <- expression(x1,x2)
##
## division <- 1000
## e <- .3
##
## yuima <- setYuima(model = model, sampling = setSampling(Terminal=Terminal, n=division))
## yuima <- setFunctional( yuima, f=f,F=F, xinit=xinit,e=e)
##
## rho <- expression(x1)
## F0 <- F0(yuima)
## get_ge <- function(x){
##  return( max(x[1],0))
## }
## g <- function(x) get_ge(x)
## set.seed(123)
## asymp <- asymptotic_term(yuima, block=10, rho,g)
## sum(asymp$d0 + e * asymp$d1)


## End(Not run)
```

`bns.test` *Barndorff-Nielsen and Shephard's Test for the Presence of Jumps Using Bipower Variation*

Description

Tests the presence of jumps using the statistic proposed in Barndorff-Nielsen and Shephard (2004,2006) for each component.

Usage

```
bns.test(yuima, r = rep(1, 4), type = "standard", adj = TRUE)
```

Arguments

yuima	an object of yuima-class or yuima.data-class.
r	a vector of non-negative numbers or a list of vectors of non-negative numbers. Theoretically, it is necessary that sum(r)=4 and max(r)<2.
type	type of the test statistic to use. standard is default.
adj	logical; if TRUE, the maximum adjustment suggested in Barndorff-Nielsen and Shephard (2004) is applied to the test statistic when type is equal to either "log" or "ratio".

Details

For the i-th component, the test statistic is equal to the i-th component of sqrt(n)*(mpv(yuima,2)-mpv(yuima,c(1,1)))/
when type="standard", sqrt(n)*log(mpv(yuima,2)/mpv(yuima,c(1,1)))/sqrt(vartheta*mpv(yuima,r)/mpv(yuim
when type="log" and sqrt(n)*(1-mpv(yuima,c(1,1))/mpv(yuima,2))/sqrt(vartheta*mpv(yuima,r)/mpv(yuima,c
when type="ratio". Here, n is equal to the length of the i-th component of the zoo.data of yuima minus 1 and vartheta is pi^2/4+pi-5. When adj=TRUE, mpv(yuima,r)[i]/mpv(yuima,c(1,1))^2)[i] is replaced with 1 if it is less than 1.

Value

A list with the same length as the zoo.data of yuima. Each component of the list has class "htest" and contains the following components:

statistic	the value of the test statistic of the corresponding component of the zoo.data of yuima.
p.value	an approximate p-value for the test of the corresponding component.
method	the character string "Barndorff-Nielsen and Shephard jump test".
data.name	the character string "xi", where i is the number of the component.

Note

Theoretically, this test may be invalid if sampling is irregular.

Author(s)

Yuta Koike with YUIMA Project Team

References

Barndorff-Nielsen, O. E. and Shephard, N. (2004) Power and bipower variation with stochastic volatility and jumps, *Journal of Financial Econometrics*, **2**, no. 1, 1–37.

Barndorff-Nielsen, O. E. and Shephard, N. (2006) Econometrics of testing for jumps in financial economics using bipower variation, *Journal of Financial Econometrics*, **4**, no. 1, 1–30.

Huang, X. and Tauchen, G. (2005) The relative contribution of jumps to total price variance, *Journal of Financial Econometrics*, **3**, no. 4, 456–499.

See Also

lm.jumptest, mpv, minrv.test, medrv.test, pz.test

Examples

```
set.seed(123)

# One-dimensional case
## Model: dXt=t*dWt+t*dzt,
## where zt is a compound Poisson process with intensity 5 and jump sizes distribution N(0,0.1).

model <- setModel(drift=0,diffusion="t",jump.coeff="t",measure.type="CP",
                  measure=list(intensity=5,df=list("dnorm(z,0,sqrt(0.1))")),
                  time.variable="t")

yuima.samp <- setSampling(Terminal = 1, n = 390)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(yuima)
plot(yuima) # The path seems to involve some jumps

bns.test(yuima) # standard type

bns.test(yuima,type="log") # log type

bns.test(yuima,type="ratio") # ratio type

# Multi-dimensional case
## Model: dXkt=t*dWk_t (k=1,2,3) (no jump case).

diff.matrix <- diag(3)
diag(diff.matrix) <- c("t","t","t")
model <- setModel(drift=c(0,0,0),diffusion=diff.matrix,time.variable="t",
                  solve.variable=c("x1","x2","x3"))

yuima.samp <- setSampling(Terminal = 1, n = 390)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(yuima)
plot(yuima)

bns.test(yuima)
```

---

carma.info-class *Class for information about CARMA(p,q) model*

Description

The carma.info-class is a class of the **yuima** package.

Details

The carma.info-class object cannot be directly specified by the user but it is constructed when the yuima.carma-class object is constructed via setCarma.

Slots

p: Number of autoregressive coefficients.

q: Number of moving average coefficients.

loc.par: Label of location coefficient.

scale.par: Label of scale coefficient.

ar.par: Label of autoregressive coefficients.

ma.par: Label of moving average coefficients.

lin.par: Label of linear coefficients.

Carma.var: Label of the observed process.

Latent.var: Label of the unobserved process.

XinExpr: Logical variable. If XinExpr=FALSE, the starting condition of Latent.var is zero otherwise each component of Latent.var has a parameter as a starting point.

Author(s)

The YUIMA Project Team

---

carmaHawkes.info-class

Class for information on the Hawkes process with a CARMA(p,q) intensity

---

Description

The carmaHawkes.info-class is a class of the **yuima** package.

Details

The carmaHawkes.info-class object cannot be directly specified by the user but it is constructed when the yuima.carmaHawkes-class object is constructed via setCarmaHawkes.

Slots

p: Number of autoregressive coefficients.

q: Number of moving average coefficients.

Counting.Process: Label of Counting process.

base.Int: Label of baseline Intensity parameter.

ar.par: Label of autoregressive coefficients.

`ma.par`: Label of moving average coefficients.

`Intensity.var`: Label of the Intensity process.

`Latent.var`: Label of the unobserved process.

`XinExpr`: Logical variable. If `XinExpr=FALSE`, the starting condition of `Latent.var` is zero otherwise each component of Latent.var has a parameter as a starting point.

`Type.Jump`: Logical variable. If `XinExpr=TRUE`, the jump size is deterministic

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

`CarmaNoise` *Estimation for the underlying Levy in a carma model*

Description

Retrieve the increment of the underlying Levy for the carma(p,q) process using the approach developed in Brockwell et al.(2011)

Usage

```
CarmaNoise(yuima, param, data=NULL, NoNeg.Noise=FALSE)
```

Arguments

`yuima`	a yuima object or an object of `yuima.carma-class`.
`param`	`list` of parameters for the carma.
`data`	an object of class `yuima.data-class` contains the observations available at uniformly spaced time. If `data=NULL`, the default, the 'CarmaNoise' uses the data in an object of `yuima.data-class`.
`NoNeg.Noise`	Estimate a non-negative Levy-Driven Carma process. By default `NoNeg.Noise=FALSE`.

Value

`incr.Levy`	a numeric object contains the estimated increments.

Note

The function `qmle` uses the function `CarmaNoise` for estimation of underlying Levy in the carma model.

Author(s)

The YUIMA Project Team

References

Brockwell, P., Davis, A. R. and Yang. Y. (2011) Estimation for Non-Negative Levy-Driven CARMA Process, *Journal of Business And Economic Statistics*, **29** - 2, 250-259.

Examples

```
## Not run:
#Ex.1: Carma(p=3, q=0) process driven by a brownian motion.

mod0<-setCarma(p=3,q=0)

# We fix the autoregressive and moving average parameters
# to ensure the existence of a second order stationary solution for the process.

true.parm0 <-list(a1=4,a2=4.75,a3=1.5,b0=1)

# We simulate a trajectory of the Carma model.

numb.sim<-1000
samp0<-setSampling(Terminal=100,n=numb.sim)
set.seed(100)
incr.W<-matrix(rnorm(n=numb.sim,mean=0,sd=sqrt(100/numb.sim)),1,numb.sim)

sim0<-simulate(mod0,
               true.parameter=true.parm0,
               sampling=samp0, increment.W=incr.W)

#Applying the CarmaNoise

system.time(
  inc.Levy0<-CarmaNoise(sim0,true.parm0)
)

# We compare the orginal with the estimated noise increments

par(mfrow=c(1,2))
plot(t(incr.W)[1:998],type="l", ylab="",xlab="time")
title(main="True Brownian Motion",font.main="1")
plot(inc.Levy0,type="l", main="Filtered Brownian Motion",font.main="1",ylab="",xlab="time")

# Ex.2: carma(2,1) driven  by a compound poisson
# where jump size is normally distributed and
# the lambda is equal to 1.

mod1<-setCarma(p=2,
               q=1,
               measure=list(intensity="Lamb",df=list("dnorm(z, 0, 1)")),
               measure.type="CP")

true.parm1 <-list(a1=1.39631, a2=0.05029,
                  b0=1,b1=2,
                  Lamb=1)
```

```
# We generate a sample path.

samp1<-setSampling(Terminal=100,n=200)
set.seed(123)
sim1<-simulate(mod1,
               true.parameter=true.parm1,
               sampling=samp1)

# We estimate the parameter using qmle.
carmaopt1 <- qmle(sim1, start=true.parm1)
summary(carmaopt1)
# Internally qmle uses CarmaNoise. The result is in
plot(carmaopt1)

# Ex.3: Carma(p=2,q=1) with scale and location parameters
# driven by a Compound Poisson
# with jump size normally distributed.
mod2<-setCarma(p=2,
               q=1,
               loc.par="mu",
               scale.par="sig",
               measure=list(intensity="Lamb",df=list("dnorm(z, 0, 1)")),
               measure.type="CP")

true.parm2 <-list(a1=1.39631,
                  a2=0.05029,
                  b0=1,
                  b1=2,
                  Lamb=1,
                  mu=0.5,
                  sig=0.23)
# We simulate the sample path
set.seed(123)
sim2<-simulate(mod2,
               true.parameter=true.parm2,
               sampling=samp1)

# We estimate the Carma and we plot the underlying noise.

carmaopt2 <- qmle(sim2, start=true.parm2)
summary(carmaopt2)

# Increments estimated by CarmaNoise
plot(carmaopt2)

## End(Not run)
```

---

cce *Nonsynchronous Cumulative Covariance Estimator*

Description

This function estimates the covariance between two Ito processes when they are observed at discrete times possibly nonsynchronously. It can apply to irregularly sampled one-dimensional data as a special case.

Usage

```
cce(x, method="HY", theta, kn, g=function(x)min(x,1-x), refreshing = TRUE,
    cwise = TRUE, delta = 0, adj = TRUE, K, c.two, J = 1, c.multi, kernel, H,
    c.RK, eta = 3/5, m = 2, ftregion = 0, vol.init = NA,
    covol.init = NA, nvar.init = NA, ncov.init = NA, mn, alpha = 0.4,
    frequency = 300, avg = TRUE, threshold, utime, psd = FALSE)
```

Arguments

x	an object of yuima-class or yuima.data-class.
method	the method to be used. See 'Details'.
theta	a numeric vector or matrix. If it is a matrix, each of its components indicates the tuning parameter which determines the pre-averaging window lengths kn to be used for estimating the corresponding component. If it is a numeric vector, it is converted to a matrix as (C+t(C))/2, where C=matrix(theta,d,d) and d=dim(x). The default value is 0.15 for the method "PHY" or "PTHY" following Christensen et al. (2013), while it is 1 for the method "MRC" following Christensen et al. (2010).
kn	an integer-valued vector or matrix indicating the pre-averaging window length(s). For the methods "PHY" or "PTHY", see 'Details' for the default value. For the method "MRC", the default value is ceiling(theta*n^(1+delta)), where n is the number of the refresh times associated with the data minus 1.
g	a function indicating the weight function to be used. The default value is the Bartlett window: function(x)min(x,1-x).
refreshing	logical. If TRUE, the data is pre-synchronized by the next-tick interpolation in the refresh times.
cwise	logical. If TRUE, the estimator is calculated componentwise.
delta	a non-negative number indicating the order of the pre-averaging window length(s) kn.
adj	logical. If TRUE, a finite-sample adjustment is performed. For the method "MRC", see Christensen et al. (2010) for details. For the method "TSCV", see Zhang (2011) and Zhang et al. (2005) for details.
K	a positive integer indicating the large time-scale parameter. The default value is ceiling(c.two*n^(2/3)), where n is the number of the refresh times associated with the data minus 1.
c.two	a positive number indicating the tuning parameter which determines the scale of the large time-scale parameter K. The default value is the average of the numeric vector each of whose components is the roughly estimated optimal value in the sense of the minimizer of the theoretical asymptotic variance of the estimator of

the corresponding diagonal component. The theoretical asymptotic variance is considered in the standard case and given by Eq.(63) of Zhang et al. (2005).

`J` a positive integer indicating the small time-scale parameter.

`c.multi` a numeric vector or matrix. If it is a matrix, each of its components indicates the tuning parameter which determines (the scale of) the number of the time scales to be used for estimating the corresponding component. If it is a numeric vector, it is converted to a matrix as `(C+t(C))/2`, where `C=matrix(c.multi,d,d)` and `d=dim(x)`. The default value is the numeric vector each of whose components is the roughly estimated optimal value in the sense of minimizing the theoretical asymptotic variance of the estimator of the corresponding diagonal component. The theoretical asymptotic variance is considered in the standard case and given by Eq.(37) of Zhang (2006).

`kernel` a function indicating the kernel function to be used. The default value is the Parzan kernel, which is recommended in Barndorff-Nielsen et al. (2009, 2011).

`H` a positive number indicating the bandwidth parameter. The default value is `c.RK*n^eta`, where `n` is the number of the refresh times associated with the data minus 1.

`c.RK` a positive number indicating the tuning parameter which determines the scale of the bandwidth parameter `H`. The default value is the average of the numeric vector each of whose components is the roughly estimated optimal value in the sense of minimizing the theoretical asymptotic variance of the estimator of the corresponding diagonal component. The theoretical asymptotic variance is considered in the standard case and given in Barndorff-Nielsen et al. (2009, 2011).

`eta` a positive number indicating the tuning parameter which determines the order of the bandwidth parameter `H`.

`m` a positive integer indicating the number of the end points to be jittered.

`ftregion` a non-negative number indicating the length of the flat-top region. `ftregion=0` (the default) means that a non-flat-top realized kernel studied in Barndorff-Nielsen et al. (2011) is used. `ftregion=1/H` means that a flat-top realized kernel studied in Barndorff-Nielsen et al. (2008) is used. See Varneskov (2015) for other values.

`vol.init` a numeric vector each of whose components indicates the initial value to be used to estimate the integrated volatility of the corresponding component, which is passed to the optimizer.

`covol.init` a numeric matrix each of whose columns indicates the initial value to be used to estimate the integrated covariance of the corresponding component, which is passed to the optimizer.

`nvar.init` a numeric vector each of whose components indicates the initial value to be used to estimate the variance of noise of the corresponding component, which is passed to the optimizer.

`ncov.init` a numeric matrix each of whose columns indicates the initial value to be used to estimate the covariance of noise of the corresponding component, which is passed to the optimizer.

`mn` a positive integer indicating the number of terms to be used for calculating the SIML estimator. The default value is `ceiling(n^alpha)`, where `n` is the number of the refresh times associated with the data minus 1.

alpha	a postive number indicating the order of mn.
frequency	a positive integer indicating the frequency (seconds) of the calendar time sampling to be used.
avg	logical. If TRUE, the averaged subsampling estimator is calculated. Otherwise the simple sparsely subsampled estimator is calculated.
threshold	a numeric vector or list indicating the threshold parameter(s). Each of its components indicates the threshold parameter or process to be used for estimating the corresponding component. If it is a numeric vector, the elements in threshold are recycled if there are two few elements in threshold. The default value is determined following Koike (2014) (for the method "THY") and Koike (2015) (for the method "PTHY").
utime	a positive number indicating what seconds the interval [0,1] corresponds to. The default value is the difference between the maximum and the minimum of the sampling times, multiplied by 23,400. Here, 23,400 seconds correspond to 6.5 hours, hence if the data is sampled on the interval [0,1], then the sampling interval is regarded as 6.5 hours.
psd	logical. If TRUE, the estimated covariance matrix C is converted to (C%*%C)^(1/2) for ensuring the positive semi-definiteness. In this case the absolute values of the estimated correlations are always ensured to be less than or equal to 1.

Details

This function is a method for objects of yuima.data-class and yuima-class. It extracts the data slot when applied to a an object of yuima-class.

Typical usages are

```
cce(x,psd=FALSE)
cce(x,method="PHY",theta,kn,g,refreshing=TRUE,cwise=TRUE,psd=FALSE)
cce(x,method="MRC",theta,kn,g,delta=0,avg=TRUE,psd=FALSE)
cce(x,method="TSCV",K,c.two,J=1,adj=TRUE,utime,psd=FALSE)
cce(x,method="GME",c.multi,utime,psd=FALSE)
cce(x,method="RK",kernel,H,c.RK,eta=3/5,m=2,ftregion=0,utime,psd=FALSE)
cce(x,method="QMLE",vol.init=NULL,covol.init=NULL,
    nvar.init=NULL,ncov.init=NULL,psd=FALSE)
cce(x,method="SIML",mn,alpha=0.4,psd=FALSE)
cce(x,method="THY",threshold,psd=FALSE)
cce(x,method="PTHY",theta,kn,g,threshold,refreshing=TRUE,cwise=TRUE,psd=FALSE)
cce(x,method="SRC",frequency=300,avg=TRUE,utime,psd=FALSE)
cce(x,method="SBPC",frequency=300,avg=TRUE,utime,psd=FALSE)
```

The default method is method "HY", which is an implementation of the Hayashi-Yoshida estimator proposed in Hayashi and Yoshida (2005).

Method "PHY" is an implementation of the Pre-averaged Hayashi-Yoshida estimator proposed in Christensen et al. (2010).

Method "MRC" is an implementation of the Modulated Realized Covariance based on refresh time

sampling proposed in Christensen et al. (2010).

Method "TSCV" is an implementation of the previous tick Two Scales realized CoVariance based on refresh time sampling proposed in Zhang (2011).

Method "GME" is an implementation of the Generalized Multiscale Estimator proposed in Bibinger (2011).

Method "RK" is an implementation of the multivariate Realized Kernel based on refresh time sampling proposed in Barndorff-Nielsen et al. (2011).

Method "QMLE" is an implementation of the nonparametric Quasi Maximum Likelihood Estimator proposed in Ait-Sahalia et al. (2010).

Method "SIML" is an implementation of the Separating Information Maximum Likelihood estimator proposed in Kunitomo and Sato (2013) with the basis of refresh time sampling.

Method "THY" is an implementation of the Truncated Hayashi-Yoshida estimator proposed in Mancini and Gobbi (2012).

Method "PTHY" is an implementation of the Pre-averaged Truncated Hayashi-Yoshida estimator, which is a thresholding version of the pre-averaged Hayashi-Yoshida estimator.

Method "SRC" is an implementation of the calendar time Subsampled Realized Covariance.

Method "SBPC" is an implementation of the calendar time Subsampled realized BiPower Covariation.

The rough estimation procedures for selecting the default values of the tuning parameters are based on those in Barndorff-Nielsen et al. (2009).

For the methods "PHY" or "PTHY", the default value of kn changes depending on the values of refreshing and cwise. If both refreshing and cwise are TRUE (the default), the default value of kn is given by the matrix ceiling(theta*N), where N is a matrix whose diagonal components are identical with the vector length(x)-1 and whose (i, j)-th component is identical with the number of the refresh times associated with i-th and j-th components of x minus 1. If refreshing is TRUE while cwise is FALSE, the default value of kn is given by ceiling(mean(theta)*sqrt(n)), where n is the number of the refresh times associated with the data minus 1. If refreshing is FALSE while cwise is TRUE, the default value of kn is given by the matrix ceiling(theta*N0), where N0 is a matrix whose diagonal components are identical with the vector length(x)-1 and whose (i, j)-th component is identical with (length(x)[i]-1)+(length(x)[j]-1). If both refreshing and cwise are FALSE, the default value of kn is given by ceiling(mean(theta)*sqrt(sum(length(x)-1))) (following Christensen et al. (2013)).

For the method "QMLE", the optimization of the quasi-likelihood function is implemented via arima0 using the fact that it can be seen as an MA(1) model's one: See Hansen et al. (2008) for details.

Value

A list with components:

covmat	the estimated covariance matrix
cormat	the estimated correlation matrix

Note

The example shows the central limit theorem for the nonsynchronous covariance estimator.

Estimation of the asymptotic variance can be implemented by hyavar. The second-order correction will be provided in a future version of the package.

Author(s)

Yuta Koike with YUIMA Project Team

References

Ait-Sahalia, Y., Fan, J. and Xiu, D. (2010) High-frequency covariance estimates with noisy and asynchronous financial data, *Journal of the American Statistical Association*, **105**, no. 492, 1504–1517.

Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A. and Shephard, N. (2008) Designing realised kernels to measure the ex-post variation of equity prices in the presence of noise, *Econometrica*, **76**, no. 6, 1481–1536.

Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A. and Shephard, N. (2009) Realized kernels in practice: trades and quotes, *Econometrics Journal*, **12**, C1–C32.

Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A. and Shephard, N. (2011) Multivariate realised kernels: Consistent positive semi-definite estimators of the covariation of equity prices with noise and non-synchronous trading, *Journal of Econometrics*, **162**, 149–169.

Bibinger, M. (2011) Efficient covariance estimation for asynchronous noisy high-frequency data, *Scandinavian Journal of Statistics*, **38**, 23–45.

Bibinger, M. (2012) An estimator for the quadratic covariation of asynchronously observed Ito processes with noise: asymptotic distribution theory, *Stochastic processes and their applications*, **122**, 2411–2453.

Christensen, K., Kinnebrock, S. and Podolskij, M. (2010) Pre-averaging estimators of the ex-post covariance matrix in noisy diffusion models with non-synchronous data, *Journal of Econometrics*, **159**, 116–133.

Christensen, K., Podolskij, M. and Vetter, M. (2013) On covariation estimation for multivariate continuous Ito semimartingales with noise in non-synchronous observation schemes, *Journal of Multivariate Analysis* **120** 59–84.

Hansen, P. R., Large, J. and Lunde, A. (2008) Moving average-based estimators of integrated variance, *Econometric Reviews*, **27**, 79–111.

Hayashi, T. and Yoshida, N. (2005) On covariance estimation of non-synchronously observed diffusion processes, *Bernoulli*, **11**, no. 2, 359–379.

Hayashi, T. and Yoshida, N. (2008) Asymptotic normality of a covariance estimator for nonsynchronously observed diffusion processes, *Annals of the Institute of Statistical Mathematics*, **60**, no. 2, 367–406.

Koike, Y. (2016) Estimation of integrated covariances in the simultaneous presence of nonsynchronicity, microstructure noise and jumps, *Econometric Theory*, **32**, 533–611.

Koike, Y. (2014) An estimator for the cumulative co-volatility of asynchronously observed semimartingales with jumps, *Scandinavian Journal of Statistics*, **41**, 460–481.

Kunitomo, N. and Sato, S. (2013) Separating information maximum likelihood estimation of realized volatility and covariance with micro-market noise, *North American Journal of Economics and Finance*, **26**, 282–309.

Mancini, C. and Gobbi, F. (2012) Identifying the Brownian covariation from the co-jumps given discrete observations, *Econometric Theory*, **28**, 249–273.

Varneskov, R. T. (2016) Flat-top realized kernel estimation of quadratic covariation with nonsynchronous and noisy asset prices, *Journal of Business & Economic Statistics*, **34**, no.1, 1–22.

Zhang, L. (2006) Efficient estimation of stochastic volatility using noisy observations: a multi-scale approach, *Bernoulli*, **12**, no.6, 1019–1043.

Zhang, L. (2011) Estimating covariation: Epps effect, microstructure noise, *Journal of Econometrics*, **160**, 33–47.

Zhang, L., Mykland, P. A. and Ait-Sahalia, Y. (2005) A tale of two time scales: Determining integrated volatility with noisy high-frequency data, *Journal of the American Statistical Association*, **100**, no. 472, 1394–1411.

See Also

`setModel`, `setData`, `hyavar`, `lmm`, `cce.factor`

Examples

```
## Not run:
## Set a model
diff.coef.1 <- function(t, x1 = 0, x2 = 0) sqrt(1+t)
diff.coef.2 <- function(t, x1 = 0, x2 = 0) sqrt(1+t^2)
cor.rho <- function(t, x1 = 0, x2 = 0) sqrt(1/2)
diff.coef.matrix <- matrix(c("diff.coef.1(t,x1,x2)",
"diff.coef.2(t,x1,x2) * cor.rho(t,x1,x2)",
"", "diff.coef.2(t,x1,x2) * sqrt(1-cor.rho(t,x1,x2)^2)"), 2, 2)
cor.mod <- setModel(drift = c("", ""),
diffusion = diff.coef.matrix,solve.variable = c("x1", "x2"))

set.seed(111)

## We use a function poisson.random.sampling to get observation by Poisson sampling.
yuima.samp <- setSampling(Terminal = 1, n = 1200)
yuima <- setYuima(model = cor.mod, sampling = yuima.samp)
yuima <- simulate(yuima)
psample<- poisson.random.sampling(yuima, rate = c(0.2,0.3), n = 1000)

## cce takes the psample and returns an estimate of the quadratic covariation.
```

```
cce(psample)$covmat[1, 2]
##cce(psample)[1, 2]

## True value of the quadratic covariation.
cc.theta <- function(T, sigma1, sigma2, rho) {
  tmp <- function(t) return(sigma1(t) * sigma2(t) * rho(t))
integrate(tmp, 0, T)
}

theta <- cc.theta(T = 1, diff.coef.1, diff.coef.2, cor.rho)$value
cat(sprintf("theta =%.5f\n", theta))

names(psample@zoo.data)




# Example. A stochastic differential equation with nonlinear feedback.

## Set a model
drift.coef.1 <- function(x1,x2) x2
drift.coef.2 <- function(x1,x2) -x1
drift.coef.vector <- c("drift.coef.1","drift.coef.2")
diff.coef.1 <- function(t,x1,x2) sqrt(abs(x1))*sqrt(1+t)
diff.coef.2 <- function(t,x1,x2) sqrt(abs(x2))
cor.rho <- function(t,x1,x2) 1/(1+x1^2)
diff.coef.matrix <- matrix(c("diff.coef.1(t,x1,x2)",
"diff.coef.2(t,x1,x2) * cor.rho(t,x1,x2)","",
"diff.coef.2(t,x1,x2) * sqrt(1-cor.rho(t,x1,x2)^2)"), 2, 2)
cor.mod <- setModel(drift = drift.coef.vector,
 diffusion = diff.coef.matrix,solve.variable = c("x1", "x2"))

## Generate a path of the process
set.seed(111)
yuima.samp <- setSampling(Terminal = 1, n = 10000)
yuima <- setYuima(model = cor.mod, sampling = yuima.samp)
yuima <- simulate(yuima, xinit=c(2,3))
plot(yuima)


## The "true" value of the quadratic covariation.
cce(yuima)

## We use the function poisson.random.sampling to generate nonsynchronous
## observations by Poisson sampling.
psample<- poisson.random.sampling(yuima, rate = c(0.2,0.3), n = 3000)

## cce takes the psample to return an estimated value  of the quadratic covariation.
## The off-diagonal elements are the value of the Hayashi-Yoshida estimator.
cce(psample)
```

```
# Example. Epps effect for the realized covariance estimator

## Set a model
drift <- c(0,0)

sigma1 <- 1
sigma2 <- 1
rho <- 0.5

diffusion <- matrix(c(sigma1,sigma2*rho,0,sigma2*sqrt(1-rho^2)),2,2)

model <- setModel(drift=drift,diffusion=diffusion,
                  state.variable=c("x1","x2"),solve.variable=c("x1","x2"))

## Generate a path of the latent process
set.seed(116)

## We regard the unit interval as 6.5 hours and generate the path on it
## with the step size equal to 2 seconds

yuima.samp <- setSampling(Terminal = 1, n = 11700)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(yuima)

## We extract nonsynchronous observations from the path generated above
## by Poisson random sampling with the average duration equal to 10 seconds

psample <- poisson.random.sampling(yuima, rate = c(1/5,1/5), n = 11700)

## Hayashi-Yoshida estimator consistetly estimates the true correlation
cce(psample)$cormat[1,2]

## If we synchronize the observation data on some regular grid
## by previous-tick interpolations and compute the correlation
## by therealized covariance based on such synchronized observations,
## we underestimate the true correlation (known as the Epps effect).
## This is illustrated by the following examples.

## Synchronization on the grid with 5 seconds steps
suppressWarnings(s1 <- cce(subsampling(psample, sampling = setSampling(n = 4680)))$cormat[1,2])
s1

## Synchronization on the grid with 10 seconds steps
suppressWarnings(s2 <- cce(subsampling(psample, sampling = setSampling(n = 2340)))$cormat[1,2])
s2

## Synchronization on the grid with 20 seconds steps
suppressWarnings(s3 <- cce(subsampling(psample, sampling = setSampling(n = 1170)))$cormat[1,2])
s3
```

```
## Synchronization on the grid with 30 seconds steps
suppressWarnings(s4 <- cce(subsampling(psample, sampling = setSampling(n = 780)))$cormat[1,2])
s4

## Synchronization on the grid with 1 minute steps
suppressWarnings(s5 <- cce(subsampling(psample, sampling = setSampling(n = 390)))$cormat[1,2])
s5

plot(zoo(c(s1,s2,s3,s4,s5),c(5,10,20,30,60)),type="b",xlab="seconds",ylab="correlation",
main = "Epps effect for the realized covariance")



# Example. Non-synchronous and noisy observations of a correlated bivariate Brownian motion

## Generate noisy observations from the model used in the previous example
Omega <- 0.005*matrix(c(1,rho,rho,1),2,2) # covariance matrix of noise
noisy.psample <- noisy.sampling(psample,var.adj=Omega)
plot(noisy.psample)

## Hayashi-Yoshida estimator: inconsistent
cce(noisy.psample)$covmat

## Pre-averaged Hayashi-Yoshida estimator: consistent
cce(noisy.psample,method="PHY")$covmat

## Generalized multiscale estimator: consistent
cce(noisy.psample,method="GME")$covmat

## Multivariate realized kernel: consistent
cce(noisy.psample,method="RK")$covmat

## Nonparametric QMLE: consistent
cce(noisy.psample,method="QMLE")$covmat

## End(Not run)
```

`cce.factor` *High-Dimensional Cumulative Covariance Estimator by Factor Modeling and Regularization*

Description

This function estimates the covariance and precision matrices of a high-dimesnional Ito process by factor modeling and regularization when it is observed at discrete times possibly nonsynchronously with noise.

Usage

```
cce.factor(yuima, method = "HY", factor = NULL, PCA = FALSE,
```

```
nfactor = "interactive", regularize = "glasso", taper,
group = 1:(dim(yuima) - length(factor)), lambda = "bic",
weight = TRUE, nlambda = 10, ratio, N, thr.type = "soft",
thr = NULL, tau = NULL, par.alasso = 1, par.scad = 3.7,
thr.delta = 0.01, frequency = 300, utime, ...)
```

Arguments

yuima	an object of yuima-class or yuima.data-class.
method	the method to be used in cce.
factor	an integer or character vector indicating which components of yuima are factors. If NULL, no factor structure is taken account of.
PCA	logical. If TRUE, a principal component analysis is performed to construct factors.
nfactor	the number of factors constructed when PCA is TRUE. If nfactor = "interactive", the scree plot of the principal component analysis is depicted and the user can set this argument interactively.
regularize	the regularizaton method to be used. Possible choices are "glasso" (the default), "tapering", "thresholding" and "eigen.cleaning". See 'Details'.
taper	the tapering matrix used when regularize = "tapering". If missing, the tapering matrix is constructed according to group. See 'Details'.
group	an integer vector having the length equal to dim(yuima)-length(factor).
lambda	the penalty parameter used when regularize = "glasso". If it is "aic" (resp. "bic"), it is selected by minimizing the formally defined AIC (resp. BIC). See 'Details'.
weight	logical. If TRUE, a weighted version is used for regularize = "glasso" as in Koike (2020).
nlambda	a positive integer indicating the number of candidate penalty parameters for which AIC or BIC is evaluated when lambda is "aic" or "bic".
ratio	a positive number indicating the ratio of the largest and smallest values in candidate penalty parameters for which AIC or BIC is evaluated when lambda is "aic" or "bic". See 'Details'. The default value is sqrt(log(d)/N), where d is the dimension of yuima.
N	a positive integer indicating the "effective" sampling size, which is necessary to evealuate AIC and BIC when lambda is "aic" or "bic". In a standard situation, it is equal to the sample size $-$ 1, but it might be different when the data are observed nonsynchronously and/or with noise. If missing, it is automatically determined according to method.
thr.type	a character string indicating the type of the thresholding method used when regularize = "thresholding". Possible choices are "hard", "soft", "alasso" and "scad". See Section 2.3 of Dai et al. (2019) for the definition of each method.
thr	a numeric matrix indicating the threshold levels used when regularize = "thresholding". Its entries indicate the threshold levels for the corresponding entries of the covariance matrix (values for λ in the notation of Dai et al. (2019)). A single

	number is converted to the matrix with common entries equal to that number. If NULL, it is determined according to tau. See 'Details'.
tau	a number between 0 and 1 used to determine the threshold levels used when regularize = "thresholding" and thr=NULL (a value for τ in the notation of Dai et al. (2019)). If NULL, it is determined by a grid search procedure as suggested in Section 4.3 of Dai et al. (2019). See 'Details'.
par.alasso	the tuning parameter for thr.type = "alasso" (a value for η in the notation of Dai et al. (2019)).
par.scad	the tuning parameter for thr.type = "scad" (a value for a in the notation of Dai et al. (2019)).
thr.delta	a positive number indicating the step size used in the grid serach procedure to determine tau.
frequency	passed to cce.
utime	passed to cce.
...	passed to cce.

Details

One basic approach to estimate the covariance matrix of high-dimensional time series is to take account of the factor structure and perform regularization for the residual covariance matrix. This function implements such an estimation procedure for high-frequency data modeled as a discretely observed semimartingale. Specifically, let Y be a d-dimensional semimartingale which describes the dynamics of the observation data. We consider the following continuous-time factor model:

$$Y_t = \beta X_t + Z_t, 0 \leq t \leq T,$$

where X is an r-dimensional semimartingale (the factor process), Z is a d-dimensional semimartingale (the residual process), and β is a constant $d \times r$ matrix (the factor loading matrix). We assume that X and Z are orthogonal in the sense that $[X, Z]_T = 0$. Then, the quadratic covariation matrix of Y is given by

$$[Y, Y]_T = \beta [X, X]_T \beta^\top + [Z, Z]_T.$$

Also, β can be written as $\beta = [Y, X]_T [X, X]_T^{-1}$. Thus, if we have observation data both for Y and X, we can construct estimators for $[Y, Y]_T$, $[X, X]_T$ and β by cce. Moreover, plugging these estimators into the above equation, we can also construct an estimator for $[Z, Z]_T$. Since this estimator is often poor due to the high-dimensionality, we regularize it by some method. Then, by plugging the regularized estimator for $[Z, Z]_T$ into the above equation, we obtain the final estimator for $[Y, Y]_T$.

Even if we do not have observation data for X, we can (at least formally) construct a pseudo factor process by performing principal component analysis for the initial estimator of $[Y, Y]_T$. See Ait-Sahalia and Xiu (2017) and Dai et al. (2019) for details.

Currently, the following four options are available for the regularization method applied to the residual covariance matrix estimate:

1. regularize = "glasso" (the default).
   This performs the glaphical Lasso. When weight=TRUE (the default), a weighted version of the graphical Lasso is performed as in Koike (2020). Otherwise, the standard graphical Lasso is performed as in Brownlees et al. (2018).

If `lambda="aic"` (resp.~`lambda="bic"`), the penalty parameter for the graphical Lasso is selected by minimizing the formally defined AIC (resp.~BIC). The minimization is carried out by grid search, where the grid is determined as in Section 5.1 of Koike (2020).

The optimization problem in the graphical Lasso is solved by the GLASSOFAST algorithm of Sustik and Calderhead (2012), which is available from the package **glassoFast**.

2. `regularize = "tapering"`.

   This performs tapering, i.e. taking the entry-wise product of the residual covariance matrix estimate and a tapering matrix specified by `taper`. See Section 3.5.1 of Pourahmadi (2011) for an overview of this method.

   If `taper` is missing, it is constructed according to `group` as follows: `taper` is a 0-1 matrix and the (i, j)-th entry is equal to 1 if and only if `group[i]==group[j]`. Thus, by default it makes the residual covariance matrix diagonal.

3. `regularize = "thresholding"`.

   This performs thresholding, i.e. entries of the residual covariance matrix are shrunk toward 0 according to a thresholding rule (specified by `thr.type`) and a threshold level (spencified by `thr`).

   If `thr=NULL`, the (i, j)-th entry of `thr` is given by $\tau\sqrt{[\hat{Z^i, Z^i}]_T[\hat{Z^j, Z^j}]_T}$, where $[\hat{Z^i, Z^i}]_T$ (resp. $[\hat{Z^j, Z^j}]_T$) denotes the i-th (resp. j-th) diagonal entry of the non-regularized estimator for the residual covariance matrix $[Z, Z]_T$, and τ is a tuning parameter specified by `tau`.

   When `tau=NULL`, the value of τ is set to the smallest value in the grid with step size `thr.delta` such that the regularized estimate of the residual covariance matrix becomes positive definite.

4. `regularize = "eigen.cleaning"`.

   This performs the eigenvalue cleaning algorithm described in Hautsch et al. (2012).

Value

A list with components:

`covmat.y`	the estimated covariance matrix
`premat.y`	the estimated precision matrix
`beta.hat`	the estimated factor loading matrix
`covmat.x`	the estimated factor covariance matrix
`covmat.z`	the estimated residual covariance matrix
`premat.z`	the estimated residual precision matrix
`sigma.z`	the estimated residual covariance matrix before regularization
`pc`	the variances of the principal components (it is `NULL` if `PCA = FALSE`)

Author(s)

Yuta Koike with YUIMA project Team

References

Ait-Sahalia, Y. and Xiu, D. (2017). Using principal component analysis to estimate a high dimensional factor model with high-frequency data, *Journal of Econometrics*, **201**, 384–399.

Brownlees, C., Nualart, E. and Sun, Y. (2018). Realized networks, *Journal of Applied Econometrics*, **33**, 986–1006.

Dai, C., Lu, K. and Xiu, D. (2019). Knowing factors or factor loadings, or neither? Evaluating estimators of large covariance matrices with noisy and asynchronous data, *Journal of Econometrics*, **208**, 43–79.

Hautsch, N., Kyj, L. M. and Oomen, R. C. (2012). A blocking and regularization approach to high-dimensional realized covariance estimation, *Journal of Applied Econometrics*, **27**, 625–645.

Koike, Y. (2020). De-biased graphical Lasso for high-frequency data, *Entropy*, **22**, 456.

Pourahmadi, M. (2011). Covariance estimation: The GLM and regularization perspectives. *Statistical Science*, **26**, 369–387.

Sustik, M. A. and Calderhead, B. (2012). GLASSOFAST: An efficient GLASSO implementation, UTCSTechnical Report TR-12-29, The University of Texas at Austin.

See Also

cce, lmm, glassoFast

Examples

```
## Not run:
set.seed(123)

## Simulating a factor process (Heston model)
drift <- c("mu*S", "-theta*(V-v)")
diffusion <- matrix(c("sqrt(max(V,0))*S", "gamma*sqrt(max(V,0))*rho",
                      0, "gamma*sqrt(max(V,0))*sqrt(1-rho^2)"),
                    2,2)
mod <- setModel(drift = drift, diffusion = diffusion,
                state.variable = c("S", "V"))
n <- 2340
samp <- setSampling(n = n)
heston <- setYuima(model = mod, sampling = samp)
param <- list(mu = 0.03, theta = 3, v = 0.09,
              gamma = 0.3, rho = -0.6)
result <- simulate(heston, xinit = c(1, 0.1),
                   true.parameter = param)

zdata <- get.zoo.data(result) # extract the zoo data
X <- log(zdata[[1]]) # log-price process
V <- zdata[[2]] # squared volatility process


## Simulating a residual process (correlated BM)
d <- 100 # dimension
Q <- 0.1 * toeplitz(0.7^(1:d-1)) # residual covariance matrix
dZ <- matrix(rnorm(n*d),n,d) %*% chol(Q)/sqrt(n)
```

```
Z <- zoo(apply(dZ, 2, "diffinv"), samp@grid[[1]])


## Constructing observation data
b <- runif(d, 0.25, 2.25) # factor loadings
Y <- X %o% b + Z
yuima <- setData(cbind(X, Y))

# We subsample yuima to construct observation data
yuima <- subsampling(yuima, setSampling(n = 78))


## Estimating the covariance matrix (factor is known)
cmat <- tcrossprod(b) * mean(V[-1]) + Q # true covariance matrix
pmat <- solve(cmat) # true precision matrix

# (1) Regularization method is glasso (the default)
est <- cce.factor(yuima, factor = 1)
norm(est$covmat.y - cmat, type = "2")
norm(est$premat.y - pmat, type = "2")

# (2) Regularization method is tapering
est <- cce.factor(yuima, factor = 1, regularize = "tapering")
norm(est$covmat.y - cmat, type = "2")
norm(est$premat.y - pmat, type = "2")

# (3) Regularization method is thresholding
est <- cce.factor(yuima, factor = 1, regularize = "thresholding")
norm(est$covmat.y - cmat, type = "2")
norm(est$premat.y - pmat, type = "2")

# (4) Regularization method is eigen.cleaning
est <- cce.factor(yuima, factor = 1, regularize = "eigen.cleaning")
norm(est$covmat.y - cmat, type = "2")
norm(est$premat.y - pmat, type = "2")


## Estimating the covariance matrix (factor is unknown)
yuima2 <- setData(Y)

# We subsample yuima to construct observation data
yuima2 <- subsampling(yuima2, setSampling(n = 78))

# (A) Ignoring the factor structure (regularize = "glasso")
est <- cce.factor(yuima2)
norm(est$covmat.y - cmat, type = "2")
norm(est$premat.y - pmat, type = "2")

# (B) Estimating the factor by PCA (regularize = "glasso")
est <- cce.factor(yuima2, PCA = TRUE, nfactor = 1) # use 1 factor
norm(est$covmat.y - cmat, type = "2")
norm(est$premat.y - pmat, type = "2")
```

```
# One can interactively select the number of factors
# after implementing PCA (the scree plot is depicted)
# Try: est <- cce.factor(yuima2, PCA = TRUE)

## End(Not run)
```

Class for Quasi Maximum Likelihood Estimation of Point Process Regression Models

Class for Quasi Maximum Likelihood Estimation of Point Process Regression Models

---

Description

The `yuima.PPR.qmle` class is a class of the **yuima** package that extends the `mle-class` of the **stats4** package.

Slots

`call`: is an object of class `language`.

`coef`: is an object of class `numeric` that contains estimated parameters.

`fullcoef`: is an object of class `numeric` that contains estimated and fixed parameters.

`vcov`: is an object of class `matrix`.

`min`: is an object of class `numeric`.

`minuslogl`: is an object of class `function`.

`method`: is an object of class `character`.

`model`: is an object of class `yuima.PPR-class`.

Methods

Methods mle All methods for `mle-class` are available.

Author(s)

The YUIMA Project Team

cogarch.est.-class *Class for Generalized Method of Moments Estimation for COGARCH(p,q) model*

Description

The cogarch.est class is a class of the **yuima** package that contains estimated parameters obtained by the function gmm or qmle.

Slots

yuima: is an object of of yuima-class.

objFun: is an object of class character that indicates the objective function used in the minimization problem. See the documentation of the function gmm or qmle for more details.

call: is an object of class language.

coef: is an object of class numeric that contains estimated parameters.

fullcoef: is an object of class numeric that contains estimated and fixed parameters.

vcov: is an object of class matrix.

min: is an object of class numeric.

minuslogl: is an object of class function.

method: is an object of class character.

Methods

Methods mle All methods for mle-class are available.

Author(s)

The YUIMA Project Team

cogarch.est.incr-class *Class for Estimation of COGARCH(p,q) model with underlying increments*

Description

The cogarch.est.incr class is a class of the **yuima** package that extends the cogarch.est-class and is filled by the function gmm or qmle.

Slots

`Incr.Lev`: is an object of class `zoo` that contains the estimated increments of the noise obtained using `cogarchNoise`.

`yuima`: is an object of of `yuima-class`.

`logL.Incr`: is an object of class `numeric` that contains the value of the log-likelihood for estimated Levy increments.

`objFun`: is an object of class `character` that indicates the objective function used in the minimization problem. See the documentation of the function `gmm` or `qmle` for more details.

`call`: is an object of class `language`.

`coef`: is an object of class `numeric` that contains estimated parameters.

`fullcoef`: is an object of class `numeric` that contains estimated and fixed parameters.

`vcov`: is an object of class `matrix`.

`min`: is an object of class `numeric`.

`minuslogl`: is an object of class `function`.

`method`: is an object of class `character`.

Methods

simulate simulation method. For more information see `simulate`.

plot Plot method for estimated increment of the noise.

Methods mle All methods for `mle-class` are available.

Author(s)

The YUIMA Project Team

`cogarch.info-class` *Class for information about CoGarch(p,q)*

Description

The `cogarch.info-class` is a class of the **yuima** package

Slots

`p`: Number of autoregressive coefficients in the variance process.

`q`: Number of moving average coefficients in the variance process.

`ar.par`: Label of autoregressive coefficients.

`ma.par`: Label of moving average coefficients.

`loc.par`: Label of location coefficient in the variance process.

`Cogarch.var`: Label of the observed process.

`V.var`: Label of the variance process.

`Latent.var`: Label of the latent process in the state representation of the variance.

`XinExpr`: Logical variable. If `XinExpr=FALSE`, the starting condition of `Latent.var` is zero otherwise each component of Latent.var has a parameter as a starting point.

`measure`: Levy measure for jump and quadratic part.

`measure.type`: Type specification for Levy measure.

Note

The `cogarch.info-class` object cannot be directly specified by the user but it is built when the `yuima.cogarch-class` object is constructed via `setCogarch`.

Author(s)

The YUIMA Project Team

`cogarchNoise` *Estimation for the underlying Levy in a COGARCH(p,q) model*

Description

Retrieve the increment of the underlying Levy for the COGARCH(p,q) process

Usage

```
cogarchNoise(yuima, data=NULL, param, mu=1)
```

Arguments

`yuima`	a yuima object or an object of `yuima.cogarch-class`.
`data`	an object of class `yuima.data-class` contains the observations available at uniformly spaced time. If `data=NULL`, the default, the `cogarchNoise` uses the data in an object of `yuima.data-class`.
`param`	`list` of parameters for the COGARCH(p,q).
`mu`	a numeric object that contains the value of the second moments of the levy measure.

Value

`incr.Levy`	a numeric object contains the estimated increments.
`model`	an object of class yuima containing the state, the variance and the cogarch process.

Note

The function cogarchNoise assumes the underlying Levy process is centered in zero.

The function gmm uses the function cogarchNoise for estimation of underlying Levy in the COGARCH(p,q) model.

Author(s)

The YUIMA Project Team

References

Chadraa. (2009) Statistical Modelling with COGARCH(P,Q) Processes, *PhD Thesis*.

Examples

```
# Insert here some examples
```

CPoint *Volatility structural change point estimator*

Description

Volatility structural change point estimator

Usage

```
CPoint(yuima, param1, param2, print=FALSE, symmetrized=FALSE, plot=FALSE)
qmleL(yuima, t,  ...)
qmleR(yuima, t,  ...)
```

Arguments

yuima	a yuima object.
param1	parameter values before the change point t
param2	parameter values after the change point t
plot	plot test statistics? Default is FALSE.
print	print some debug output. Default is FALSE.
t	time value. See Details.
symmetrized	if TRUE uses the symmetrized version of the quasi maximum-likelihood approximation.
...	passed to qmle method. See Examples.

Details

CPoint estimates the change point using quasi-maximum likelihood approach.

Function qmleL estimates the parameters in the diffusion matrix using observations up to time t.

Function qmleR estimates the parameters in the diffusion matrix using observations from time t to the end.

Arguments in both qmleL and qmleR follow the same rules as in qmle.

Value

ans	a list with change point instant, and paramters before and after the change point.

Author(s)

The YUIMA Project Team

Examples

```
## Not run:
diff.matrix <- matrix(c("theta1.1*x1","0*x2","0*x1","theta1.2*x2"), 2, 2)

drift.c <- c("1-x1", "3-x2")
drift.matrix <- matrix(drift.c, 2, 1)

ymodel <- setModel(drift=drift.matrix, diffusion=diff.matrix, time.variable="t",
state.variable=c("x1", "x2"), solve.variable=c("x1", "x2"))
n <- 1000

set.seed(123)

t1 <- list(theta1.1=.1, theta1.2=0.2)
t2 <- list(theta1.1=.6, theta1.2=.6)

tau <- 0.4
ysamp1 <- setSampling(n=tau*n, Initial=0, delta=0.01)
yuima1 <- setYuima(model=ymodel, sampling=ysamp1)
yuima1 <- simulate(yuima1, xinit=c(1, 1), true.parameter=t1)

x1 <- yuima1@data@zoo.data[[1]]
x1 <- as.numeric(x1[length(x1)])
x2 <- yuima1@data@zoo.data[[2]]
x2 <- as.numeric(x2[length(x2)])

ysamp2 <- setSampling(Initial=n*tau*0.01, n=n*(1-tau), delta=0.01)
yuima2 <- setYuima(model=ymodel, sampling=ysamp2)

yuima2 <- simulate(yuima2, xinit=c(x1, x2), true.parameter=t2)


yuima <- yuima1
yuima@data@zoo.data[[1]] <- c(yuima1@data@zoo.data[[1]], yuima2@data@zoo.data[[1]][-1])
```

```
yuima@data@zoo.data[[2]] <- c(yuima1@data@zoo.data[[2]], yuima2@data@zoo.data[[2]][-1])

plot(yuima)

# estimation of change point for given parameter values
t.est <- CPoint(yuima,param1=t1,param2=t2, plot=TRUE)


low <- list(theta1.1=0, theta1.2=0)

# first state estimate of parameters using small
# portion of data in the tails
tmp1 <- qmleL(yuima,start=list(theta1.1=0.3,theta1.2=0.5),t=1.5,
        lower=low, method="L-BFGS-B")
tmp1
tmp2 <- qmleR(yuima,start=list(theta1.1=0.3,theta1.2=0.5), t=8.5,
        lower=low, method="L-BFGS-B")
tmp2


# first stage changepoint estimator
t.est2 <- CPoint(yuima,param1=coef(tmp1),param2=coef(tmp2))
t.est2$tau


# second stage estimation of parameters given first stage
# change point estimator
tmp11 <- qmleL(yuima,start=as.list(coef(tmp1)), t=t.est2$tau-0.1,
 lower=low, method="L-BFGS-B")
tmp11

tmp21 <- qmleR(yuima,start=as.list(coef(tmp2)), t=t.est2$tau+0.1,
 lower=low, method="L-BFGS-B")
tmp21

# second stage estimator of the change point
CPoint(yuima,param1=coef(tmp11),param2=coef(tmp21))


## One dimensional example: non linear case
diff.matrix <- matrix("(1+x1^2)^theta1", 1, 1)
drift.c <- c("x1")

ymodel <- setModel(drift=drift.c, diffusion=diff.matrix, time.variable="t",
state.variable=c("x1"), solve.variable=c("x1"))
n <- 500

set.seed(123)

y0 <- 5 # initial value
theta00 <- 1/5
gamma <- 1/4
```

```
theta01 <- theta00+n^(-gamma)


t1 <- list(theta1= theta00)
t2 <- list(theta1= theta01)

tau <- 0.4
ysamp1 <- setSampling(n=tau*n, Initial=0, delta=1/n)
yuima1 <- setYuima(model=ymodel, sampling=ysamp1)
yuima1 <- simulate(yuima1, xinit=c(5), true.parameter=t1)
x1 <- yuima1@data@zoo.data[[1]]
x1 <- as.numeric(x1[length(x1)])

ysamp2 <- setSampling(Initial=tau, n=n*(1-tau), delta=1/n)
yuima2 <- setYuima(model=ymodel, sampling=ysamp2)

yuima2 <- simulate(yuima2, xinit=c(x1), true.parameter=t2)


yuima <- yuima1
yuima@data@zoo.data[[1]] <- c(yuima1@data@zoo.data[[1]], yuima2@data@zoo.data[[1]][-1])


plot(yuima)


t.est <- CPoint(yuima,param1=t1,param2=t2)
t.est$tau

low <- list(theta1=0)
upp <- list(theta1=1)

# first state estimate of parameters using small
# portion of data in the tails
tmp1 <- qmleL(yuima,start=list(theta1=0.5),t=.15,lower=low, upper=upp,method="L-BFGS-B")
tmp1
tmp2 <- qmleR(yuima,start=list(theta1=0.5), t=.85,lower=low, upper=upp,method="L-BFGS-B")
tmp2



# first stage changepoint estimator
t.est2 <- CPoint(yuima,param1=coef(tmp1),param2=coef(tmp2))
t.est2$tau


# second stage estimation of parameters given first stage
# change point estimator
tmp11 <- qmleL(yuima,start=as.list(coef(tmp1)), t=t.est2$tau-0.1,
   lower=low, upper=upp,method="L-BFGS-B")
tmp11
```

```
tmp21 <- qmleR(yuima,start=as.list(coef(tmp2)), t=t.est2$tau+0.1,
  lower=low, upper=upp,method="L-BFGS-B")
tmp21


# second stage estimator of the change point
CPoint(yuima,param1=coef(tmp11),param2=coef(tmp21),plot=TRUE)

## End(Not run)
```

DataPPR *From* zoo *data to* yuima.PPR.

Description

The function converts an object of class zoo to an object of class yuima.PPR.

Usage

```
DataPPR(CountVar, yuimaPPR, samp)
```

Arguments

CountVar	An object of class zoo that contains counting variables and covariates. index(CountVar) returns the arrival times.
yuimaPPR	An object of class yuima.PPR that contains a mathematical description of the point process regression model assumed to be the generator of the observed data.
samp	An object of class yuima.sampling.

Value

The function returns an object of class yuima.PPR where the slot model contains the Point process described in yuimaPPR@model, the slot data contains the counting variables and the covariates observed on the grid in samp.

Examples

```
## Not run:
# In this example we generate a dataset contains the Counting Variable N
# and the Covariate X.
# The covariate X is an OU driven by a Gamma process.

# Values of parameters.
mu <- 2
alpha <- 4
beta <-5

# Law definition
```

```
my.rKern <- function(n,t){
  res0 <- t(t(rgamma(n, 0.1*t)))
  res1 <- t(t(rep(1,n)))
  res <- cbind(res0,res1)
  return(res)
}

Law.PPRKern <- setLaw(rng = my.rKern)

# Point Process definition
modKern <- setModel(drift = c("0.4*(0.1-X)","0"),
                    diffusion = c("0","0"),
                    jump.coeff = matrix(c("1","0","0","1"),2,2),
                    measure = list(df = Law.PPRKern),
                    measure.type = c("code","code"),
                    solve.variable = c("X","N"),
                    xinit=c("0.25","0"))

gFun <- "exp(mu*log(1+X))"
#
Kernel <- "alpha*exp(-beta*(t-s))"

prvKern <- setPPR(yuima = modKern,
                  counting.var="N", gFun=gFun,
                  Kernel = as.matrix(Kernel),
                  lambda.var = "lambda", var.dx = "N",
                  lower.var="0", upper.var = "t")

# Simulation

Term<-200
seed<-1
n<-20000

true.parKern <- list(mu=mu, alpha=alpha, beta=beta)


set.seed(seed)
# set.seed(1)

time.simKern <-system.time(
  simprvKern <- simulate(object = prvKern, true.parameter = true.parKern,
                         sampling = setSampling(Terminal =Term, n=n))
)


plot(simprvKern,main ="Counting Process with covariates" ,cex.main=0.9)

# Using the function get.counting.data we extract from an object of class
# yuima.PPR the counting process N and the covariate X at the arrival times.

CountVar <- get.counting.data(simprvKern)
```

```
plot(CountVar)

# We convert the zoo object in the yuima.PPR object.

sim2 <- DataPPR(CountVar, yuimaPPR=simprvKern, samp=simprvKern@sampling)


## End(Not run)
```

`Diagnostic.Carma` *Diagnostic Carma model*

Description

This function verifies if the condition of stationarity is satisfied.

Usage

```
Diagnostic.Carma(carma)
```

Arguments

`carma`	An object of class `yuima.qmle-class` where the slot `model` is a carma process.

Value

Logical variable. If `TRUE`, Carma is stationary.

Author(s)

YUIMA TEAM

Examples

```
mod1 <- setCarma(p = 2, q = 1, scale.par = "sig",
          Carma.var = "y")

param1 <- list(a1 = 1.39631, a2 = 0.05029, b0 = 1,
            b1 = 1, sig = 1)
samp1 <- setSampling(Terminal = 100, n = 200)

set.seed(123)

sim1 <- simulate(mod1, true.parameter = param1,
          sampling = samp1)

est1 <- qmle(sim1, start = param1)

Diagnostic.Carma(est1)
```

`Diagnostic.Cogarch` *Function for checking the statistical properties of the COGARCH(p,q) model*

Description

The function check the statistical properties of the COGARCH(p,q) model. We verify if the process has a strict positive stationary variance model.

Usage

```
Diagnostic.Cogarch(yuima.cogarch, param = list(), matrixS = NULL, mu = 1, display = TRUE)
```

Arguments

`yuima.cogarch`	an object of class `yuima.cogarch`, `yuima` or a class `cogarch.gmm-class`
`param`	a list containing the values of the parameters
`matrixS`	a Square matrix.
`mu`	first moment of the Levy measure.
`display`	a logical variable, if `TRUE` the function displays the result in the `console`.

Value

The functon returns a List with entries:

`meanVarianceProc`
: Unconditional Stationary mean of the variance process.

`meanStateVariable`
: Unconditional Stationary mean of the state process.

`stationary`
: If `TRUE`, the COGARCH(p,q) has stationary variance.

`positivity`
: If `TRUE`, the variance process is strictly positive.

Author(s)

YUIMA Project Team

Examples

```
## Not run:
# Definition of the COGARCH(1,1) process driven by a Variance Gamma nois:
param.VG <- list(a1 = 0.038,  b1 =  0.053,
                 a0 = 0.04/0.053,lambda = 1, alpha = sqrt(2), beta = 0, mu = 0,
                 x01 = 50.33)

cog.VG <- setCogarch(p = 1, q = 1, work = FALSE,
                     measure=list(df="rvgamma(z, lambda, alpha, beta, mu)"),
                     measure.type = "code",
```

```
                      Cogarch.var = "y",
                      V.var = "v", Latent.var="x",
                      XinExpr=TRUE)

# Verify the stationarity and the positivity of th variance process

test <- Diagnostic.Cogarch(cog.VG,param=param.VG)
show(test)

# Simulate a sample path

set.seed(210)

Term=800
num=24000

samp.VG <- setSampling(Terminal=Term, n=num)

sim.VG <- simulate(cog.VG,
                   true.parameter=param.VG,
                   sampling=samp.VG,
                   method="euler")
plot(sim.VG)

# Estimate the model

res.VG <- gmm(sim.VG, start = param.VG, Est.Incr = "IncrPar")

summary(res.VG)

#  Check if the estimated COGARCH(1,1) has a positive and stationary variance

test1<-Diagnostic.Cogarch(res.VG)
show(test1)

# Simulate a COGARCH sample path using the estimated COGARCH(1,1)
# and the recovered increments of underlying Variance Gamma Noise

esttraj<-simulate(res.VG)
plot(esttraj)



## End(Not run)
```

`estimation_LRM` *Estimation of the t-Levy Regression Model*

Description

The function estimates a t-Levy Regression Model

Usage

```
estimation_LRM(start, model, data, upper, lower, PT = 500, n_obs1 = NULL)
```

Arguments

start	Initial values to be passed to the optimizer.
model	A yuima.LevyRM-class that contains the mathematical representation of the t-Levy Regression Model. Its slot @data can contain either real or simulated data.
data	An object of class yuima.data-class contains the observations available at uniformly spaced time. If data=NULL, the default, the function uses the data in the object model.
upper	A named list for specifying upper bounds of parameters.
lower	A named list for specifying lower bounds of parameters.
PT	The number of the data for the estimation of the regressor coefficients and the scale parameter.
n_obs1	The number of data used in the estimation of the degree of freedom. As default the number of the whole data is used in this part

Details

A two-step estimation procedure. Regressor coefficients and scale parameters are obtained by maximizing the quasi-likelihood function based on the Cauchy density. The degree of freedom is estimated used the unitary increment of the t-noise.

Value

Estimated parameters

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

EstimCarmaHawkes *Estimation Methods for a CARMA(p,q)-Hawkes Counting Process*

Description

The function provides two estimation procedures: Maximum Likelihood Estimation and Matching Empirical Correlation

Usage

```
EstimCarmaHawkes(yuima, start, est.method = "qmle", method = "BFGS",
lower = NULL, upper = NULL, lags = NULL, display = FALSE)
```

Arguments

yuima	a yuima object.
start	initial values to be passed to the optimizer.
est.method	The method used to estimate the parameters. The default est.method = "qmle" indicates the MLE while the alternative approach is based on the minimization of the empirical and theoretical autocorrelation.
method	The optimization method to be used. See optim.
lower	Lower Bounds.
upper	Upper Bounds.
lags	Number of lags used in the autocorrelation.
display	you can see a progress of the estimation when display=TRUE.

Value

The output contains the estimated parameters.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

References

Mercuri, L., Perchiazzo, A., & Rroji, E. (2022). A Hawkes model with CARMA (p, q) intensity. doi:10.48550/arXiv.2208.02659.

Examples

```
## Not run:
## MLE For A CARMA(2,1)-Hawkes ##

# Inputs:
a <- c(3,2)
b <- c(1,0.3)
mu<-0.30

true.par<-c(mu,a,b)

# step 1) Model Definition => Constructor 'setCarmaHawkes'
p <- 2
q <- 1
mod1 <- setCarmaHawkes(p = p,q = q)

# step 2) Grid Construction => Constructor 'setSampling'
FinalTime <- 5000
t0 <- 0
samp <- setSampling(t0, FinalTime, n = FinalTime)
```

```
# step 3) Simulation => method 'simulate'
# We use method 'simulate' to generate our dataset.
# For the estimation from real data,
# we use the constructors 'setData' and
#'setYuima' (input 'model' is an object of
#           'yuima.CarmaHawkes-class').

names(true.par) <- c(mod1@info@base.Int, mod1@info@ar.par, mod1@info@ma.par)

set.seed(1)
system.time(
sim1 <- simulate(object = mod1, true.parameter = true.par,
    sampling = samp)
)

plot(sim1)

# step 4) Estimation using the likelihood function.
system.time(
  res <- EstimCarmaHawkes(yuima = sim1,
    start = true.par)
)


## End(Not run)
```

`fitCIR` *Calculate preliminary estimator and one-step improvements of a Cox-Ingersoll-Ross diffusion*

Description

This is a function to simulate the preliminary estimator and the corresponding one step estimators based on the Newton-Raphson and the scoring method of the Cox-Ingersoll-Ross process given via the SDE

$\mathrm{d}X_t = (\alpha - \beta X_t)\mathrm{d}t + \sqrt{\gamma X_t}\mathrm{d}W_t$

with parameters $\beta > 0$, $2\alpha > 5\gamma > 0$ and a Brownian motion $(W_t)_{t\geq 0}$. This function uses the Gaussian quasi-likelihood, hence requires that data is sampled at high-frequency.

Usage

```
fitCIR(data)
```

Arguments

`data`	a numeric matrix containing the realization of $(t_0, X_{t_0}), \ldots, (t_n, X_{t_n})$ with t_j denoting the j-th sampling times. `data[1,]` contains the sampling times $t_0, \ldots, t_n$ and `data[2,]` the corresponding value of the process $X_{t_0}, \ldots, X_{t_n}$. In other words `data[,j]`=(t_j, X_{t_j}). The observations should be equidistant.

Details

The estimators calculated by this function can be found in the reference below.

Value

A list with three entries each contain a vector in the following order: The result of the preliminary estimator, Newton-Raphson method and the method of scoring.

If the sampling points are not equidistant the function will return `'Please use equidistant sampling points'`.

Author(s)

Nicole Hufnagel

Contacts: <nicole.hufnagel@math.tu-dortmund.de>

References

Y. Cheng, N. Hufnagel, H. Masuda. Estimation of ergodic square-root diffusion under high-frequency sampling. Econometrics and Statistics, Article Number: 346 (2022).

Examples

```
#You can make use of the function simCIR to generate the data
data <- simCIR(alpha=3,beta=1,gamma=1, n=5000, h=0.05, equi.dist=TRUE)
results <- fitCIR(data)
```

FromCF2yuima_law *From a Characteristic Function to an* yuima.law-object.

Description

This function returns an object of yuima.law-class and requires the characteristic function as the only input. Density, Random Number Generator, Cumulative Distribution Function and quantile function are internally constructed

Usage

```
FromCF2yuima_law(myfun, time.names = "t", var_char = "u", up = 45,
low = -45, N_grid = 50001, N_Fourier = 2^10)
```

Arguments

myfun	A string that is the name of the characteristic function defined by Users.
time.names	Label of time.
var_char	Argument of the characteristic function.
up	Upper bound for the internal integration.

low	Lower bound for the internal integration.
N_grid	Observation grid.
N_Fourier	Number of points for the Fourier Inversion.

Details

The density function is obtained by means of the Fourier Transform.

Value

An object of yuima.law-class.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

---

get.counting.data *Extract arrival times from an object of class* yuima.PPR

Description

This function extracts arrival times from an object of class yuima.PPR.

Usage

```
get.counting.data(yuimaPPR,type="zoo")
```

Arguments

yuimaPPR	An object of class yuima.PPR.
type	By default type="zoo" the function returns an object of class zoo. Other values are yuima.PPR and matrix.

Value

By default the function returns an object of class zoo. The arrival times can be extracted by applying the method index to the output

Examples

```
## Not run:
##################
# Hawkes Process #
##################

# Values of parameters.
mu <- 2
alpha <- 4
beta <-5

# Law definition

my.rHawkes <- function(n){
  res <- t(t(rep(1,n)))
  return(res)
}

Law.Hawkes <- setLaw(rng = my.rHawkes)

# Point Process Definition

gFun <- "mu"
Kernel <- "alpha*exp(-beta*(t-s))"

modHawkes <- setModel(drift = c("0"), diffusion = matrix("0",1,1),
  jump.coeff = matrix(c("1"),1,1), measure = list(df = Law.Hawkes),
  measure.type = "code", solve.variable = c("N"),
  xinit=c("0"))

prvHawkes <- setPPR(yuima = modHawkes, counting.var="N", gFun=gFun,
  Kernel = as.matrix(Kernel), lambda.var = "lambda",
  var.dx = "N", lower.var="0", upper.var = "t")

true.par <- list(mu=mu, alpha=alpha,  beta=beta)

set.seed(1)

Term<-70
n<-7000

# Simulation trajectory

time.Hawkes <-system.time(
  simHawkes <- simulate(object = prvHawkes, true.parameter = true.par,
     sampling = setSampling(Terminal =Term, n=n))
)

# Arrival times of the Counting process.

DataHawkes <- get.counting.data(simHawkes)
TimeArr <- index(DataHawkes)
```

```
##################################
# Point Process Regression Model #
##################################

# Values of parameters.
mu <- 2
alpha <- 4
beta <-5

# Law definition
my.rKern <- function(n,t){
  res0 <- t(t(rgamma(n, 0.1*t)))
  res1 <- t(t(rep(1,n)))
  res <- cbind(res0,res1)
  return(res)
}

Law.PPRKern <- setLaw(rng = my.rKern)

# Point Process definition
modKern <- setModel(drift = c("0.4*(0.1-X)","0"),
                    diffusion = c("0","0"),
                    jump.coeff = matrix(c("1","0","0","1"),2,2),
                    measure = list(df = Law.PPRKern),
                    measure.type = c("code","code"),
                    solve.variable = c("X","N"),
                    xinit=c("0.25","0"))

gFun <- "exp(mu*log(1+X))"
#
Kernel <- "alpha*exp(-beta*(t-s))"

prvKern <- setPPR(yuima = modKern,
                  counting.var="N", gFun=gFun,
                  Kernel = as.matrix(Kernel),
                  lambda.var = "lambda", var.dx = "N",
                  lower.var="0", upper.var = "t")

# Simulation

Term<-100
seed<-1
n<-10000

true.parKern <- list(mu=mu, alpha=alpha, beta=beta)


set.seed(seed)
# set.seed(1)

time.simKern <-system.time(
  simprvKern <- simulate(object = prvKern, true.parameter = true.parKern,
```

```
                          sampling = setSampling(Terminal =Term, n=n))
)


plot(simprvKern,main ="Counting Process with covariates" ,cex.main=0.9)

# Arrival Times
CountVar <- get.counting.data(simprvKern)
TimeArr <- index(CountVar)



## End(Not run)
```

---

gmm *Method of Moments for COGARCH(P,Q).*

Description

The function returns the estimated parameters of a COGARCH(P,Q) model. The parameters are abtained by matching theoretical vs empirical autocorrelation function. The theoretical autocorrelation function is computed according the methodology developed in Chadraa (2009).

Usage

```
gmm(yuima, data = NULL, start,
 method="BFGS", fixed = list(), lower, upper, lag.max = NULL,
 equally.spaced = FALSE, aggregation=TRUE, Est.Incr = "NoIncr", objFun = "L2")
```

Arguments

yuima	a yuima object or an object of yuima.cogarch-class.
data	an object of class yuima.data-class contains the observations available at uniformly spaced time. If data=NULL, the default, the function uses the data in an object of yuima-class.
start	a list containing the starting values for the optimization routine.
method	a string indicating one of the methods available in optim.
fixed	a list of fixed parameters in optimization routine.
lower	a named list for specifying lower bounds of parameters.
upper	a named list for specifying upper bounds of parameters.
lag.max	maximum lag at which to calculate the theoretical and empirical acf. Default is sqrt{N} where N is the number of observation.
equally.spaced	Logical variable. If equally.spaced = TRUE., the function use the returns of COGARCH(P,Q) evaluated at unitary length for the computation of the empirical autocorrelations. If equally.spaced = FALSE, the increments are evaluated on the interval with frequency specified in an object of class yuima.data-class that contains the observed time series.

aggregation	If aggregation=TRUE, before the estimation of the levy parameters we aggregate the estimated increments
Est.Incr	a string variable, If Est.Incr = "NoIncr", default value, gmm returns an object of class cogarch.est-class that contains the COGARCH parameters. If Est.Incr = "Incr" or Est.Incr = "IncrPar" the output is an object of class cogarch.est.incr-class. In the first case the object contains the increments of underlying noise while in the second case also the estimated parameter of levy measure.
objFun	a string variable that indentifies the objective function in the optimization step. objFun = "L2", default value, the objective function is a quadratic form where the weighting Matrix is the identity one. objFun = "L2CUE" the weighting matrix is estimated using Continuously Updating GMM (L2CUE). objFun = "L1", the objective function is the mean absolute error. In the last case the standard error for estimators are not available.

Details

The routine is based on three steps: estimation of the COGARCH parameters, recovering the increments of the underlying Levy process and estimation of the levy measure parameters. The last two steps are available on request by the user.

Value

The function returns a list with the same components of the object obtained when the function optim is used.

Author(s)

The YUIMA Project Team.

References

Chadraa, E. (2009) Statistical Modeling with COGARCH(P,Q) Processes. Phd Thesis

Examples

```
## Not run:
# Example COGARCH(1,1): the parameters are the same used in Haugh et al. 2005. In this case
# we assume the underlying noise is a symmetric variance gamma.
# As first step we define the COGARCH(1,1) in yuima:

mod1 <- setCogarch(p = 1, q = 1, work = FALSE,
                   measure=list(df="rbgamma(z,1,sqrt(2),1,sqrt(2))"),
                    measure.type = "code", Cogarch.var = "y",
                    V.var = "v", Latent.var="x",XinExpr=TRUE)

param <- list(a1 = 0.038,  b1 =  0.053,
              a0 = 0.04/0.053, x01 = 20)

# We generate a trajectory
```

```
samp <- setSampling(Terminal=10000, n=100000)
set.seed(210)
sim1 <- simulate(mod1, sampling = samp, true.parameter = param)

# We estimate the model

res1 <- gmm(yuima = sim1, start = param)

summary(res1)


## End(Not run)
```

---

hyavar *Asymptotic Variance Estimator for the Hayashi-Yoshida estimator*

Description

This function estimates the asymptotic variances of covariance and correlation estimates by the Hayashi-Yoshida estimator.

Usage

```
hyavar(yuima, bw, nonneg = TRUE, psd = TRUE)
```

Arguments

yuima	an object of yuima-class or yuima.data-class.
bw	a positive number or a numeric matrix. If it is a matrix, each component indicate the bandwidth parameter for the kernel estimators used to estimate the asymptotic variance of the corresponding component (necessary only for off-diagonal components). If it is a number, it is converted to a matrix as `matrix(bw,d,d)`, where `d=dim(x)`. The default value is the matrix whose (i, j)-th component is given by $min(n_i, n_j)^{0.45}$, where n_i denotes the number of the observations for the i-th component of the data.
nonneg	logical. If `TRUE`, the asymptotic variance estimates for correlations are always ensured to be non-negative. See 'Details'.
psd	passed to cce.

Details

The precise description of the method used to estimate the asymptotic variances is as follows. For diagonal components, they are estimated by the realized quarticity multiplied by `2/3`. Its theoretical validity is ensured by Hayashi et al. (2011), for example. For off-diagonal components, they are estimated by the naive kernel approach descrived in Section 8.2 of Hayashi and Yoshida (2011). Note that the asymptotic covariance between a diagonal component and another component, which is necessary to evaluate the asymptotic variances of correlation estimates, is not provided in Hayashi

and Yoshida (2011), but it can be derived in a similar manner to that paper.

If nonneg is TRUE, negative values of the asymptotic variances of correlations are avoided in the following way. The computed asymptotic varaince-covariance matrix of the vector $(HY_{ii}, HY_{ij}, HY_{jj})$ is converted to its spectral absolute value. Here, HY_{ij} denotes the Hayashi-Yohida estimator for the (i, j)-th component.

The function also returns the covariance and correlation matrices calculated by the Hayashi-Yoshida estimator (using cce).

Value

A list with components:

covmat	the estimated covariance matrix
cormat	the estimated correlation matrix
avar.cov	the estimated asymptotic variances for covariances
avar.cor	the estimated asymptotic variances for correlations

Note

Construction of kernel-type estimators for off-diagonal components is implemented after pseudo-aggregation described in Bibinger (2011).

Author(s)

Yuta Koike with YUIMA Project Team

References

Barndorff-Nilesen, O. E. and Shephard, N. (2004) Econometric analysis of realized covariation: High frequency based covariance, regression, and correlation in financial economics, *Econometrica*, **72**, no. 3, 885–925.

Bibinger, M. (2011) Asymptotics of Asynchronicity, technical report, Available at doi:10.48550/arXiv.1106.4222.

Hayashi, T., Jacod, J. and Yoshida, N. (2011) Irregular sampling and central limit theorems for power variations: The continuous case, *Annales de l'Institut Henri Poincare - Probabilites et Statistiques*, **47**, no. 4, 1197–1218.

Hayashi, T. and Yoshida, N. (2011) Nonsynchronous covariation process and limit theorems, *Stochastic processes and their applications*, **121**, 2416–2454.

See Also

setData, cce

Examples

```
## Not run:
## Set a model
diff.coef.1 <- function(t, x1 = 0, x2 = 0) sqrt(1+t)
diff.coef.2 <- function(t, x1 = 0, x2 = 0) sqrt(1+t^2)
cor.rho <- function(t, x1 = 0, x2 = 0) sqrt(1/2)
diff.coef.matrix <- matrix(c("diff.coef.1(t,x1,x2)",
"diff.coef.2(t,x1,x2) * cor.rho(t,x1,x2)",
"", "diff.coef.2(t,x1,x2) * sqrt(1-cor.rho(t,x1,x2)^2)"), 2, 2)
cor.mod <- setModel(drift = c("", ""),
diffusion = diff.coef.matrix,solve.variable = c("x1", "x2"))

set.seed(111)

## We use a function poisson.random.sampling to get observation by Poisson sampling.
yuima.samp <- setSampling(Terminal = 1, n = 1200)
yuima <- setYuima(model = cor.mod, sampling = yuima.samp)
yuima <- simulate(yuima)
psample<- poisson.random.sampling(yuima, rate = c(0.2,0.3), n = 1000)

## Constructing a 95% confidence interval for the quadratic covariation from psample
result <- hyavar(psample)
thetahat <- result$covmat[1,2] # estimate of the quadratic covariation
se <- sqrt(result$avar.cov[1,2]) # estimated standard error
c(lower = thetahat + qnorm(0.025) * se, upper = thetahat + qnorm(0.975) * se)

## True value of the quadratic covariation.
cc.theta <- function(T, sigma1, sigma2, rho) {
  tmp <- function(t) return(sigma1(t) * sigma2(t) * rho(t))
  integrate(tmp, 0, T)
}

# contained in the constructed confidence interval
cc.theta(T = 1, diff.coef.1, diff.coef.2, cor.rho)$value

# Example. A stochastic differential equation with nonlinear feedback.

## Set a model
drift.coef.1 <- function(x1,x2) x2
drift.coef.2 <- function(x1,x2) -x1
drift.coef.vector <- c("drift.coef.1","drift.coef.2")
diff.coef.1 <- function(t,x1,x2) sqrt(abs(x1))*sqrt(1+t)
diff.coef.2 <- function(t,x1,x2) sqrt(abs(x2))
cor.rho <- function(t,x1,x2) 1/(1+x1^2)
diff.coef.matrix <- matrix(c("diff.coef.1(t,x1,x2)",
"diff.coef.2(t,x1,x2) * cor.rho(t,x1,x2)","",
"diff.coef.2(t,x1,x2) * sqrt(1-cor.rho(t,x1,x2)^2)"), 2, 2)
cor.mod <- setModel(drift = drift.coef.vector,
 diffusion = diff.coef.matrix,solve.variable = c("x1", "x2"))

## Generate a path of the process
set.seed(111)
```

```
yuima.samp <- setSampling(Terminal = 1, n = 10000)
yuima <- setYuima(model = cor.mod, sampling = yuima.samp)
yuima <- simulate(yuima, xinit=c(2,3))
plot(yuima)


## The "true" values of the covariance and correlation.
result.full <- cce(yuima)
(cov.true <- result.full$covmat[1,2]) # covariance
(cor.true <- result.full$cormat[1,2]) # correlation

## We use the function poisson.random.sampling to generate nonsynchronous
## observations by Poisson sampling.
psample<- poisson.random.sampling(yuima, rate = c(0.2,0.3), n = 3000)

## Constructing 95% confidence intervals for the covariation from psample
result <- hyavar(psample)
cov.est <- result$covmat[1,2] # estimate of covariance
cor.est <- result$cormat[1,2] # estimate of correlation
se.cov <- sqrt(result$avar.cov[1,2]) # estimated standard error of covariance
se.cor <- sqrt(result$avar.cor[1,2]) # estimated standard error of correlation

## 95% confidence interval for covariance
c(lower = cov.est + qnorm(0.025) * se.cov,
 upper = cov.est + qnorm(0.975) * se.cov) # contains cov.true

## 95% confidence interval for correlation
c(lower = cor.est + qnorm(0.025) * se.cor,
 upper = cor.est + qnorm(0.975) * se.cor) # contains cor.true

## We can also use the Fisher z transformation to construct a
## 95% confidence interval for correlation
## It often improves the finite sample behavior of the asymptotic
## theory (cf. Section 4.2.3 of Barndorff-Nielsen and Shephard (2004))
z <- atanh(cor.est) # the Fisher z transformation of the estimated correlation
se.z <- se.cor/(1 - cor.est^2) # standard error for z (calculated by the delta method)
## 95% confidence interval for correlation via the Fisher z transformation
c(lower = tanh(z + qnorm(0.025) * se.z), upper = tanh(z + qnorm(0.975) * se.z))

## End(Not run)
```

IC *Information criteria for the stochastic differential equation*

Description

Information criteria BIC, Quasi-BIC (QBIC) and CIC for the stochastic differential equation.

Usage

```
IC(drif = NULL, diff = NULL, jump.coeff = NULL, data = NULL, Terminal = 1,
   add.settings = list(), start, lower, upper, ergodic = TRUE,
   stepwise = FALSE, weight = FALSE, rcpp = FALSE, ...)
```

Arguments

drif	a character vector that each element presents the candidate drift coefficient.
diff	a character vector that each element presents the candidate diffusion coefficient.
jump.coeff	a character vector that each element presents the candidate scale coefficient.
data	the data to be used.
Terminal	terminal time of the grid.
add.settings	details of model settings(see setModel).
start	a named list of the initial values of the parameters for optimization.
lower	a named list for specifying lower bounds of the parameters.
upper	a named list for specifying upper bounds of the parameters.
ergodic	whether the candidate models are ergodic SDEs or not(default ergodic=TRUE).
stepwise	specifies joint procedure or stepwise procedure(default stepwise=FALSE).
weight	calculate model weight? (default weight=FALSE)
rcpp	use C++ code? (default rcpp=FALSE)
...	passed to qmle

Details

Calculate the information criteria BIC, QBIC, and CIC for stochastic processes. The calculation and model selection are performed by joint procedure or stepwise procedure.

Value

BIC	values of BIC for all candidates.
QBIC	values of QBIC for all candidates.
AIC	values of AIC-type information criterion for all candidates.
model	information of all candidate models.
par	quasi-maximum likelihood estimator for each candidate.
weight	model weights for all candidates.
selected	selected model number and selected drift and diffusion coefficients

Note

The function IC uses the function qmle with method="L-BFGS-B" internally.

Author(s)

The YUIMA Project Team

Contacts: Shoichi Eguchi <shoichi.eguchi@oit.ac.jp>

References

AIC, BIC

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In Second International Symposium on Information Theory (Tsahkadsor, 1971), 267-281. doi:10.1007/9781461216940_15

Schwarz, G. (1978). Estimating the dimension of a model. The Annals of Statistics, 6(2), 461-464. doi:10.1214/aos/1176344136

BIC, Quasi-BIC

Eguchi, S. and Masuda, H. (2018). Schwarz type model comparison for LAQ models. Bernoulli, 24(3), 2278-2327. doi:10.3150/17BEJ928.

CIC

Uchida, M. (2010). Contrast-based information criterion for ergodic diffusion processes from discrete observations. Annals of the Institute of Statistical Mathematics, 62(1), 161-187. doi:10.1007/s1046300902451

Model weight

Burnham, K. P. and Anderson, D. R. (2002). Model Selection and Multimodel Inference. Springer-Verlag, New York.

Examples

```
## Not run:
### Ex.1
set.seed(123)

N <- 1000   # number of data
h <- N^(-2/3)  # sampling stepsize
Ter <- N*h  # terminal sampling time

## Data generate (dXt = -Xt*dt + exp((-2*cos(Xt) + 1)/2)*dWt)
mod <- setModel(drift="theta21*x", diffusion="exp((theta11*cos(x)+theta12)/2)")
samp <- setSampling(Terminal=Ter, n = N)
yuima <- setYuima(model=mod, sampling=setSampling(Terminal=Ter, n=50*N))
simu.yuima <- simulate(yuima, xinit=1, true.parameter=list(theta11=-2, theta12=1,
                       theta21=-1), subsampling=samp)
Xt <- NULL
for(i in 1:(N+1)){
  Xt <- c(Xt, simu.yuima@data@original.data[50*(i-1)+1])
}

## Candidate coefficients
diffusion <- c("exp((theta11*cos(x)+theta12*sin(x)+theta13)/2)",
               "exp((theta11*cos(x)+theta12*sin(x))/2)",
```

```
              "exp((theta11*cos(x)+theta13)/2)", "exp((theta12*sin(x)+theta13)/2)")
drift <- c("theta21*x + theta22", "theta21*x")

## Parameter settings
para.init <- list(theta11=runif(1,max=5,min=-5), theta12=runif(1,max=5,min=-5),
                  theta13=runif(1,max=5,min=-5), theta21=runif(1,max=-0.5,min=-1.5),
                  theta22=runif(1,max=-0.5,min=-1.5))
para.low <- list(theta11=-10, theta12=-10, theta13=-10, theta21=-5, theta22=-5)
para.upp <- list(theta11=10, theta12=10, theta13=10, theta21=-0.001, theta22=-0.001)

## Ex.1.1 Joint
ic1 <- IC(drif=drift, diff=diffusion, data=Xt, Terminal=Ter, start=para.init, lower=para.low,
          upper=para.upp, stepwise = FALSE, weight = FALSE, rcpp = TRUE)
ic1

## Ex.1.2 Stepwise
ic2 <- IC(drif=drift, diff=diffusion, data=Xt, Terminal=Ter,
          start=para.init, lower=para.low, upper=para.upp,
          stepwise = TRUE, weight = FALSE, rcpp = TRUE)
ic2


### Ex.2 (multidimansion case)
set.seed(123)

N <- 3000   # number of data
h <- N^(-2/3)  # sampling stepsize
Ter <- N*h  # terminal sampling time

## Data generate
diff.coef.matrix <- matrix(c("beta1*x1+beta3", "1", "-1", "beta1*x1+beta3"), 2, 2)
drif.coef.vec <- c("alpha1*x1", "alpha2*x2")
mod <- setModel(drift = drif.coef.vec, diffusion = diff.coef.matrix,
                state.variable = c("x1", "x2"), solve.variable = c("x1", "x2"))
samp <- setSampling(Terminal = Ter, n = N)
yuima <- setYuima(model = mod, sampling = setSampling(Terminal = N^(1/3), n = 50*N))
simu.yuima <- simulate(yuima, xinit = c(1,1), true.parameter = list(alpha1=-2, alpha2=-1,
                       beta1=-1, beta3=2), subsampling = samp)
Xt <- matrix(0,(N+1),2)
for(i in 1:(N+1)){
  Xt[i,] <- simu.yuima@data@original.data[50*(i-1)+1,]
}

## Candidate coefficients
diffusion <- list(matrix(c("beta1*x1+beta2*x2+beta3", "1", "-1", "beta1*x1+beta2*x2+beta3"), 2, 2),
                  matrix(c("beta1*x1+beta2*x2", "1", "-1", "beta1*x1+beta2*x2"), 2, 2),
                  matrix(c("beta1*x1+beta3", "1", "-1", "beta1*x1+beta3"), 2, 2),
                  matrix(c("beta2*x2+beta3", "1", "-1", "beta2*x2+beta3"), 2, 2),
                  matrix(c("beta1*x1", "1", "-1", "beta1*x1"), 2, 2),
                  matrix(c("beta2*x2", "1", "-1", "beta2*x2"), 2, 2),
                  matrix(c("beta3", "1", "-1", "beta3"), 2, 2))
drift <- list(c("alpha1*x1", "alpha2*x2"), c("alpha1*x2", "alpha2*x1"))
modsettings <- list(state.variable = c("x1", "x2"), solve.variable = c("x1", "x2"))
```

```
## Parameter settings
para.init <- list(alpha1 = runif(1,min=-3,max=-1), alpha2 = runif(1,min=-2,max=0),
                  beta1 = runif(1,min=-2,max=0), beta2 = runif(1,min=0,max=2),
                  beta3 = runif(1,min=1,max=3))
para.low <- list(alpha1 = -5, alpha2 = -5, beta1 = -5, beta2 = -5, beta3 = 1)
para.upp <- list(alpha1 = 0.01, alpha2 = -0.01, beta1 = 5, beta2 = 5, beta3 = 10)

## Ex.2.1 Joint
ic3 <- IC(drif=drift, diff=diffusion, data=Xt, Terminal=Ter, add.settings=modsettings,
          start=para.init, lower=para.low, upper=para.upp,
          weight=FALSE, rcpp=FALSE)
ic3

## Ex.2.2 Stepwise
ic4 <- IC(drif=drift, diff=diffusion, data=Xt, Terminal=Ter, add.settings=modsettings,
             start=para.init, lower=para.low, upper=para.upp,
             stepwise = TRUE, weight=FALSE, rcpp=FALSE)
ic4


## End(Not run)
```

`info.Map-class` *Class for information about Map/Operators*

Description

Auxiliar class for definition of an object of class `yuima.Map`. see the documentation of `yuima.Map` for more details.

`info.PPR` *Class for information about Point Process*

Description

Auxiliar class for definition of an object of class `yuima.PPR` and `yuima.Hawkes`. see the documentation for more details.

`Integral.sde` *Class for the mathematical description of integral of a stochastic process*

Description

Auxiliar class for definition of an object of class `yuima.Integral`. see the documentation of `yuima.Integral` for more details.

Integrand — *Class for the mathematical description of integral of a stochastic process*

Description

Auxiliar class for definition of an object of class yuima.Integral. see the documentation of yuima.Integral for more details.

Intensity.PPR — *Intesity Process for the Point Process Regression Model*

Description

This function returns the intensity process of a Point Process Regression Model

Usage

```
Intensity.PPR(yuimaPPR, param)
```

Arguments

yuimaPPR	An object of class yuima.PPR
param	Model parameters

Value

On obejct of class yuima.data

Author(s)

YUIMA TEAM

Examples

```
#INSERT HERE AN EXAMPLE
```

JBtest *Remove jumps and calculate the Gaussian quasi-likelihood estimator based on the Jarque-Bera normality test*

Description

Remove jumps and calculate the Gaussian quasi-likelihood estimator based on the Jarque-Bera normality test

Usage

```
JBtest(yuima,start,lower,upper,alpha,skewness=TRUE,kurtosis=TRUE,withdrift=FALSE)
```

Arguments

yuima	a yuima object (diffusion with compound Poisson jumps).
lower	a named list for specifying lower bounds of parameters.
upper	a named list for specifying upper bounds of parameters.
alpha	Insert Description Here.
start	initial values to be passed to the optimizer.
skewness	use third moment information ? by default, skewness=TRUE
kurtosis	use fourth moment information ? by default, kurtosis=TRUE
withdrift	use drift information for constructing self-normalized residuals or not? by default, withdrift = FALSE

Details

This function removes large increments which are regarded as jumps based on the iterative Jarque-Bera normality test, and after that, calculates the Gaussian quasi maximum likelihood estimator.

Value

Removed	Removed jumps and jump times
OGQMLE	Gaussian quasi maximum likelihood estimator before jump removal
JRGQMLE	Gaussian quasi maximum likelihood estimator after jump removal
Figures	For visualization, the jump points are presented. In addition, the histgram of the jump removed self-normalized residuals, transition of the estimators and the logarithm of Jarque-Bera statistics are given as figures

Author(s)

The YUIMA Project Team

Contacts: Yuma Uehara <y-uehara@ism.ac.jp>

References

Masuda, H. (2013). Asymptotics for functionals of self-normalized residuals of discretely observed stochastic processes. Stochastic Processes and their Applications 123 (2013), 2752–2778

Masuda, H and Uehara, Y. (2018) Estimating Diffusion With Compound Poisson Jumps Based On Self-normalized Residuals, arXiv:1802.03945

Examples

```
## Not run:
set.seed(123)
mod <- setModel(drift="10-3*x",
                diffusion="theta*(2+x^2)/(1+x^2)",
               jump.coeff="1",
               measure=list(intensity="1",df=list("dunif(z, 3, 5)")),
               measure.type="CP")

T <- 10 ## Terminal
n <- 5000 ## generation size
samp <- setSampling(Terminal=T, n=n) ## define sampling scheme
yuima <- setYuima(model = mod, sampling = samp)

yuima <- simulate(yuima, xinit=1,true.parameter=list(theta=sqrt(2)), sampling = samp)

JBtest(yuima,start=list(theta=0.5),upper=c(theta=100)
,lower=c(theta=0),alpha=0.01)

## End(Not run)
```

---

lambdaFromData *Intensity of a Point Process Regression Model*

Description

This function returns the intensity process of a PPR model when covariates and counting processes are obsered on discrete time

Usage

```
lambdaFromData(yuimaPPR, PPRData = NULL, parLambda = list())
```

Arguments

yuimaPPR	Mathematical Description of PPR model
PPRData	Observed data
parLambda	Values of intesity parameters

Details

...

Value

...

Note

...

Author(s)

YUIMA TEAM

References

...

See Also

...

`lasso` *Adaptive LASSO estimation for stochastic differential equations*

Description

Adaptive LASSO estimation for stochastic differential equations.

Usage

```
lasso(yuima, lambda0, start, delta=1, ...)
```

Arguments

`yuima`	a yuima object.
`lambda0`	a named list with penalty for each parameter.
`start`	initial values to be passed to the optimizer.
`delta`	controls the amount of shrinking in the adaptive sequences.
`...`	passed to `optim` method. See Examples.

Details

`lasso` behaves more likely the standard `qmle` function in and argument `method` is one of the methods available in `optim`.

From initial guess of QML estimates, performs adaptive LASSO estimation using the Least Squares Approximation (LSA) as in Wang and Leng (2007, JASA).

Value

ans a list with both QMLE and LASSO estimates.

Author(s)

The YUIMA Project Team

Examples

```
## Not run:
##multidimension case
diff.matrix <- matrix(c("theta1.1","theta1.2", "1", "1"), 2, 2)

drift.c <- c("-theta2.1*x1", "-theta2.2*x2", "-theta2.2", "-theta2.1")
drift.matrix <- matrix(drift.c, 2, 2)

ymodel <- setModel(drift=drift.matrix, diffusion=diff.matrix, time.variable="t",
                   state.variable=c("x1", "x2"), solve.variable=c("x1", "x2"))
n <- 100
ysamp <- setSampling(Terminal=(n)^(1/3), n=n)
yuima <- setYuima(model=ymodel, sampling=ysamp)
set.seed(123)

truep <- list(theta1.1=0.6, theta1.2=0,theta2.1=0.5, theta2.2=0)
yuima <- simulate(yuima, xinit=c(1, 1),
 true.parameter=truep)


est <- lasso(yuima, start=list(theta2.1=0.8, theta2.2=0.2, theta1.1=0.7, theta1.2=0.1),
 lower=list(theta1.1=1e-10,theta1.2=1e-10,theta2.1=.1,theta2.2=1e-10),
 upper=list(theta1.1=4,theta1.2=4,theta2.1=4,theta2.2=4), method="L-BFGS-B")

# TRUE
unlist(truep)

# QMLE
round(est$mle,3)

# LASSO
round(est$lasso,3)

## End(Not run)
```

LawMethods *Methods for an object of class* yuima.law

Description

Methods for yuima.law

Usage

```
rand(object, n, param, ...)
dens(object, x, param, log = FALSE, ...)
cdf(object, q, param, ...)
quant(object, p, param, ...)
```

Arguments

object	...
n	...
param	...
...	...
x	...
log	...
q	...
p	...

Value

Methods for an object of yuima.law-class

Note

Insert additional info

Author(s)

YUIMA TEAM

---

limiting.gamma *calculate the value of limiting covariance matrices : Gamma*

Description

To confirm assysmptotic normality of theta estimators.

Usage

```
limiting.gamma(obj,theta,verbose=FALSE)
```

Arguments

obj	an yuima or yuima.model object.
theta	true theta
verbose	an option for display a verbose process.

Details

Calculate the value of limiting covariance matrices Gamma. The returned values gamma1 and gamma2 are used to confirm assysmptotic normality of theta estimators. this program is limitted to 1-dimention-sde model for now.

Value

gamma1	a theoretical figure for variance of theta1 estimator
gamma2	a theoretical figure for variance of theta2 estimator

Note

we need to fix this routine.

Author(s)

The YUIMA Project Team

Examples

```
set.seed(123)

## Yuima
diff.matrix <- matrix(c("theta1"), 1, 1)
myModel <- setModel(drift=c("(-1)*theta2*x"), diffusion=diff.matrix,
time.variable="t", state.variable="x")
n <- 100
mySampling <- setSampling(Terminal=(n)^(1/3), n=n)
myYuima <- setYuima(model=myModel, sampling=mySampling)
myYuima <- simulate(myYuima, xinit=1, true.parameter=list(theta1=0.6, theta2=0.3))

## theorical figure of theta
theta1 <- 3.5
theta2 <- 1.3

theta <- list(theta1, theta2)
lim.gamma <- limiting.gamma(obj=myYuima, theta=theta, verbose=TRUE)

## return theta1 and theta2 with list
lim.gamma$list

## return theta1 and theta2 with vector
lim.gamma$vec
```

llag *Lead Lag Estimator*

Description

Estimate the lead-lag parameters of discretely observed processes by maximizing the shifted Hayashi-Yoshida covariation contrast functions, following Hoffmann et al. (2013).

Usage

```
llag(x, from = -Inf, to = Inf, division = FALSE, verbose = (ci || ccor),
     grid, psd = TRUE, plot = ci, ccor = ci, ci = FALSE, alpha = 0.01,
     fisher = TRUE, bw, tol = 1e-6)
```

Arguments

x	an object of yuima-class or yuima.data-class.
verbose	logical. If FALSE, llag returns lead-lag time estimates only. The default is FALSE.
from	a numeric vector each of whose component(s) indicates the lower end of a finite grid on which the contrast function is evaluated, if grid is missing.
to	a numeric vector each of whose component(s) indicates the upper end of a finite grid on which the contrast function is evaluated, if grid is missing.
division	a numeric vector each of whose component(s) indicates the number of the points of a finite grid on which the contrast function is evaluated, if grid is missing.
grid	a numeric vector or a list of numeric vectors. See 'Details'.
psd	logical. If TRUE, the estimated cross-correlation functions are converted to the interval [-1,1]. See 'Details'.
plot	logical. If TRUE, the estimated cross-correlation functions are plotted. If ci is also TRUE, the pointwise confidence intervals (under the null hypothesis that the corresponding correlation is zero) are also plotted. The default is FALSE.
ccor	logical. If TRUE, the estimated cross-correlation functions are returned. This argument is ignored if verbose is FALSE. The default is FALSE.
ci	logical. If TRUE, (pointwise) confidence intervals of the estimated cross-correlation functions and p-values for the significance of the correlations at the estimated lead-lag parameters are calculated. Note that the confidence intervals are only plotted when plot=TRUE.
alpha	a posive number indicating the significance level of the confidence intervals for the cross-correlation functions.
fisher	logical. If TRUE, the p-values and the confidence intervals for the cross-correlation functions is evaluated after applying the Fisher z transformation. This argument is only meaningful if pval = "corr".
bw	bandwidth parameter to compute the asymptotic variances. See 'Details' and hyavar for details.

`tol` tolelance parameter to avoid numerical errors in comparison of time stamps. All time stamps are divided by `tol` and rounded to integers. Note that the values of `grid` are also divided by `tol` and rounded to integers. A reasonable choice of `tol` is the minimum unit of time stamps. The default value `1e-6` supposes that the minimum unit of time stamps is greater or equal to 1 micro-second.

Details

Let d be the number of the components of the `zoo.data` of the object `x`.

Let $X^i_{t^i_0}, X^i_{t^i_1}, \ldots, X^i_{t^i_{n(i)}}$ be the observation data of the i-th component (i.e. the i-th component of the `zoo.data` of the object `x`).

The shifted Hayashi-Yoshida covariation contrast function $U_{ij}(\theta)$ of the observations X^i and X^j $(i < j)$ is defined by the same way as in Hoffmann et al. (2013), which corresponds to their cross-covariance function. The lead-lag parameter θ_{ij} is defined as a maximizer of $|U_{ij}(\theta)|$. $U_{ij}(\theta)$ is evaluated on a finite grid G_{ij} defined below. Thus θ_{ij} belongs to this grid. If there exist more than two maximizers, the lowest one is selected.

If `psd` is `TRUE`, for any i, j the matrix $C := (U_{kl}(\theta))_{k,l \in i,j}$ is converted to `(C%*%C)^(1/2)` for ensuring the positive semi-definiteness, and $U_{ij}(\theta)$ is redefined as the $(1,2)$-component of the converted C. Here, $U_{kk}(\theta)$ is set to the realized volatility of Xk. In this case θ_{ij} is given as a maximizer of the cross-correlation functions.

The grid G_{ij} is defined as follows. First, if `grid` is missing, G_{ij} is given by

$$a, a + (b-a)/(N-1), \ldots, a + (N-2)(b-a)/(N-1), b,$$

where a, b and N are the $(d(i-1) - (i-1)i/2 + (j-i))$-th components of `from`, `to` and `division` respectively. If the corresponding component of `from` (resp. `to`) is `-Inf` (resp. `Inf`), $a = -(t^j_{n(j)} - t^i_0)$ (resp. $b = t^i_{n(i)} - t^j_0$) is used, while if the corresponding component of `division` is `FALSE`, $N = round(2max(n(i), n(j))) + 1$ is used. Missing components are filled with `-Inf` (resp. `Inf`, `FALSE`). The default value `-Inf` (resp. `Inf`, `FALSE`) means that all components are `-Inf` (resp. `Inf`, `FALSE`). Next, if `grid` is a numeric vector, G_{ij} is given by `grid`. If `grid` is a list of numeric vectors, G_{ij} is given by the $(d(i-1) - (i-1)i/2 + (j-i))$-th component of `grid`.

The estimated lead-lag parameters are returned as the skew-symmetric matrix $(\theta_{ij})_{i,j=1,\ldots,d}$. If `verbose` is `TRUE`, the covariance matrix $(U_{ij}(\theta_{ij}))_{i,j=1,\ldots,d}$ corresponding to the estimated lead-lag parameters, the corresponding correlation matrix and the computed contrast functions are also returned. If further `ccor` is `TRUE`,the computed cross-correlation functions are returned as a list with the length $d(d-1)/2$. For $i < j$, the $(d(i-1) - (i-1)i/2 + (j-i))$-th component of the list consists of an object $U_{ij}(\theta)/sqrt(U_{ii}(\theta) * U_{jj}(\theta))$ of class zoo indexed by G_{ij}.

If `plot` is `TRUE`, the computed cross-correlation functions are plotted sequentially.

If `ci` is `TRUE`, the asymptotic variances of the cross-correlations are calculated at each point of the grid by using the naive kernel approach descrived in Section 8.2 of Hayashi and Yoshida (2011). The implementation is the same as that of `hyavar` and more detailed description is found there.

Value

If `verbose` is `FALSE`, a skew-symmetric matrix corresponding to the estimated lead-lag parameters is returned. Otherwise, an object of class `"yuima.llag"`, which is a list with the following components, is returned:

lagcce	a skew-symmetric matrix corresponding to the estimated lead-lag parameters.
covmat	a covariance matrix corresponding to the estimated lead-lag parameters.
cormat	a correlation matrix corresponding to the estimated lead-lag parameters.
LLR	a matrix consisting of lead-lag ratios. See Huth and Abergel (2014) for details.

If ci is TRUE, the following component is added to the returned list:

p.values	a matrix of p-values for the significance of the correlations corresponding to the estimated lead-lag parameters.

If further ccor is TRUE, the following components are added to the returned list:

ccor	a list of computed cross-correlation functions.
avar	a list of computed asymptotic variances of the cross-correlations (if ci = TRUE).

Note

The default grid usually contains too many points, so it is better for users to specify this argument in order to reduce the computational time. See 'Examples' below for an example of the specification.

The evaluated p-values should carefully be interpreted because they are calculated based on *pointwise confidence intervals* rather than *simultaneous confidence intervals* (so there would be a multiple testing problem). Evaluation of p-values based on the latter will be implemented in the future extension of this function: Indeed, so far no theory has been developed for this. However, it is conjectured that the error distributions of the estimated cross-correlation functions are asymptotically independent if the grid is not dense too much, so p-values evaluated by this function will still be meaningful as long as sufficiently low significance levels are used.

Author(s)

Yuta Koike with YUIMA Project Team

References

Hayashi, T. and Yoshida, N. (2011) Nonsynchronous covariation process and limit theorems, *Stochastic processes and their applications*, **121**, 2416–2454.

Hoffmann, M., Rosenbaum, M. and Yoshida, N. (2013) Estimation of the lead-lag parameter from non-synchronous data, *Bernoulli*, **19**, no. 2, 426–461.

Huth, N. and Abergel, F. (2014) High frequency lead/lag relationships — Empirical facts, *Journal of Empirical Finance*, **26**, 41–58.

See Also

cce, hyavar, mllag, llag.test

Examples

```
## Set a model
diff.coef.matrix <- matrix(c("sqrt(x1)", "3/5*sqrt(x2)",
 "1/3*sqrt(x3)", "", "4/5*sqrt(x2)","2/3*sqrt(x3)",
 "","","2/3*sqrt(x3)"), 3, 3)
drift <- c("1-x1","2*(10-x2)","3*(4-x3)")
cor.mod <- setModel(drift = drift,
 diffusion = diff.coef.matrix,
 solve.variable = c("x1", "x2","x3"))

set.seed(111)

## We use a function poisson.random.sampling
## to get observation by Poisson sampling.
yuima.samp <- setSampling(Terminal = 1, n = 1200)
yuima <- setYuima(model = cor.mod, sampling = yuima.samp)
yuima <- simulate(yuima,xinit=c(1,7,5))

## intentionally displace the second time series

  data2 <- yuima@data@zoo.data[[2]]
  time2 <- time(data2)
  theta2 <- 0.05   # the lag of x2 behind x1
  stime2 <- time2 + theta2
  time(yuima@data@zoo.data[[2]]) <- stime2

  data3 <- yuima@data@zoo.data[[3]]
  time3 <- time(data3)
  theta3 <- 0.12   # the lag of x3 behind x1
  stime3 <- time3 + theta3
  time(yuima@data@zoo.data[[3]]) <- stime3




## sampled data by Poisson rules
psample<- poisson.random.sampling(yuima,
 rate = c(0.2,0.3,0.4), n = 1000)


## plot
plot(psample)


## cce
cce(psample)

## lead-lag estimation (with cross-correlation plots)
par(mfcol=c(3,1))
result <- llag(psample, plot=TRUE)
```

```
## estimated lead-lag parameter
result

## computing pointwise confidence intervals
llag(psample, ci = TRUE)

## In practice, it is better to specify the grid because the default grid contains too many points.
## Here we give an example for how to specify it.

## We search lead-lag parameters on the interval [-0.1, 0.1] with step size 0.01
G <- seq(-0.1,0.1,by=0.01)

## lead-lag estimation (with computing confidence intervals)
result <- llag(psample, grid = G, ci = TRUE)

## Since the true lead-lag parameter 0.12 between x1 and x3 is not contained
## in the searching grid G, we see that the corresponding cross-correlation
## does not exceed the cofidence interval

## detailed output
## the p-value for the (1,3)-th component is high
result

## Finally, we can examine confidence intervals of other significant levels
## and/or without the Fisher z-transformation via the plot-method defined
## for yuima.llag-class objects as follows
plot(result, alpha = 0.001)
plot(result, fisher = FALSE)

par(mfcol=c(1,1))
```

---

llag.test *Wild Bootstrap Test for the Absence of Lead-Lag Effects*

Description

Tests the absence of lead-lag effects (time-lagged correlations) by the wild bootstrap procedure proposed in Koike (2017) for each pair of components.

Usage

```
llag.test(x, from = -Inf, to = Inf, division = FALSE, grid, R = 999,
          parallel = "no", ncpus = getOption("boot.ncpus", 1L),
          cl = NULL, tol = 1e-06)
```

Arguments

x	an object of yuima-class or yuima.data-class.

from	a numeric vector each of whose component(s) indicates the lower end of a finite grid on which the contrast function is evaluated, if grid is missing.
to	a numeric vector each of whose component(s) indicates the upper end of a finite grid on which the contrast function is evaluated, if grid is missing.
division	a numeric vector each of whose component(s) indicates the number of the points of a finite grid on which the contrast function is evaluated, if grid is missing.
grid	a numeric vector or a list of numeric vectors. See 'Details' of llag.
R	a single positive integer indicating the number of bootstrap replicates.
parallel	passed to boot.
ncpus	passed to boot.
cl	passed to boot.
tol	tolelance parameter to avoid numerical errors in comparison of time stamps. All time stamps are divided by tol and rounded to integers. Note that the values of grid are also divided by tol and rounded to integers. A reasonable choice of tol is the minimum unit of time stamps. The default value 1e-6 supposes that the minimum unit of time stamps is greater or equal to 1 micro-second.

Details

For each pair of components, this function performs the wild bootstrap procedure proposed in Koike (2017) to test whether there is a (possibly) time-lagged correlation. The null hypothesis of the test is that there is no time-lagged correlation and the alternative is its negative. The test regects the null hypothesis if the maximum of the absolute values of cross-covariances is too large. The critical region is constructed by a wild bootstrap procedure with Rademacher variables as the multiplier variables.

Value

p.values	a matrix whose components indicate the bootstrap p-values for the corresponding pair of components.
max.cov	a matrix whose componenets indicate the maxima of the absolute values of cross-covariances for the corresponding pair of components.
max.corr	a matrix whose componenets indicate the maxima of the absolute values of cross-correlations for the corresponding pair of components.

Author(s)

Yuta Koike with YUIMA Project Team

References

Koike, Y. (2019). Gaussian approximation of maxima of Wiener functionals and its application to high-frequency data, *Annals of Statistics*, **47**, 1663–1687. doi:10.1214/18AOS1731.

See Also

cce, hyavar, mllag, llag

Examples

```
## Not run:
# The following example is taken from mllag

## Set a model
diff.coef.matrix <- matrix(c("sqrt(x1)", "3/5*sqrt(x2)",
 "1/3*sqrt(x3)", "", "4/5*sqrt(x2)","2/3*sqrt(x3)",
 "","","2/3*sqrt(x3)"), 3, 3)
drift <- c("1-x1","2*(10-x2)","3*(4-x3)")
cor.mod <- setModel(drift = drift,
 diffusion = diff.coef.matrix,
 solve.variable = c("x1", "x2","x3"))

set.seed(111)

## We use a function poisson.random.sampling
## to get observation by Poisson sampling.
yuima.samp <- setSampling(Terminal = 1, n = 1200)
yuima <- setYuima(model = cor.mod, sampling = yuima.samp)
yuima <- simulate(yuima,xinit=c(1,7,5))

## intentionally displace the second time series

  data2 <- yuima@data@zoo.data[[2]]
  time2 <- time(data2)
  theta2 <- 0.05   # the lag of x2 behind x1
  stime2 <- time2 + theta2
  time(yuima@data@zoo.data[[2]]) <- stime2

  data3 <- yuima@data@zoo.data[[3]]
  time3 <- time(data3)
  theta3 <- 0.12   # the lag of x3 behind x1
  stime3 <- time3 + theta3
  time(yuima@data@zoo.data[[3]]) <- stime3

## sampled data by Poisson rules
psample<- poisson.random.sampling(yuima,
 rate = c(0.2,0.3,0.4), n = 1000)

 ## We search lead-lag parameters on the interval [-0.1, 0.1] with step size 0.01
G <- seq(-0.1,0.1,by=0.01)

## perform lead-lag test
llag.test(psample, grid = G, R = 999)

## Since the lead-lag parameter for the pair(x1, x3) is not contained in G,
## the null hypothesis is not rejected for this pair

## End(Not run)
```

`lm.jumptest` *Lee and Mykland's Test for the Presence of Jumps Using Normalized Returns*

Description

Performs a test for the null hypothesis that the realized path has no jump following Lee and Mykland (2008).

Usage

```
lm.jumptest(yuima, K)
```

Arguments

`yuima`	an object of `yuima-class` or `yuima.data-class`.
`K`	a positive integer indicating the window size to compute local variance estimates. It can be specified as a vector to use different window sizes for different components. The default value is `K=pmin(floor(sqrt(252*n)), n)` with `n=length(yuima)-1`, following Lee and Mykland (2008) as well as Dumitru and Urga (2012).

Value

A list with the same length as `dim(yuima)`. Each component of the list has class "`htest`" and contains the following components:

`statistic`	the value of the test statistic of the corresponding component of `yuima`.
`p.value`	an approximate p-value for the test of the corresponding component.
`method`	the character string "`Lee and Mykland jump test`".
`data.name`	the character string "`xi`", where `i` is the number of the component.

Author(s)

Yuta Koike with YUIMA Project Team

References

Dumitru, A.-M. and Urga, G. (2012) Identifying jumps in financial assets: A comparison between nonparametric jump tests. *Journal of Business and Economic Statistics*, **30**, 242–255.

Lee, S. S. and Mykland, P. A. (2008) Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies*, **21**, 2535–2563.

Maneesoonthorn, W., Martin, G. M. and Forbes, C. S. (2020) High-frequency jump tests: Which test should we use? *Journal of Econometrics*, **219**, 478–487.

Theodosiou, M. and Zikes, F. (2011) A comprehensive comparison of alternative tests for jumps in asset prices. Central Bank of Cyprus Working Paper 2011-2.

See Also

bns.test, minrv.test, medrv.test, pz.test

Examples

```
set.seed(123)

# One-dimensional case
## Model: dXt=t*dWt+t*dzt,
## where zt is a compound Poisson process with intensity 5 and jump sizes distribution N(0,1).

model <- setModel(drift=0,diffusion="t",jump.coeff="t",measure.type="CP",
                  measure=list(intensity=5,df=list("dnorm(z,0,sqrt(0.1))")),
                  time.variable="t")

yuima.samp <- setSampling(Terminal = 1, n = 390)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(yuima)
plot(yuima) # The path seems to involve some jumps

lm.jumptest(yuima) # p-value is very small, so the path would have a jump
lm.jumptest(yuima, K = floor(sqrt(390))) # different value of K

# Multi-dimensional case
## Model: Bivariate standard BM + CP
## Only the first component has jumps

mod <- setModel(drift = c(0, 0), diffusion = diag(2),
                jump.coeff = diag(c(1, 0)),
                measure = list(intensity = 5,
                               df = "dmvnorm(z,c(0,0),diag(2))"),
                jump.variable = c("z"), measure.type=c("CP"),
                solve.variable=c("x1","x2"))

samp <- setSampling(Terminal = 1, n = 390)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(object = mod, sampling = samp)
plot(yuima)

lm.jumptest(yuima) # test is performed component-wise
```

LogSPX *Five minutes Log SPX prices*

Description

Intraday five minutes Standard and Poor 500 Log-prices data ranging from 09 july 2012 to 01 april 2015.

Usage

```
data(LogSPX)
```

Details

The dataset is composed by a list where the element `Data$allObs` contains the intraday five minutes Standard and Poor cumulative Log-return data computed as `Log(P_t)-Log(P_0)` and `P_0` is the open SPX price at 09 july 2012. `Data$logdayprice` contains daily SPX log prices and. Each day we have the same number of observation and the value is reported in `Data$obsinday`.

Examples

```
data(LogSPX)
```

---

lseBayes *Adaptive Bayes estimator for the parameters in sde model by using LSE functions*

Description

Adaptive Bayes estimator for the parameters in a specific type of sde by using LSE functions.

Usage

```
lseBayes(yuima, start, prior, lower, upper, method = "mcmc", mcmc = 1000,
rate =1, algorithm = "randomwalk")
```

Arguments

`yuima`	a 'yuima' object.
`start`	initial suggestion for parameter values
`prior`	a list of prior distributions for the parameters specified by 'code'. Currently, dunif(z, min, max), dnorm(z, mean, sd), dbeta(z, shape1, shape2), dgamma(z, shape, rate) are available.
`lower`	a named list for specifying lower bounds of parameters
`upper`	a named list for specifying upper bounds of parameters
`method`	nomcmc requires package `cubature`
`mcmc`	number of iteration of Markov chain Monte Carlo method
`rate`	a thinning parameter. Only the first n^rate observation will be used for inference.
`algorithm`	Logical value when `method = mcmc`. If `algorithm = "randomwalk"` (default), the random-walk Metropolis algorithm will be performed. If `algorithm = "MpCN"`, the Mixed preconditioned Crank-Nicolson algorithm will be performed.

Details

lseBayes is always performed by Rcpp code.Calculate the Bayes estimator for stochastic processes by using Least Square Estimate functions. The calculation is performed by the Markov chain Monte Carlo method. Currently, the Random-walk Metropolis algorithm and the Mixed preconditioned Crank-Nicolson algorithm is implemented.In lseBayes,the LSE function for estimating diffusion parameter differs from the LSE function for estimating drift parameter.lseBayes is similar to adaBayes,but lseBayes calculate faster than adaBayes because of LSE functions.

Value

vector a vector of the parameter estimate

Note

algorithm = "nomcmc" is unstable. nomcmc is going to be stopped.

Author(s)

Yuto Yoshida with YUIMA project Team

References

Yoshida, N. (2011). Polynomial type large deviation inequalities and quasi-likelihood analysis for stochastic differential equations. Annals of the Institute of Statistical Mathematics, 63(3), 431-479.

Uchida, M., & Yoshida, N. (2014). Adaptive Bayes type estimators of ergodic diffusion processes from discrete observations. Statistical Inference for Stochastic Processes, 17(2), 181-219.

Kamatani, K. (2017). Ergodicity of Markov chain Monte Carlo with reversible proposal. Journal of Applied Probability, 54(2).

Examples

```
## Not run:
####2-dim model
set.seed(123)

b <- c("-theta1*x1+theta2*sin(x2)+50","-theta3*x2+theta4*cos(x1)+25")
a <- matrix(c("4+theta5*sin(x1)^2","1","1","2+theta6*sin(x2)^2"),2,2)

true = list(theta1 = 0.5, theta2 = 5,theta3 = 0.3,
            theta4 = 5, theta5 = 1, theta6 = 1)
lower = list(theta1=0.1,theta2=0.1,theta3=0,
             theta4=0.1,theta5=0.1,theta6=0.1)
upper = list(theta1=1,theta2=10,theta3=0.9,
             theta4=10,theta5=10,theta6=10)
start = list(theta1=runif(1),
             theta2=rnorm(1),
             theta3=rbeta(1,1,1),
             theta4=rnorm(1),
             theta5=rgamma(1,1,1),
             theta6=rexp(1))
```

```
yuimamodel <- setModel(drift=b,diffusion=a,state.variable=c("x1", "x2"),solve.variable=c("x1","x2"))
yuimasamp <- setSampling(Terminal=50,n=50*100)
yuima <- setYuima(model = yuimamodel, sampling = yuimasamp)
yuima <- simulate(yuima, xinit = c(100,80),
                  true.parameter = true,sampling = yuimasamp)

prior <-
    list(
        theta1=list(measure.type="code",df="dunif(z,0,1)"),
        theta2=list(measure.type="code",df="dnorm(z,0,1)"),
        theta3=list(measure.type="code",df="dbeta(z,1,1)"),
        theta4=list(measure.type="code",df="dgamma(z,1,1)"),
        theta5=list(measure.type="code",df="dnorm(z,0,1)"),
        theta6=list(measure.type="code",df="dnorm(z,0,1)")
    )


mle <- qmle(yuima, start = start, lower = lower, upper = upper, method = "L-BFGS-B",rcpp=TRUE)
print(mle@coef)
set.seed(123)
bayes1 <- lseBayes(yuima, start=start, prior=prior,
                                    method="mcmc",
                            mcmc=1000,lower = lower, upper = upper,algorithm = "randomwalk")
bayes1@coef
set.seed(123)
bayes2 <- lseBayes(yuima, start=start, prior=prior,
                                    method="mcmc",
                                 mcmc=1000,lower = lower, upper = upper,algorithm = "MpCN")
bayes2@coef


## End(Not run)
```

`mllag` *Multiple Lead-Lag Detector*

Description

Detecting the lead-lag parameters of discretely observed processes by picking time shifts at which the Hayashi-Yoshida cross-correlation functions exceed thresholds, which are constructed based on the asymptotic theory of Hayashi and Yoshida (2011).

Usage

```
mllag(x, from = -Inf, to = Inf, division = FALSE, grid, psd = TRUE,
      plot = TRUE, alpha = 0.01, fisher = TRUE, bw)
```

Arguments

x	an object of yuima-class or yuima.data-class or yuima.llag-class (output of llag) or yuima.mllag-class (output of this function).
from	passed to llag.
to	passed to llag.
division	passed to llag.
grid	passed to llag.
psd	passed to llag.
plot	logical. If TRUE, the estimated cross-correlation functions and the pointwise confidence intervals (under the null hypothesis that the corresponding correlation is zero) as well as the detected lead-lag parameters are plotted.
alpha	a posive number indicating the significance level of the confidence intervals for the cross-correlation functions.
fisher	logical. If TRUE, the p-values and the confidence intervals for the cross-correlation functions is evaluated after applying the Fisher z transformation.
bw	passed to llag.

Details

The computation method of cross-correlation functions and confidence intervals is the same as the one used in llag. The exception between this function and llag is how to detect the lead-lag parameters. While llag only returns the maximizer of the absolute value of the cross-correlations following the theory of Hoffmann et al. (2013), this function returns all the time shifts at which the cross-correlations exceed (so there is also the possiblity that *no* lead-lag is returned). Note that this approach is mathematically debetable because there would be a multiple testing problem (see also 'Note' of llag), so the interpretation of the result from this function should carefully be addressed. In particular, the significance level alpha probably does not give the "correct" level.

Value

An object of class "yuima.mllag", which is a list with the following elements:

mlagcce	a list of data.frame-class objects consisting of lagcce (lead-lag parameters), p.value and correlation.
LLR	a matrix consisting of lead-lag ratios. See Huth and Abergel (2014) for details.
ccor	a list of computed cross-correlation functions.
avar	a list of computed asymptotic variances of the cross-correlations (if ci = TRUE).
CI	a list of computed confidence intervals.

Author(s)

Yuta Koike with YUIMA Project Team

References

Hayashi, T. and Yoshida, N. (2011) Nonsynchronous covariation process and limit theorems, *Stochastic processes and their applications*, **121**, 2416–2454.

Hoffmann, M., Rosenbaum, M. and Yoshida, N. (2013) Estimation of the lead-lag parameter from non-synchronous data, *Bernoulli*, **19**, no. 2, 426–461.

Huth, N. and Abergel, F. (2014) High frequency lead/lag relationships — Empirical facts, *Journal of Empirical Finance*, **26**, 41–58.

See Also

llag, hyavar, llag.test

Examples

```
# The first example is taken from llag

## Set a model
diff.coef.matrix <- matrix(c("sqrt(x1)", "3/5*sqrt(x2)",
 "1/3*sqrt(x3)", "", "4/5*sqrt(x2)","2/3*sqrt(x3)",
 "","","2/3*sqrt(x3)"), 3, 3)
drift <- c("1-x1","2*(10-x2)","3*(4-x3)")
cor.mod <- setModel(drift = drift,
 diffusion = diff.coef.matrix,
 solve.variable = c("x1", "x2","x3"))

set.seed(111)

## We use a function poisson.random.sampling
## to get observation by Poisson sampling.
yuima.samp <- setSampling(Terminal = 1, n = 1200)
yuima <- setYuima(model = cor.mod, sampling = yuima.samp)
yuima <- simulate(yuima,xinit=c(1,7,5))

## intentionally displace the second time series

  data2 <- yuima@data@zoo.data[[2]]
  time2 <- time(data2)
  theta2 <- 0.05   # the lag of x2 behind x1
  stime2 <- time2 + theta2
  time(yuima@data@zoo.data[[2]]) <- stime2

  data3 <- yuima@data@zoo.data[[3]]
  time3 <- time(data3)
  theta3 <- 0.12   # the lag of x3 behind x1
  stime3 <- time3 + theta3
  time(yuima@data@zoo.data[[3]]) <- stime3

## sampled data by Poisson rules
psample<- poisson.random.sampling(yuima,
 rate = c(0.2,0.3,0.4), n = 1000)
```

```
 ## We search lead-lag parameters on the interval [-0.1, 0.1] with step size 0.01
G <- seq(-0.1,0.1,by=0.01)

## lead-lag estimation by mllag
par(mfcol=c(3,1))
result <- mllag(psample, grid = G)

## Since the lead-lag parameter for the pair(x1, x3) is not contained in G,
## no lead-lag parameter is detected for this pair

par(mfcol=c(1,1))

# The second example is a situation where multiple lead-lag effects exist
set.seed(222)

n <- 3600
Times <- seq(0, 1, by = 1/n)
R1 <- 0.6
R2 <- -0.3

dW1 <- rnorm(n + 10)/sqrt(n)
dW2 <- rnorm(n + 5)/sqrt(n)
dW3 <- rnorm(n)/sqrt(n)

x <- zoo(diffinv(dW1[-(1:10)] + dW2[1:n]), Times)
y <- zoo(diffinv(R1 * dW1[1:n] + R2 * dW2[-(1:5)] +
                 sqrt(1- R1^2 - R2^2) * dW3), Times)

## In this setting, both x and y have a component leading to the other,
## but x's leading component dominates y's one

yuima <- setData(list(x, y))

## Lead-lag estimation by llag
G <- seq(-30/n, 30/n, by = 1/n)
est <- llag(yuima, grid = G, ci = TRUE)

## The shape of the plotted cross-correlation is evidently bimodal,
## so there are likely two lead-lag parameters

## Lead-lag estimation by mllag
mllag(est) # succeeds in detecting two lead-lag parameters

## Next consider a non-synchronous sampling case
psample <- poisson.random.sampling(yuima, n = n, rate = c(0.8, 0.7))

## Lead-lag estimation by mllag
est <- mllag(psample, grid = G)
est # detects too many lead-lag parameters

## Using a lower significant level
mllag(est, alpha = 0.001) # insufficient
```

```
## As the plot reveals, one reason is because the grid is too dense
## In fact, this phenomenon can be avoided by using a coarser grid
mllag(psample, grid = seq(-30/n, 30/n, by=5/n)) # succeeds!
```

`mmfrac` *mmfrac*

Description

Estimates the drift of a fractional Ornstein-Uhlenbeck and, if necessary, also the Hurst and diffusion parameters.

Usage

```
mmfrac(yuima, ...)
```

Arguments

`yuima`	a `yuima` object.
`...`	arguments passed to `qgv`.

Details

Estimates the drift of s fractional Ornstein-Uhlenbeck and, if necessary, also the Hurst and diffusion parameters.

Value

an object of class mmfrac

Author(s)

The YUIMA Project Team

References

Brouste, A., Iacus, S.M. (2013) Parameter estimation for the discretely observed fractional Ornstein-Uhlenbeck process and the Yuima R package, Computational Statistics, pp. 1129–1147.

See Also

See also `qgv`.

Examples

```
# Estimating all Hurst parameter, diffusion coefficient  and drift coefficient
# in fractional Ornstein-Uhlenbeck

model<-setModel(drift="-x*lambda",hurst=NA,diffusion="theta")
sampling<-setSampling(T=100,n=10000)
yui1<-simulate(model,true.param=list(theta=1,lambda=4),hurst=0.7,sampling=sampling)
mmfrac(yui1)
```

---

model.parameter-class *Class for the parameter description of stochastic differential equations*

Description

The model.parameter-class is a class of the **yuima** package.

Details

The model.parameter-class object cannot be directly specified by the user but it is constructed when the yuima.model-class object is constructed via setModel. All the terms which are not in the list of *solution, state, time, jump* variables are considered as parameters. These parameters are identified in the different components of the model (drift, diffusion and jump part). This information is later used to draw inference jointly or separately for the different parameters depending on the model in hands.

Slots

drift: A vector of names belonging to the drift coefficient.

diffusion: A vector of names of parameters belonging to the diffusion coefficient.

jump: A vector of names of parameters belonging to the jump coefficient.

measure: A vector of names of parameters belonging to the Levy measure.

xinit: A vector of names of parameters belonging to the initial condition.

all: A vector of names of all the parameters found in the components of the model.

common: A vector of names of the parameters in common among drift, diffusion, jump and measure term.

Author(s)

The YUIMA Project Team

mpv *Realized Multipower Variation*

Description

The function returns the realized MultiPower Variation (mpv), defined in Barndorff-Nielsen and Shephard (2004), for each component.

Usage

```
mpv(yuima, r = 2, normalize = TRUE)
```

Arguments

yuima	an object of yuima-class or yuima.data-class.
r	a vector of non-negative numbers or a list of vectors of non-negative numbers.
normalize	logical. See 'Details'.

Details

Let d be the number of the components of the zoo.data of yuima.

Let $X^i_{t_0}, X^i_{t_1}, \ldots, X^i_{t_n}$ be the observation data of the i-th component (i.e. the i-th component of the zoo.data of yuima).

When r is a k-dimensional vector of non-negative numbers, mpv(yuima,r,normalize=TRUE) is defined as the d-dimensional vector with i-th element equal to

$$\mu_{r[1]}^{-1} \cdots \mu_{r[k]}^{-1} n^{\frac{r[1]+\cdots+r[k]}{2}-1} \sum_{j=1}^{n-k+1} |\Delta X^i_{t_j}|^{r[1]} |\Delta X^i_{t_{j+1}}|^{r[2]} \cdots |\Delta X^i_{t_{j+k-1}}|^{r[k]},$$

where μ_p is the p-th absolute moment of the standard normal distribution and $\Delta X^i_{t_j} = X^i_{t_j} - X^i_{t_{j-1}}$. If normalize is FALSE the result is not multiplied by $\mu_{r[1]}^{-1} \cdots \mu_{r[k]}^{-1}$.

When r is a list of vectors of non-negative numbers, mpv(yuima,r,normalize=TRUE) is defined as the d-dimensional vector with i-th element equal to

$$\mu_{r_1^i}^{-1} \cdots \mu_{r_{k_i}^i}^{-1} n^{\frac{r_1^i+\cdots+r_{k_i}^i}{2}-1} \sum_{j=1}^{n-k_i+1} |\Delta X^i_{t_j}|^{r_1^i} |\Delta X^i_{t_{j+1}}|^{r_2^i} \cdots |\Delta X^i_{t_{j+k_i-1}}|^{r_{k_i}^i},$$

where $r_1^i, \ldots, r_{k_i}^i$ is the i-th component of r. If normalize is FALSE the result is not multiplied by $\mu_{r_1^i}^{-1} \cdots \mu_{r_{k_i}^i}^{-1}$.

Value

A numeric vector with the same length as the zoo.data of yuima

Author(s)

Yuta Koike with YUIMA Project Team

References

Barndorff-Nielsen, O. E. and Shephard, N. (2004) Power and bipower variation with stochastic volatility and jumps, *Journal of Financial Econometrics*, **2**, no. 1, 1–37.

Barndorff-Nielsen, O. E. , Graversen, S. E. , Jacod, J. , Podolskij M. and Shephard, N. (2006) A central limit theorem for realised power and bipower variations of continuous semimartingales, in: Kabanov, Y. , Lipster, R. , Stoyanov J. (Eds.), From Stochastic Calculus to Mathematical Finance: The Shiryaev Festschrift, Springer-Verlag, Berlin, pp. 33–68.

See Also

setData, cce, minrv, medrv

Examples

```
## Not run:
set.seed(123)

# One-dimensional case
## Model: dXt=t*dWt+t*dzt,
## where zt is a compound Poisson process with intensity 5 and jump sizes distribution N(0,0.1).

model <- setModel(drift=0,diffusion="t",jump.coeff="t",measure.type="CP",
                  measure=list(intensity=5,df=list("dnorm(z,0,sqrt(0.1))")),
                  time.variable="t")

yuima.samp <- setSampling(Terminal = 1, n = 390)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(yuima)
plot(yuima)

mpv(yuima) # true value is 1/3
mpv(yuima,1) # true value is 1/2
mpv(yuima,rep(2/3,3)) # true value is 1/3

# Multi-dimensional case
## Model: dXkt=t*dWk_t (k=1,2,3).

diff.matrix <- diag(3)
diag(diff.matrix) <- c("t","t","t")
model <- setModel(drift=c(0,0,0),diffusion=diff.matrix,time.variable="t",
                  solve.variable=c("x1","x2","x3"))

yuima.samp <- setSampling(Terminal = 1, n = 390)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(yuima)
plot(yuima)
```

```
mpv(yuima,list(c(1,1),1,rep(2/3,3))) # true varue is c(1/3,1/2,1/3)


## End(Not run)
```

MWK151 *Graybill - Methuselah Walk - PILO - ITRDB CA535*

Description

Graybill - Methuselah Walk - PILO - ITRDB CA535, pine tree width in mm from -608 to 1957.

Usage

```
data(MWK151)
```

Details

The full data records of past temperature, precipitation, and climate and environmental change derived from tree ring measurements. Parameter keywords describe what was measured in this data set. Additional summary information can be found in the abstracts of papers listed in the data set citations, however many of the data sets arise from unpublished research contributed to the International Tree Ring Data Bank. Additional information on data processing and analysis for International Tree Ring Data Bank (ITRDB) data sets can be found on the Tree Ring Page https://www.ncei.noaa.gov/products/paleoclimatology.

The MWK151 is only a small part of the data relative to one tree and contains measurement of a tree's ring width in mm, from -608 to 1957.

Source

doi:10.25921/ppqjxv48

References

Graybill, D.A., and Shiyatov, S.G., Dendroclimatic evidence from the northern Soviet Union, in Climate since A.D. 1500, edited by R.S. Bradley and P.D. Jones, Routledge, London, 393-414, 1992.

Examples

```
data(MWK151)
```

noisy.sampling *Noisy Observation Generator*

Description

Generates a new observation data contaminated by noise.

Usage

```
noisy.sampling(x, var.adj = 0, rng = "rnorm", mean.adj = 0, ...,
               end.coef = 0, n, order.adj = 0, znoise)
```

Arguments

x	an object of yuima-class or yuima.data-class.
var.adj	a matrix or list to be used for adjusting the variance matrix of the exogenous noise.
rng	a function to be used for generating the random numbers for the exogenous noise.
mean.adj	a numeric vector to be used for adjusting the mean vector of the exogenous noise.
...	passed to rng.
end.coef	a numeric vector or list to be used for adjusting the variance of the endogenous noise.
n	a numeric vector to be used for adjusting the scale of the endogenous noise.
order.adj	a positive number to be used for adjusting the order of the noise.
znoise	a list indicating other sources of noise processes. The default value is as.list(double(dim(x))).

Details

This function simulates microstructure noise and adds it to the path of x. Currently, this function can deal with Kalnina and Linton (2011) type microstructure noise. See 'Examples' below for more details.

Value

an object of yuima.data-class.

Author(s)

The YUIMA Project Team

References

Kalnina, I. and Linton, O. (2011) Estimating quadratic variation consistently in the presence of endogenous and diurnal measurement error, *Journal of Econometrics*, **147**, 47–59.

See Also

cce, lmm

Examples

```
## Set a model (a two-dimensional normal model sampled by a Poisson random sampling)
set.seed(123)

drift <- c(0,0)

sigma1 <- 1
sigma2 <- 1
rho <- 0.7

diffusion <- matrix(c(sigma1,sigma2*rho,0,sigma2*sqrt(1-rho^2)),2,2)

model <- setModel(drift=drift,diffusion=diffusion,
                  state.variable=c("x1","x2"),solve.variable=c("x1","x2"))

yuima.samp <- setSampling(Terminal = 1, n = 2340)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(yuima)

## Poisson random sampling
psample<- poisson.random.sampling(yuima, rate = c(1/3,1/6), n = 2340)

## Plot the path without noise
plot(psample)

# Set a matrix as the variance of noise
Omega <- 0.01*diffusion %*% t(diffusion)

## Contaminate the observation data by centered normal distributed noise
## with the variance matrix equal to 1% of the diffusion
noisy.psample1 <- noisy.sampling(psample,var.adj=Omega)
plot(noisy.psample1)

## Contaminate the observation data by centered uniformly distributed noise
## with the variance matrix equal to 1% of the diffusion
noisy.psample2 <- noisy.sampling(psample,var.adj=Omega,rng="runif",min=-sqrt(3),max=sqrt(3))
plot(noisy.psample2)

## Contaminate the observation data by centered exponentially distributed noise
## with the variance matrix equal to 1% of the diffusion
noisy.psample3 <- noisy.sampling(psample,var.adj=Omega,rng="rexp",rate=1,mean.adj=1)
plot(noisy.psample3)

## Contaminate the observation data by its return series
## multiplied by -0.1 times the square root of the intensity vector
## of the Poisson random sampling
noisy.psample4 <- noisy.sampling(psample,end.coef=-0.1,n=2340*c(1/3,1/6))
plot(noisy.psample4)
```

```
## An application:
## Adding a compound Poisson jumps to the observation data

## Set a compound Poisson process
intensity <- 5
j.num <- rpois(1,intensity) # Set a number of jumps
j.idx <- unique(ceiling(2340*runif(j.num))) # Set time indices of jumps
jump <- matrix(0,2,2341)
jump[,j.idx+1] <- sqrt(0.25/intensity)*diffusion %*% matrix(rnorm(length(j.idx)),2,length(j.idx))
grid <- seq(0,1,by=1/2340)
CPprocess <- list(zoo(cumsum(jump[1,]),grid),zoo(cumsum(jump[2,]),grid))

## Adding the jumps
yuima.jump <- noisy.sampling(yuima,znoise=CPprocess)
plot(yuima.jump)

## Poisson random sampling
psample.jump <- poisson.random.sampling(yuima.jump, rate = c(1/3,1/6), n = 2340)
plot(psample.jump)
```

---

ntv *Volatility Estimation and Jump Test Using Nearest Neighbor Truncation*

Description

`minrv` and `medrv` respectively compute the MinRV and MedRV estimators introduced in Andersen, Dobrev and Schaumburg (2012).

`minrv.test` and `medrv.test` respectively perform Haussman type tests for the null hypothesis that the realized path has no jump using the MinRV and MedRV estimators. See Section 4.4 in Andersen, Dobrev and Schaumburg (2014) for a concise discussion.

Usage

```
minrv(yuima)
medrv(yuima)

minrv.test(yuima, type = "ratio", adj = TRUE)
medrv.test(yuima, type = "ratio", adj = TRUE)
```

Arguments

`yuima`	an object of `yuima-class` or `yuima.data-class`.
`type`	type of the test statistic to use. `ratio` is default.
`adj`	logical; if `TRUE`, the maximum adjustment suggested in Barndorff-Nielsen and Shephard (2004) is applied to the test statistic when `type` is equal to either "`log`" or "`ratio`". See also Section 2.5 in Dumitru and Urga (2012).

Value

minrv and medrv return a numeric vector with the same length as dim(yuima). Each component of the vector is a volatility estimate for the corresponding component of yuima.

minrv.test and medrv.test return a list with the same length as dim(yuima). Each component of the list has class "htest" and contains the following components:

statistic	the value of the test statistic of the corresponding component of yuima.
p.value	an approximate p-value for the test of the corresponding component.
method	the character string "Andersen-Dobrev-Schaumburg jump test based on xxx", where xxx is either MinRV or MedRV.
data.name	the character string "xi", where i is the number of the component.

Author(s)

Yuta Koike with YUIMA Project Team

References

Andersen, T. G., Dobrev D. and Schaumburg, E. (2012) Jump-robust volatility estimation using nearest neighbor truncation. *Journal of Econometrics*, **169**, 75–93.

Andersen, T. G., Dobrev D. and Schaumburg, E. (2014) A robust neighborhood truncation approach to estimation of integrated quarticity. *Econometric Theory*, **30**, 3–59.

Dumitru, A.-M. and Urga, G. (2012) Identifying jumps in financial assets: A comparison between nonparametric jump tests. *Journal of Business and Economic Statistics*, **30**, 242–255.

Maneesoonthorn, W., Martin, G. M. and Forbes, C. S. (2020) High-frequency jump tests: Which test should we use? *Journal of Econometrics*, **219**, 478–487.

Theodosiou, M. and Zikes, F. (2011) A comprehensive comparison of alternative tests for jumps in asset prices. Central Bank of Cyprus Working Paper 2011-2.

See Also

mpv, cce, bns.test, lm.jumptest, pz.test

Examples

```
## Not run:
set.seed(123)

# One-dimensional case
## Model: dXt=t*dWt+t*dzt,
## where zt is a compound Poisson process with intensity 5
## and jump sizes distribution N(0,1).

model <- setModel(drift=0,diffusion="t",jump.coeff="t",measure.type="CP",
                  measure=list(intensity=5,df=list("dnorm(z,0,1)")),
                  time.variable="t")

yuima.samp <- setSampling(Terminal = 1, n = 390)
```

```
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(yuima)
plot(yuima) # The path evidently has some jumps

## Volatility estimation
minrv(yuima) # minRV (true value = 1/3)
medrv(yuima) # medRV (true value = 1/3)

## Jump test
minrv.test(yuima, type = "standard")
minrv.test(yuima,type="log")
minrv.test(yuima,type="ratio")

medrv.test(yuima, type = "standard")
medrv.test(yuima,type="log")
medrv.test(yuima,type="ratio")


# Multi-dimensional case
## Model: Bivariate standard BM + CP
## Only the first component has jumps

mod <- setModel(drift = c(0, 0), diffusion = diag(2),
                jump.coeff = diag(c(1, 0)),
                measure = list(intensity = 5,
                               df = "dmvnorm(z,c(0,0),diag(2))"),
                jump.variable = c("z"), measure.type=c("CP"),
                solve.variable=c("x1","x2"))

samp <- setSampling(Terminal = 1, n = 390)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(object = mod, sampling = samp)
plot(yuima)

## Volatility estimation
minrv(yuima) # minRV (true value = c(1, 1))
medrv(yuima) # medRV (true value = c(1, 1))

## Jump test
minrv.test(yuima) # test is performed component-wise
medrv.test(yuima) # test is performed component-wise

## End(Not run)
```

`param.Integral` *Class for the mathematical description of integral of a stochastic process*

Description

Auxiliar class for definition of an object of class `yuima.Integral`. see the documentation of `yuima.Integral` for more details.

param.Map-class *Class for information about Map/Operators*

Description

Auxiliar class for definition of an object of class yuima.Map. see the documentation of yuima.Map for more details.

phi.test *Phi-divergence test statistic for stochastic differential equations*

Description

Phi-divergence test statistic for stochastic differential equations.

Usage

```
phi.test(yuima, H0, H1, phi, print=FALSE,...)
```

Arguments

yuima	a yuima object.
H0	a named list of parameter under H0.
H1	a named list of parameter under H1.
phi	the phi function to be used in the test. See Details.
print	you can see a progress of the estimation when print is TRUE.
...	passed to qmle function.

Details

phi.test executes a Phi-divergence test. If H1 is not specified this hypothesis is filled with the QMLE estimates.

If phi is missing, then phi(x)=1-x+x*log(x) and the Phi-divergence statistic corresponds to the likelihood ratio test statistic.

Value

ans	an obkect of class phitest.

Author(s)

The YUIMA Project Team

Examples

```
## Not run:
model<- setModel(drift="t1*(t2-x)",diffusion="t3")
T<-10
n<-1000
sampling <- setSampling(Terminal=T,n=n)
yuima<-setYuima(model=model, sampling=sampling)

h0 <- list(t1=0.3, t2=1, t3=0.25)
X <- simulate(yuima, xinit=1, true=h0)
h1 <- list(t1=0.3, t2=0.2, t3=0.1)

phi1 <- function(x) 1-x+x*log(x)

phi.test(X, H0=h0, H1=h1,phi=phi1)
phi.test(X, H0=h0, phi=phi1, start=h0, lower=list(t1=0.1, t2=0.1, t3=0.1),
   upper=list(t1=2,t2=2,t3=2),method="L-BFGS-B")
phi.test(X, H0=h1, phi=phi1, start=h0, lower=list(t1=0.1, t2=0.1, t3=0.1),
  upper=list(t1=2,t2=2,t3=2),method="L-BFGS-B")

## End(Not run)
```

---

poisson.random.sampling

Poisson random sampling method

Description

Poisson random sampling method.

Usage

```
poisson.random.sampling(x, rate, n)
```

Arguments

x	an object of yuima.data-class or yuima-class.
rate	a Poisson intensity or a vector of Poisson intensities.
n	a common multiplier to the Poisson intensities. The default value is 1.

Details

It returns an object of type yuima.data-class which is a copy of the original input data where observations are sampled according to the Poisson process. The unsampled data are set to NA.

Value

an object of yuima.data-class.

Author(s)

The YUIMA Project Team

See Also

cce

Examples

```
## Set a model
diff.coef.1 <- function(t, x1=0, x2) x2*(1+t)
diff.coef.2 <- function(t, x1, x2=0) x1*sqrt(1+t^2)
cor.rho <- function(t, x1=0, x2=0) sqrt((1+cos(x1*x2))/2)
diff.coef.matrix <- matrix(c("diff.coef.1(t,x1,x2)",
"diff.coef.2(t,x1,x2)*cor.rho(t,x1,x2)", "",
"diff.coef.2(t,x1,x2)*sqrt(1-cor.rho(t,x1,x2)^2)"),2,2)
cor.mod <- setModel(drift=c("","",""), diffusion=diff.coef.matrix,
solve.variable=c("x1", "x2"), xinit=c(3,2))
set.seed(111)

## We first simulate the two dimensional diffusion model
yuima.samp <- setSampling(Terminal=1, n=1200)
yuima <- setYuima(model=cor.mod, sampling=yuima.samp)
yuima.sim <- simulate(yuima)

## Then we use function poisson.random.sampling to get observations
## by Poisson sampling.
psample <- poisson.random.sampling(yuima.sim,  rate = c(0.2, 0.3), n=1000)
str(psample)
```

---

pz.test — *Podolskij and Ziggel's Test for the Presence of Jumps Using Power Variation with Perturbed Truncation*

Description

Performs a test for the null hypothesis that the realized path has no jump following Podolskij and Ziggel (2010).

Usage

```
pz.test(yuima, p = 4, threshold = "local", tau = 0.05)
```

Arguments

yuima	an object of yuima-class or yuima.data-class.
p	a positive number indicating the exponent of the (truncated) power variation to compute test statistic(s). Theoretically, it must be greater than or equal to 2.

`threshold` a numeric vector or list indicating the threshold parameter(s). Each of its components indicates the threshold parameter or process to be used for estimating the corresponding component. If it is a numeric vector, the elements in `threshold` are recycled if there are two few elements in `threshold`.

Alternatively, you can specify either `"PZ"` or `"local"` to automatically select a (hopefully) appropriate threshold. When `threshold="PZ"`, selection is performed following Section 5.1 in Podolskij and Ziggel (2010). When `threshold="local"`, selection is performed following Section 5.1 in Koike (2014). The default is `threshold="local"`.

`tau` a probability controlling the strength of perturbation. See Section 2.3 in Podolskij and Ziggel (2010) for details. Podolskij and Ziggel (2010) suggests using a relatively small value for `tau`, e.g. `tau=0.1` or `tau=0.05`.

Value

A list with the same length as `dim(yuima)`. Each component of the list has class "`htest`" and contains the following components:

`statistic` the value of the test statistic of the corresponding component of `yuima`.

`p.value` an approximate p-value for the test of the corresponding component.

`method` the character string "`Podolskij and Ziggel jump test`".

`data.name` the character string "`xi`", where `i` is the number of the component.

Note

Podolskij and Ziggel (2010) also introduce a pre-averaged version of the test to deal with noisy observations. Such a test will be implemented in the future version of the package.

Author(s)

Yuta Koike with YUIMA Project Team

References

Dumitru, A.-M. and Urga, G. (2012) Identifying jumps in financial assets: A comparison between nonparametric jump tests. *Journal of Business and Economic Statistics*, **30**, 242–255.

Koike, Y. (2014) An estimator for the cumulative co-volatility of asynchronously observed semimartingales with jumps, *Scandinavian Journal of Statistics*, **41**, 460–481.

Maneesoonthorn, W., Martin, G. M. and Forbes, C. S. (2020) High-frequency jump tests: Which test should we use? *Journal of Econometrics*, **219**, 478–487.

Podolskij, M. and Ziggel, D. (2010) New tests for jumps in semimartingale models, *Statistical Inference for Stochastic Processes*, **13**, 15–41.

Theodosiou, M. and Zikes, F. (2011) A comprehensive comparison of alternative tests for jumps in asset prices. Central Bank of Cyprus Working Paper 2011-2.

See Also

`bns.test`, `lm.jumptest`, `minrv.test`, `medrv.test`

Examples

```
## Not run:
set.seed(123)

# One-dimensional case
## Model: dXt=t*dWt+t*dzt,
## where zt is a compound Poisson process with intensity 5 and jump sizes distribution N(0,1).

model <- setModel(drift=0,diffusion="t",jump.coeff="t",measure.type="CP",
                  measure=list(intensity=5,df=list("dnorm(z,0,sqrt(0.1))")),
                  time.variable="t")

yuima.samp <- setSampling(Terminal = 1, n = 390)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(yuima)
plot(yuima) # The path seems to involve some jumps

#lm.jumptest(yuima) # p-value is very small, so the path would have a jump
#lm.jumptest(yuima, K = floor(sqrt(390))) # different value of K
pz.test(yuima) # p-value is very small, so the path would have a jump
pz.test(yuima, p = 2) # different value of p
pz.test(yuima, tau = 0.1) # different value of tau

# Multi-dimensional case
## Model: Bivariate standard BM + CP
## Only the first component has jumps

mod <- setModel(drift = c(0, 0), diffusion = diag(2),
                jump.coeff = diag(c(1, 0)),
                measure = list(intensity = 5,
                               df = "dmvnorm(z,c(0,0),diag(2))"),
                jump.variable = c("z"), measure.type=c("CP"),
                solve.variable=c("x1","x2"))

samp <- setSampling(Terminal = 1, n = 390)
yuima <- setYuima(model = model, sampling = yuima.samp)
yuima <- simulate(object = mod, sampling = samp)
plot(yuima)

pz.test(yuima) # test is performed component-wise

## End(Not run)
```

---

qgv *qgv*

Description

Estimate the local Holder exponent with quadratic generalized variations method

Usage

```
qgv(yuima, filter.type = "Daubechies", order = 2, a = NULL)
```

Arguments

yuima	A yuima object.
filter.type	The filter.type can be set to "Daubechies" or "Classical".
order	The order of the filter a to be chosen
a	Any other filter

Details

Estimation of the Hurst index and the constant of the fractional Ornstein-Uhlenbeck process.

Value

an object of class qgv

Author(s)

The YUIMA Project Team

References

Brouste, A., Iacus, S.M. (2013) Parameter estimation for the discretely observed fractional Ornstein-Uhlenbeck process and the Yuima R package, Computational Statistics, pp. 1129–1147.

See Also

See also mmfrac.

Examples

```
# Estimating both Hurst parameter and diffusion coefficient in fractional Ornstein-Uhlenbeck

model<-setModel(drift="-x*lambda",hurst=NA,diffusion="theta")
sampling<-setSampling(T=100,n=10000)
yui1<-simulate(model,true.param=list(theta=1,lambda=4),hurst=0.7,sampling=sampling)
qgv(yui1)


# Estimating Hurst parameter only in diffusion processes

model2<-setModel(drift="-x*lambda",hurst=NA,diffusion="theta*sqrt(x)")
sampling<-setSampling(T=1,n=10000)
yui2<-simulate(model2,true.param=list(theta=1,lambda=4),hurst=0.7,sampling=sampling,xinit=10)
qgv(yui2)
```

qmle *Calculate quasi-likelihood and ML estimator of least squares estimator*

Description

Calculate the quasi-likelihood and estimate of the parameters of the stochastic differential equation by the maximum likelihood method or least squares estimator of the drift parameter.

Usage

```
qmle(yuima, start, method = "L-BFGS-B", fixed = list(),
print = FALSE, envir = globalenv(), lower, upper, joint = FALSE, Est.Incr ="NoIncr",
aggregation = TRUE, threshold = NULL, rcpp =FALSE, ...)

quasilogl(yuima, param, print = FALSE, rcpp = FALSE)
lse(yuima, start, lower, upper, method = "BFGS", ...)
```

Arguments

yuima	a yuima object.
print	you can see a progress of the estimation when print is TRUE.
envir	an environment where the model coefficients are evaluated.
method	see Details.
param	list of parameters for the quasi loglikelihood.
lower	a named list for specifying lower bounds of parameters
upper	a named list for specifying upper bounds of parameters
start	initial values to be passed to the optimizer.
fixed	for conditional (quasi)maximum likelihood estimation.
joint	perform joint estimation or two stage estimation? by default joint=FALSE.
Est.Incr	If the yuima model is an object of yuima.carma-class or yuima.cogarch-class the qmle returns an object of yuima.carma.qmle-class, cogarch.est.incr-class,cogarch.est-clas or object of class mle-class. By default Est.Incr="NoIncr", alternative values are IncrPar and Incr.
aggregation	If aggregation=TRUE, before the estimation of the levy parameters we aggregate the increments.
threshold	If the model has Compund Poisson type jumps, the threshold is used to perform thresholding of the increments.
...	passed to optim method. See Examples.
rcpp	use C++ code?

Details

qmle behaves more likely the standard mle function in **stats4** and argument method is one of the methods available in optim.

lse calculates least squares estimators of the drift parameters. This is useful for initial guess of qmle estimation. quasilogl returns the value of the quasi loglikelihood for a given yuima object and list of parameters coef.

Value

QL	a real value.
opt	a list with components the same as 'optim' function.
carmaopt	if the model is an object of yuima.carma-class, qmle returns an object yuima.carma.qmle-class
cogarchopt	if the model is an object of yuima.cogarch-class, qmle returns an object of class cogarch.est-class. The estimates are obtained by maximizing the pseudo-loglikelihood function as shown in Iacus et al. (2015)

Note

The function qmle uses the function optim internally.

The function qmle uses the function CarmaNoise internally for estimation of underlying Levy if the model is an object of yuima.carma-class.

Author(s)

The YUIMA Project Team

References

Non-ergodic diffucion

Genon-Catalot, V., & Jacod, J. (1993). On the estimation of the diffusion coefficient for multi-dimensional diffusion processes. In Annales de l'IHP Probabilités et statistiques, 29(1), 119-151.

Uchida, M., & Yoshida, N. (2013). Quasi likelihood analysis of volatility and nondegeneracy of statistical random field. Stochastic Processes and their Applications, 123(7), 2851-2876.

Ergodic diffusion

Kessler, M. (1997). Estimation of an ergodic diffusion from discrete observations. Scandinavian Journal of Statistics, 24(2), 211-229.

Jump diffusion

Shimizu, Y., & Yoshida, N. (2006). Estimation of parameters for diffusion processes with jumps from discrete observations. Statistical Inference for Stochastic Processes, 9(3), 227-277.

Ogihara, T., & Yoshida, N. (2011). Quasi-likelihood analysis for the stochastic differential equation with jumps. Statistical Inference for Stochastic Processes, 14(3), 189-229.

COGARCH

Iacus S. M., Mercuri L. and Rroji E.(2015) Discrete time approximation of a COGARCH (p, q) model and its estimation. doi:10.48550/arXiv.1511.00253

CARMA

Iacus S. M., Mercuri L. (2015) Implementation of Levy CARMA model in Yuima package. Comp. Stat. (30) 1111-1141. doi:10.1007/s0018001505697

Examples

```
#dXt^e = -theta2 * Xt^e * dt + theta1 * dWt
diff.matrix <- matrix(c("theta1"), 1, 1)
ymodel <- setModel(drift=c("(-1)*theta2*x"), diffusion=diff.matrix,
  time.variable="t", state.variable="x", solve.variable="x")
n <- 100

ysamp <- setSampling(Terminal=(n)^(1/3), n=n)
yuima <- setYuima(model=ymodel, sampling=ysamp)
set.seed(123)
yuima <- simulate(yuima, xinit=1, true.parameter=list(theta1=0.3,
theta2=0.1))
QL <- quasilogl(yuima, param=list(theta2=0.8, theta1=0.7))
##QL <- ql(yuima, 0.8, 0.7, h=1/((n)^(2/3)))
QL

## another way of parameter specification
##param <- list(theta2=0.8, theta1=0.7)
##QL <- ql(yuima, h=1/((n)^(2/3)), param=param)
##QL


## old code
##system.time(
##opt <- ml.ql(yuima, 0.8, 0.7, h=1/((n)^(2/3)), c(0, 1), c(0, 1))
##)
##cat(sprintf("\nTrue param. theta2 = .3, theta1 = .1\n"))
##print(coef(opt))


system.time(
opt2 <- qmle(yuima, start=list(theta1=0.8, theta2=0.7), lower=list(theta1=0,theta2=0),
 upper=list(theta1=1,theta2=1), method="L-BFGS-B")
)
cat(sprintf("\nTrue param. theta1 = .3, theta2 = .1\n"))
print(coef(opt2))

## initial guess for theta2 by least squares estimator
tmp <- lse(yuima, start=list(theta2=0.7), lower=list(theta2=0), upper=list(theta2=1))
tmp

system.time(
opt3 <- qmle(yuima, start=list(theta1=0.8, theta2=tmp), lower=list(theta1=0,theta2=0),
 upper=list(theta1=1,theta2=1), method="L-BFGS-B")
)
cat(sprintf("\nTrue param. theta1 = .3, theta2 = .1\n"))
print(coef(opt3))
```

```
## perform joint estimation? Non-optimal, just for didactic purposes
system.time(
opt4 <- qmle(yuima, start=list(theta1=0.8, theta2=0.7), lower=list(theta1=0,theta2=0),
 upper=list(theta1=1,theta2=1), method="L-BFGS-B", joint=TRUE)
)
cat(sprintf("\nTrue param. theta1 = .3, theta2 = .1\n"))
print(coef(opt4))

## fix theta1 to the true value
system.time(
opt5 <- qmle(yuima, start=list(theta2=0.7), lower=list(theta2=0),
upper=list(theta2=1),fixed=list(theta1=0.3), method="L-BFGS-B")
)
cat(sprintf("\nTrue param. theta1 = .3, theta2 = .1\n"))
print(coef(opt5))

## old code
##system.time(
##opt <- ml.ql(yuima, 0.8, 0.7, h=1/((n)^(2/3)), c(0, 1), c(0, 1), method="Newton")
##)
##cat(sprintf("\nTrue param. theta1 = .3, theta2 = .1\n"))
##print(coef(opt))


## Not run:
###multidimension case
##dXt^e = - drift.matrix * Xt^e * dt + diff.matrix * dWt
diff.matrix <- matrix(c("theta1.1","theta1.2", "1", "1"), 2, 2)

drift.c <- c("-theta2.1*x1", "-theta2.2*x2", "-theta2.2", "-theta2.1")
drift.matrix <- matrix(drift.c, 2, 2)

ymodel <- setModel(drift=drift.matrix, diffusion=diff.matrix, time.variable="t",
                   state.variable=c("x1", "x2"), solve.variable=c("x1", "x2"))
n <- 100
ysamp <- setSampling(Terminal=(n)^(1/3), n=n)
yuima <- setYuima(model=ymodel, sampling=ysamp)
set.seed(123)

##xinit=c(x1, x2) #true.parameter=c(theta2.1, theta2.2, theta1.1, theta1.2)
yuima <- simulate(yuima, xinit=c(1, 1),
true.parameter=list(theta2.1=0.5, theta2.2=0.3, theta1.1=0.6, theta1.2=0.2))

## theta2 <- c(0.8, 0.2) #c(theta2.1, theta2.2)
##theta1 <- c(0.7, 0.1) #c(theta1.1, theta1.2)
## QL <- ql(yuima, theta2, theta1, h=1/((n)^(2/3)))
## QL

## ## another way of parameter specification
## #param <- list(theta2=theta2, theta1=theta1)
## #QL <- ql(yuima, h=1/((n)^(2/3)), param=param)
```

```
## #QL

## theta2.1.lim <- c(0, 1)
## theta2.2.lim <- c(0, 1)
## theta1.1.lim <- c(0, 1)
## theta1.2.lim <- c(0, 1)
## theta2.lim <- t( matrix( c(theta2.1.lim, theta2.2.lim), 2, 2) )
## theta1.lim <- t( matrix( c(theta1.1.lim, theta1.2.lim), 2, 2) )

## system.time(
## opt <- ml.ql(yuima, theta2, theta1, h=1/((n)^(2/3)), theta2.lim, theta1.lim)
## )
## opt@coef

system.time(
opt2 <- qmle(yuima, start=list(theta2.1=0.8, theta2.2=0.2, theta1.1=0.7, theta1.2=0.1),
 lower=list(theta1.1=.1,theta1.2=.1,theta2.1=.1,theta2.2=.1),
 upper=list(theta1.1=4,theta1.2=4,theta2.1=4,theta2.2=4), method="L-BFGS-B")
)
opt2@coef
summary(opt2)

## unconstrained optimization
system.time(
opt3 <- qmle(yuima, start=list(theta2.1=0.8, theta2.2=0.2, theta1.1=0.7, theta1.2=0.1))
)
opt3@coef
summary(opt3)

quasilogl(yuima, param=list(theta2.1=0.8, theta2.2=0.2, theta1.1=0.7, theta1.2=0.1))

##system.time(
##opt <- ml.ql(yuima, theta2, theta1, h=1/((n)^(2/3)), theta2.lim, theta1.lim, method="Newton")
##)
##opt@coef
##

# carma(p=2,q=0) driven by a brownian motion without location parameter

mod0<-setCarma(p=2,
               q=0,
               scale.par="sigma")

true.parm0 <-list(a1=1.39631,
                  a2=0.05029,
                  b0=1,
                  sigma=0.23)

samp0<-setSampling(Terminal=100,n=250)
set.seed(123)
sim0<-simulate(mod0,
               true.parameter=true.parm0,
               sampling=samp0)
```

```
system.time(
carmaopt0 <- qmle(sim0, start=list(a1=1.39631,a2=0.05029,
                                   b0=1,
                                    sigma=0.23))
)

summary(carmaopt0)

# carma(p=2,q=1) driven by a brownian motion without location parameter

mod1<-setCarma(p=2,
               q=1)

true.parm1 <-list(a1=1.39631,
                  a2=0.05029,
                  b0=1,
                  b1=2)

samp1<-setSampling(Terminal=100,n=250)
set.seed(123)
sim1<-simulate(mod1,
               true.parameter=true.parm1,
               sampling=samp1)

system.time(
  carmaopt1 <- qmle(sim1, start=list(a1=1.39631,a2=0.05029,
                                     b0=1,b1=2),joint=TRUE)
)

summary(carmaopt1)

# carma(p=2,q=1) driven by a compound poisson process where the jump size is normally distributed.

mod2<-setCarma(p=2,
               q=1,
               measure=list(intensity="1",df=list("dnorm(z, 0, 1)")),
               measure.type="CP")

true.parm2 <-list(a1=1.39631,
                  a2=0.05029,
                  b0=1,
                  b1=2)

samp2<-setSampling(Terminal=100,n=250)
set.seed(123)
sim2<-simulate(mod2,
               true.parameter=true.parm2,
               sampling=samp2)

system.time(
  carmaopt2 <- qmle(sim2, start=list(a1=1.39631,a2=0.05029,
                                     b0=1,b1=2),joint=TRUE)
```

```
)

summary(carmaopt2)

# carma(p=2,q=1) driven by a normal inverse gaussian process
mod3<-setCarma(p=2,q=1,
               measure=list(df=list("rNIG(z, alpha, beta, delta1, mu)")),
               measure.type="code")
#

# True param
true.param3<-list(a1=1.39631,
                  a2=0.05029,
                  b0=1,
                  b1=2,
                  alpha=1,
                  beta=0,
                  delta1=1,
                  mu=0)

samp3<-setSampling(Terminal=100,n=200)
set.seed(123)

sim3<-simulate(mod3,
               true.parameter=true.param3,
               sampling=samp3)


carmaopt3<-qmle(sim3,start=true.param3)

summary(carmaopt3)

# Simulation and Estimation of COGARCH(1,1) with CP driven noise

# Model parameters
eta<-0.053
b1 <- eta
beta <- 0.04
a0 <- beta/b1
phi<- 0.038
a1 <- phi


# Definition

cog11<-setCogarch(p = 1,q = 1,
  measure = list(intensity = "1",
                 df = list("dnorm(z, 0, 1)")),
  measure.type = "CP",
  XinExpr=TRUE)

# Parameter
paramCP11 <- list(a1 = a1, b1 =  b1,
```

```
                  a0 = a0, y01 = 50.31)
# Sampling scheme
samp11 <- setSampling(0, 3200, n=64000)

# Simulation
set.seed(125)

SimTime11 <- system.time(
  sim11 <- simulate(object = cog11,
    true.parameter = paramCP11,
    sampling = samp11,
    method="mixed")
)

plot(sim11)

# Estimation

timeComp11<-system.time(
  res11 <- qmle(yuima = sim11,
    start = paramCP11,
    grideq = TRUE,
    method = "Nelder-Mead")
)

timeComp11

unlist(paramCP11)

coef(res11)

# COGARCH(2,2) model driven by CP

cog22 <- setCogarch(p = 2,q = 2,
  measure = list(intensity = "1",
                 df = list("dnorm(z, 0, 1)")),
  measure.type = "CP",
  XinExpr=TRUE)

# Parameter

paramCP22 <- list(a1 = 0.04, a2 = 0.001,
  b1 =  0.705, b2 = 0.1, a0 = 0.1, y01 = (1 + 2 / 3),
  y02=0)

# Use diagnostic.cog for checking the stat and positivity

check22 <- Diagnostic.Cogarch(cog22, param = paramCP22)

# Sampling scheme

samp22 <- setSampling(0, 3600, n = 64000)
```

```
# Simulation

set.seed(125)
SimTime22 <- system.time(
  sim22 <- simulate(object = cog22,
    true.parameter = paramCP22,
    sampling = samp22,
    method = "Mixed")
)

plot(sim22)

timeComp22 <- system.time(
  res22 <- qmle(yuima = sim22,
    start = paramCP22,
    grideq=TRUE,
    method = "Nelder-Mead")
)

timeComp22

unlist(paramCP22)

coef(res22)


## End(Not run)
```

---

qmleLevy *Gaussian quasi-likelihood estimation for Levy driven SDE*

Description

Calculate the Gaussian quasi-likelihood and Gaussian quasi-likelihood estimators of Levy driven SDE.

Usage

```
qmleLevy(yuima, start, lower, upper, joint = FALSE,
third = FALSE, Est.Incr = "NoIncr",
aggregation = TRUE)
```

Arguments

yuima	a yuima object.
lower	a named list for specifying lower bounds of parameters.
upper	a named list for specifying upper bounds of parameters.
start	initial values to be passed to the optimizer.

joint	perform joint estimation or two stage estimation, by default joint=FALSE. If there exists an overlapping parameter, joint=TRUE does not work for the theoretical reason
third	perform third estimation by default third=FALSE. If there exists an overlapping parameter, third=TRUE does not work for the theoretical reason.
Est.Incr	the qmleLevy returns an object of mle-clas, by default Est.Incr="NoIncr", other options as "Inc" or "IncrPar".
aggregation	If aggregation=TRUE, the function returns the unit-time Levy increments. If Est.Incr="IncrPar", the function estimates Levy parameters using the unit-time Levy increments.

Details

This function performs Gaussian quasi-likelihood estimation for Levy driven SDE.

Value

first	estimated values of first estimation (scale parameters)
second	estimated values of second estimation (drift parameters)
third	estimated values of third estimation (scale parameters)

Note

The function qmleLevy uses the function qmle internally. It can be applied only for the standardized Levy noise whose moments of any order exist. In present yuima package, birateral gamma (bgamma) process, normal inverse Gaussian (NIG) process, variance gamma (VG) process, and normal tempered stable process are such candidates. In the current version, the standardization condition on the driving noise is internally checked only for the one-dimensional noise. The standardization condition for the multivariate noise is given in

https://docs.google.com/viewer?a=v&pid=sites&srcid=ZGVmYXVsdGRvbWFpbnx5dW1hdWVoYXJhMTkyOHxneDo3Z

or

https://docs.google.com/viewer?a=v&pid=sites&srcid=ZGVmYXVsdGRvbWFpbnx5dW1hdWVoYXJhMTkyOHxneDo3Z

They also contain more presice explanation of this function.

Author(s)

The YUIMA Project Team

Contacts: Yuma Uehara <y-uehara@ism.ac.jp>

References

Masuda, H. (2013). Convergence of Gaussian quasi-likelihood random fields for ergodic Levy driven SDE observed at high frequency. The Annals of Statistics, 41(3), 1593-1641.

Masuda, H. and Uehara, Y. (2017). On stepwise estimation of Levy driven stochastic differential equation (Japanese) ., Proc. Inst. Statist. Math., accepted.

Examples

```
## Not run:
## One-dimensional case
dri<-"-theta0*x" ## set drift
jum<-"theta1/(1+x^2)^(-1/2)" ## set jump
yuima<-setModel(drift = dri
                ,jump.coeff = jum
                ,solve.variable = "x",state.variable = "x"
                ,measure.type = "code"
                ,measure = list(df="rbgamma(z,1,sqrt(2),1,sqrt(2))")) ## set true model
n<-3000
T<-30 ## terminal
hn<-T/n ## stepsize

sam<-setSampling(Terminal = T, n=n) ## set sampling scheme
yuima<-setYuima(model = yuima, sampling = sam) ## model

true<-list(theta0 = 1,theta1 = 2) ## true values
upper<-list(theta0 = 4, theta1 = 4) ## set upper bound
lower<-list(theta0 = 0.5, theta1 = 1) ## set lower bound
set.seed(123)
yuima<-simulate(yuima, xinit = 0, true.parameter = true,sampling = sam) ## generate a path
start<-list(theta0 = runif(1,0.5,4), theta1 = runif(1,1,4)) ## set initial values
qmleLevy(yuima,start=start,lower=lower,upper=upper, joint = TRUE)

## Multi-dimensional case

lambda<-1/2
alpha<-1
beta<-c(0,0)
mu<-c(0,0)
Lambda<-matrix(c(1,0,0,1),2,2) ## set parameters in noise

dri<-c("1-theta0*x1-x2","-theta1*x2")
jum<-matrix(c("x1*theta2+1","0","0","1"),2,2) ## set coefficients

yuima <- setModel(drift=dri,
                  solve.variable=c("x1","x2"),state.variable = c("x1","x2"),
                  jump.coeff=jum, measure.type="code",
                  measure=list(df="rvgamma(z, lambda, alpha, beta, mu, Lambda
                  )"))

n<-3000 ## the number of total samples
T<-30 ## terminal
hn<-T/n ## stepsize

sam<-setSampling(Terminal = T, n=n) ## set sampling scheme
yuima<-setYuima(model = yuima, sampling = sam) ## model

true<-list(theta0 = 1,theta1 = 2,theta2 = 3,lambda=lambda, alpha=alpha,
beta=beta,mu=mu, Lambda=Lambda) ## true values
upper<-list(theta0 = 4, theta1 = 4, theta2 = 5, lambda=lambda, alpha=alpha,
```

```
beta=beta,mu=mu, Lambda=Lambda) ## set upper bound
lower<-list(theta0 = 0.5, theta1 = 1, theta2 = 1, lambda=lambda, alpha=alpha,
beta=beta,mu=mu, Lambda=Lambda) ## set lower bound
set.seed(123)
yuima<-simulate(yuima, xinit = c(0,0), true.parameter = true,sampling = sam) ## generate a path
plot(yuima)
start<-list(theta0 = runif(1,0.5,4), theta1 = runif(1,1,4),
theta2 = runif(1,1,5),lambda=lambda, alpha=alpha,
beta=beta,mu=mu, Lambda=Lambda) ## set initial values
qmleLevy(yuima,start=start,lower=lower,upper=upper,joint = FALSE,third=TRUE)

## End(Not run)
```

`rconst` *Fictitious rng for the constant random variable used to generate and describe Poisson jumps.*

Description

Fictitious rng for the constant random variable used to generate and describe Poisson jumps.

Usage

```
rconst(n, k = 1)
dconst(x, k = 1)
```

Arguments

`n`	number of replications
`k`	the size of the jump
`x`	the fictitious argument

Value

returns a numeric vector

Author(s)

The YUIMA Project Team

Examples

```
dconst(1,1)
dconst(2,1)
dconst(2,2)

rconst(10,3)
```

rng *Random numbers and densities*

Description

simulate function can use the specific random number generators to generate Levy paths.

Usage

```
rGIG(x,lambda,delta,gamma)
dGIG(x,lambda,delta,gamma)
rGH(x,lambda,alpha,beta,delta,mu,Lambda)
dGH(x,lambda,alpha,beta,delta,mu,Lambda)
rIG(x,delta,gamma)
dIG(x,delta,gamma)
rNIG(x,alpha,beta,delta,mu,Lambda)
dNIG(x,alpha,beta,delta,mu,Lambda)
rvgamma(x,lambda,alpha,beta,mu,Lambda)
dvgamma(x,lambda,alpha,beta,mu,Lambda)
rbgamma(x,delta.plus,gamma.plus,delta.minus,gamma.minus)
dbgamma(x,delta.plus,gamma.plus,delta.minus,gamma.minus)
rstable(x,alpha,beta,sigma,gamma)
rpts(x,alpha,a,b)
rnts(x,alpha,a,b,beta,mu,Lambda)
```

Arguments

x	Number of R.Ns to be geneated.
a	parameter
b	parameter
delta	parameter written as δ below
gamma	parameter written as γ below
mu	parameter written as μ below
Lambda	parameter written as Λ below
alpha	parameter written as α below
lambda	parameter written as λ below
sigma	parameter written as σ below
beta	parameter written as β below
delta.plus	parameter written as δ_+ below
gamma.plus	parameter written as γ_+ below
delta.minus	parameter written as δ_- below
gamma.minus	parameter written as γ_- below

Details

GIG (generalized inverse Gaussian): The density function of GIG distribution is expressed as:

$f(x) = 1/2 * (\gamma/\delta)^{\lambda} * 1/bK_{\lambda}(\gamma * \delta) * x^(\lambda - 1) * exp(-1/2 * (\delta^2/x + \gamma^2 * x))$

where $bK_{\lambda}()$ is the modified Bessel function of the third kind with order lambda. The parameters λ, δ and γ vary within the following regions:

$\delta >= 0, \gamma > 0$ if $\lambda > 0$,

$\delta > 0, \gamma > 0$ if $\lambda = 0$,

$\delta > 0, \gamma >= 0$ if $\lambda < 0$.

The corresponding Levy measure is given in Eberlein, E., & Hammerstein, E. A. V. (2004) (it contains IG).

GH (generalized hyperbolic): Generalized hyperbolic distribution is defined by the normal mean-variance mixture of generalized inverse Gaussian distribution. The parameters $\alpha, \beta, \delta, \mu$ express heaviness of tails, degree of asymmetry, scale and location, respectively. Here the parameter Λ is supposed to be symmetric and positive definite with $det(\Lambda) = 1$ and the parameters vary within the following region:

$\delta >= 0, \alpha > 0, \alpha^2 > \beta^T \Lambda \beta$ if $\lambda > 0$,

$\delta > 0, \alpha > 0, \alpha^2 > \beta^T \Lambda \beta$ if $\lambda = 0$,

$\delta > 0, \alpha >= 0, \alpha^2 >= \beta^T \Lambda \beta$ if $\lambda < 0$.

The corresponding Levy measure is given in Eberlein, E., & Hammerstein, E. A. V. (2004) (it contains NIG and vgamma).

IG (inverse Gaussian (the element of GIG)): Δ and γ are positive (the case of $\gamma = 0$ corresponds to the positive half stable, provided by the "rstable").

NIG (normal inverse Gaussian (the element of GH)): Normal inverse Gaussian distribution is defined by the normal mean-variance mixuture of inverse Gaussian distribution. The parameters α, β, δ and μ express the heaviness of tails, degree of asymmetry, scale and location, respectively. They satisfy the following conditions: Λ is symmetric and positive definite with $det(\Lambda) = 1; \delta > 0; \alpha > 0$ with $\alpha^2 - \beta^T \Lambda \beta > 0$.

vgamma (variance gamma (the element of GH)): Variance gamma distribution is defined by the normal mean-variance mixture of gamma distribution. The parameters satisfy the following conditions: Lambda is symmetric and positive definite with $det(\Lambda) = 1; \lambda > 0; \alpha > 0$ with $\alpha^2 - \beta^T \Lambda \beta > 0$. Especially in the case of $\beta = 0$ it is variance gamma distribution.

bgamma (bilateral gamma): Bilateral gamma distribution is defined by the difference of independent gamma distributions $Gamma(\delta_+, \gamma_+) and Gamma(\delta_-, \gamma_-)$. Its Levy density $f(z)$ is given by: $f(z) = \delta_+/z * exp(-\gamma_+ * z) * ind(z > 0) + \delta_-/|z| * exp(-\gamma_- * |z|) * ind(z < 0)$, where the function $ind()$ denotes an indicator function.

stable (stable): Parameters α, β, σ and γ express stability, degree of skewness, scale and location, respectively. They satisfy the following condition: $0 < \alpha <= 2; -1 <= \beta <= 1; \sigma > 0; \gamma$ is a real number.

pts (positive tempered stable): Positive tempered stable distribution is defined by the tilting of positive stable distribution. The parameters α, a and b express stability, scale and degree of tilting, respectively. They satisfy the following condition: $0 < \alpha < 1; a > 0; b > 0$. Its Levy density $f(z)$ is given by: $f(z) = az^(-1-\alpha) exp(-bz)$.

`nts` (normal tempered stable): Normal tempered stable distribution is defined by the normal mean-variance mixture of positive tempered stable distribution. The parameters α, a, b, β, μ and Λ express stability, scale, degree of tilting, degree of asymmemtry, location and degree of mixture, respectively. They satisfy the following condition: Lambda is symmetric and positive definite with $det(\Lambda) = 1; 0 < \alpha < 1; a > 0; b > 0$. In one-dimensional case, its Levy density $f(z)$ is given by: $f(z) = 2a/(2\pi)^(1/2) * \exp(\beta * z) * (z^2/(2b+\beta^2))^(-\alpha/2-1/4) * bK_(\alpha+1/2)(z^2(2b+\beta^2)^(1/2))$.

Value

`rXXX`	Collection of of random numbers or vectors
`dXXX`	Density function

Note

Some density-plot functions are still missing: as for the non-Gaussian stable densities, one can use, e.g., stabledist package. The rejection-acceptance method is used for generating pts and nts. It should be noted that its acceptance rate decreases at exponential order as a and b become larger: specifically, the rate is given by $exp(a * \Gamma(-\alpha) * b^(\alpha))$

Author(s)

The YUIMA Project Team

Contacts: Hiroki Masuda <hmasuda@ms.u-tokyo.ac.jp> and Yuma Uehara <y-uehara@kansai-u.ac.jp>

References

rGIG, dGIG, rIG, dIG

Chhikara, R. (1988). The Inverse Gaussian Distribution: Theory: Methodology, and Applications (Vol. 95). CRC Press.

Hormann, W., & Leydold, J. (2014). Generating generalized inverse Gaussian random variates. Statistics and Computing, 24(4), 547-557. doi:10.1111/14679469.00045

Jorgensen, B. (2012). Statistical properties of the generalized inverse Gaussian distribution (Vol. 9). Springer Science & Business Media. https://link.springer.com/book/10.1007/978-1-4612-5698-4

Michael, J. R., Schucany, W. R., & Haas, R. W. (1976). Generating random variates using transformations with multiple roots. The American Statistician, 30(2), 88-90. doi:10.1080/00031305.1976.10479147

rGH, dGH, rNIG, dNIG, rvgamma, dvgamma

Barndorff-Nielsen, O. (1977). Exponentially decreasing distributions for the logarithm of particle size. In Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences (Vol. 353, No. 1674, pp. 401-419). The Royal Society. doi:10.1098/rspa.1977.0041

Barndorff-Nielsen, O. E. (1997). Processes of normal inverse Gaussian type. Finance and stochastics, 2(1), 41-68. doi:10.1007/s007800050032

Eberlein, E. (2001). Application of generalized hyperbolic Levy motions to finance. In Levy processes (pp. 319-336). Birkhauser Boston. doi:10.1007/9781461201977_14

Eberlein, E., & Hammerstein, E. A. V. (2004). Generalized hyperbolic and inverse Gaussian distributions: limiting cases and approximation of processes. In Seminar on stochastic analysis, random fields and applications IV (pp. 221-264). Birkh??user Basel. doi:10.1007/9781461201977_14

Madan, D. B., Carr, P. P., & Chang, E. C. (1998). The variance gamma process and option pricing. European finance review, 2(1), 79-105. doi:10.1111/14679469.00045

rbgamma, dbgamma

Kuchler, U., & Tappe, S. (2008). Bilateral Gamma distributions and processes in financial mathematics. Stochastic Processes and their Applications, 118(2), 261-283. doi:10.1016/j.spa.2007.04.006

Kuchler, U., & Tappe, S. (2008). On the shapes of bilateral Gamma densities. Statistics & Probability Letters, 78(15), 2478-2484. doi:10.1016/j.spa.2007.04.006

rstable

Chambers, John M., Colin L. Mallows, and B. W. Stuck. (1976) A method for simulating stable random variables, Journal of the american statistical association, 71(354), 340-344. doi:10.1080/01621459.1976.10480344

Weron, Rafal. (1996) On the Chambers-Mallows-Stuck method for simulating skewed stable random variables, Statistics & probability letters, 28.2, 165-171. doi:10.1016/01677152(95)001131

Weron, Rafal. (2010) Correction to:" On the Chambers-Mallows-Stuck Method for Simulating Skewed Stable Random Variables", No. 20761, University Library of Munich, Germany. https://ideas.repec.org/p/pra/mprapa

rpts

Kawai, R., & Masuda, H. (2011). On simulation of tempered stable random variates. Journal of Computational and Applied Mathematics, 235(8), 2873-2887. doi:10.1016/j.cam.2010.12.014

rnts

Barndorff-Nielsen, O. E., & Shephard, N. (2001). Normal modified stable processes. Aarhus: MaPhySto, Department of Mathematical Sciences, University of Aarhus.

Examples

```
## Not run:
set.seed(123)

# Ex 1. (One-dimensional standard Cauchy distribution)
# The value of parameters is alpha=1,beta=0,sigma=1,gamma=0.
# Choose the values of x.
x<-10 # the number of r.n
rstable(x,1,0,1,0)

# Ex 2. (One-dimensional Levy distribution)
# Choose the values of sigma, gamma, x.
# alpha = 0.5, beta=1
x<-10 # the number of r.n
beta <- 1
sigma <- 0.1
gamma <- 0.1
rstable(x,0.5,beta,sigma,gamma)

# Ex 3. (Symmetric bilateral gamma)
# delta=delta.plus=delta.minus, gamma=gamma.plus=gamma.minus.
# Choose the values of delta and gamma and x.
x<-10 # the number of r.n
rbgamma(x,1,1,1,1)
```

```
# Ex 4. ((Possibly skewed) variance gamma)
# lambda, alpha, beta, mu
# Choose the values of lambda, alpha, beta, mu and x.
x<-10 # the number of r.n
rvgamma(x,2,1,-0.5,0)

# Ex 5. (One-dimensional normal inverse Gaussian distribution)
# Lambda=1.
# Choose the parameter values and x.
x<-10 # the number of r.n
rNIG(x,1,1,1,1)

# Ex 6. (Multi-dimensional normal inverse Gaussian distribution)
# Choose the parameter values and x.
beta<-c(.5,.5)
mu<-c(0,0)
Lambda<-matrix(c(1,0,0,1),2,2)
x<-10 # the number of r.n
rNIG(x,1,beta,1,mu,Lambda)

# Ex 7. (Positive tempered stable)
# Choose the parameter values and x.
alpha<-0.7
a<-0.2
b<-1
x<-10 # the number of r.n
rpts(x,alpha,a,b)

# Ex 8. (Generarized inverse Gaussian)
# Choose the parameter values and x.
lambda<-0.3
delta<-1
gamma<-0.5
x<-10 # the number of r.n
rGIG(x,lambda,delta,gamma)

# Ex 9. (Multi-variate generalized hyperbolic)
# Choose the parameter values and x.
lambda<-0.4
alpha<-1
beta<-c(0,0.5)
delta<-1
mu<-c(0,0)
Lambda<-matrix(c(1,0,0,1),2,2)
x<-10 # the number of r.n
rGH(x,lambda,alpha,beta,delta,mu,Lambda)

## End(Not run)
```

---

setCarma *Continuous Autoregressive Moving Average (p, q) model*

Description

'setCarma' describes the following model:

`Vt = c0 + sigma (b0 Xt(0) + ... + b(q) Xt(q))`

`dXt(0) = Xt(1) dt`

`...`

`dXt(p-2) = Xt(p-1) dt`

`dXt(p-1) = (-a(p) Xt(0) - ... - a(1) Xt(p-1))dt + (gamma(0) + gamma(1) Xt(0) + ... + gamma(p) Xt(p-1))dZt`

The continuous ARMA process using the state-space representation as in Brockwell (2000) is obtained by choosing:

`gamma(0) = 1, gamma(1) = gamma(2) = ... = gamma(p) = 0.`

Please refer to the vignettes and the examples or the **yuima** documentation for details.

Usage

```
setCarma(p,q,loc.par=NULL,scale.par=NULL,ar.par="a",ma.par="b",
lin.par=NULL,Carma.var="v",Latent.var="x",XinExpr=FALSE, Cogarch=FALSE, ...)
```

Arguments

`p`	a non-negative integer that indicates the number of the autoregressive coefficients.
`q`	a non-negative integer that indicates the number of the moving average coefficients.
`loc.par`	location coefficient. The default value `loc.par=NULL` implies that `c0=0`.
`scale.par`	scale coefficient. The default value `scale.par=NULL` implies that `sigma=1`.
`ar.par`	a character-string that is the label of the autoregressive coefficients. The default Value is `ar.par="a"`.
`ma.par`	a character-string that is the label of the moving average coefficients. The default Value is `ma.par="b"`.
`Carma.var`	a character-string that is the label of the observed process. Defaults to `"v"`.
`Latent.var`	a character-string that is the label of the unobserved process. Defaults to `"x"`.
`lin.par`	a character-string that is the label of the linear coefficients. If `lin.par=NULL`, the default, the 'setCarma' builds the CARMA(p, q) model defined as in Brockwell (2000).
`XinExpr`	a logical variable. The default value `XinExpr=FALSE` implies that the starting condition for `Latent.var` is zero. If `XinExpr=TRUE`, each component of `Latent.var` has a parameter as a initial value.
`Cogarch`	a logical variable. The default value `Cogarch=FALSE` implies that the parameters are specified according to Brockwell (2000).
`...`	Arguments to be passed to 'setCarma', such as the slots of `yuima.model-class`
	`measure` Levy measure of jump variables.

`measure.type` type specification for Levy measure.

`xinit` a vector of `expressions` identyfying the starting conditions for CARMA model.

Details

Please refer to the vignettes and the examples or to the **yuimadocs** package.

An object of `yuima.carma-class` contains:

`info`**:** It is an object of `carma.info-class` which is a list of arguments that identifies the carma(p,q) model

and the same slots in an object of `yuima.model-class` .

Value

`model` an object of `yuima.carma-class`.

Note

There may be missing information in the model description. Please contribute with suggestions and fixings.

Author(s)

The YUIMA Project Team

References

Brockwell, P. (2000) Continuous-time ARMA processes, *Stochastic Processes: Theory and Methods. Handbook of Statistics*, **19**, (C. R. Rao and D. N. Shandhag, eds.) 249-276. North-Holland, Amsterdam.

Examples

```
# Ex 1. (Continuous ARMA process driven by a Brownian Motion)
# To describe the state-space representation of a CARMA(p=3,q=1) model:
# Vt=c0+alpha0*X0t+alpha1*X1t
# dX0t = X1t*dt
# dX1t = X2t*dt
# dX2t = (-beta3*X0t-beta2*X1t-beta1*X2t)dt+dWt
# we set
mod1<-setCarma(p=3,
               q=1,
               loc.par="c0")
# Look at the model structure by
str(mod1)

# Ex 2. (General setCarma model driven by a Brownian Motion)
# To describe the model defined as:
# Vt=c0+alpha0*X0t+alpha1*X1t
```

```
# dX0t = X1t*dt
# dX1t = X2t*dt
# dX2t = (-beta3*X0t-beta2*X1t-beta1*X2t)dt+(c0+alpha0*X0t)dWt
# we set
mod2 <- setCarma(p=3,
                 q=1,
                 loc.par="c0",
                 ma.par="alpha",
                 ar.par="beta",
                 lin.par="alpha")
# Look at the model structure by
str(mod2)

# Ex 3. (Continuous Arma model driven by a Levy process)
# To specify the CARMA(p=3,q=1) model driven by a Compound Poisson process defined as:
# Vt=c0+alpha0*X0t+alpha1*X1t
# dX0t = X1t*dt
# dX1t = X2t*dt
# dX2t = (-beta3*X0t-beta2*X1t-beta1*X2t)dt+dzt
# we set the Levy measure as in setModel
mod3 <- setCarma(p=3,
                 q=1,
                 loc.par="c0",
                 measure=list(intensity="1",df=list("dnorm(z, 0, 1)")),
                 measure.type="CP")
# Look at the model structure by
str(mod3)

# Ex 4. (General setCarma  model driven by a Levy process)
# Vt=c0+alpha0*X0t+alpha1*X1t
# dX0t = X1t*dt
# dX1t = X2t*dt
# dX2t = (-beta3*X1t-beta2*X2t-beta1*X3t)dt+(c0+alpha0*X0t)dzt
mod4 <- setCarma(p=3,
                 q=1,
                 loc.par="c0",
                 ma.par="alpha",
                 ar.par="beta",
                 lin.par="alpha",
                 measure=list(intensity="1",df=list("dnorm(z, 0, 1)")),
                 measure.type="CP")
# Look at the model structure by
str(mod4)
```

`setCarmaHawkes` *Hawkes Process with a Continuous Autoregressive Moving Average(p, q) intensity*

Description

'setCarmaHawkes' describes a self-exciting Hawkes process where the intensity is a CARMA(p,q) process. The model admits the Hawkes process with exponential kernel as a special case but it is able to reproduce a more complex time-dependence structure

Usage

```
setCarmaHawkes(p, q, law = NULL, base.Int = "mu0",
ar.par = "a", ma.par = "b", Counting.Process = "N",
Intensity.var = "lambda", Latent.var = "x", time.var = "t",
Type.Jump = FALSE, XinExpr = FALSE)
```

Arguments

p	a non-negative integer that indicates the number of the autoregressive coefficients.
q	a non-negative integer that indicates the number of the moving average coefficients.
law	An object of yuima.law-class that describes the jump size. If it is NULL, the jump size is unitary.
base.Int	a character-string that is the label of the baseline Intensity parameter. Defaults to "mu0".
ar.par	a character-string that is the label of the autoregressive coefficients. The default Value is ar.par="a".
ma.par	a character-string that is the label of the moving average coefficients. The default Value is ma.par="b".
Counting.Process	a character-string that is the label of the Counting process. Defaults to "N".
Intensity.var	a character-string that is the label of the Intensity process. Defaults to "lambda"
Latent.var	a character-string that is the label of the unobserved process. Defaults to "x".
time.var	the name of the time variable.
Type.Jump	a logical value. If it is TRUE, the jump size is deterministic.
XinExpr	a logical variable. The default value XinExpr=FALSE implies that the starting condition for Latent.var is zero. If XinExpr=TRUE, each component of Latent.var has a parameter as a initial value.

Value

Model an object of yuima.carmaHawkes-class.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

References

Mercuri, L., Perchiazzo, A., & Rroji, E. (2022). A Hawkes model with CARMA (p, q) intensity. doi:10.48550/arXiv.2208.02659.

Examples

```
## Not run:
# Definition of an Hawkes with exponential Kernel
mod1 <- setCarmaHawkes(p = 1, q = 0)

# Definition of an Hawkes with a CARMA(2,1) Intensity process
mod2 <- setCarmaHawkes(p = 2, q = 1)

## End(Not run)
```

---

setCharacteristic *Set characteristic information and create a 'characteristic' object.*

Description

`setCharacteristic` is a constructor for `characteristic` class.

Usage

```
setCharacteristic(equation.number,time.scale)
```

Arguments

`equation.number`	The number of equations modeled in `yuima` object.
`time.scale`	time.scale assumed in the model.

Details

class `characteristic` has two slots, `equation.number` is the number of equations handled in the yuima object, and `time.scale` is a hoge of `characteristic`.

Value

An object of class `characteristic`.

Author(s)

The YUIMA Project Team

setCogarch *Continuous-time GARCH (p,q) process*

Description

setCogarch describes the Cogarch(p,q) model introduced in Brockwell et al. (2006):

dGt = sqrt(Vt)dZt

Vt = a0 + (a1 Yt(1) + ... + a(p) Yt(p))

dYt(1) = Yt(2) dt

...

dYt(q-1) = Yt(q) dt

dYt(q) = (-b(q) Yt(1) - ... - b(1) Yt(q))dt + (a0 + (a1 Yt(1) + ... + a(p) Yt(p))d[ZtZt]^{q}

Usage

```
setCogarch(p, q, ar.par = "b", ma.par = "a", loc.par = "a0", Cogarch.var = "g",
   V.var = "v", Latent.var = "y", jump.variable = "z",  time.variable = "t",
   measure = NULL, measure.type = NULL, XinExpr = FALSE, startCogarch = 0,
   work = FALSE, ...)
```

Arguments

p	a non negative integer that is the number of the moving average coefficients of the Variance process.
q	a non-negative integer that indicates the number of the autoregressive coefficients of the Variance process.
ar.par	a character-string that is the label of the autoregressive coefficients.
ma.par	a character-string that is the label of the autoregressive coefficients.
loc.par	the location coefficient.
Cogarch.var	a character-string that is the label of the observed cogarch process.
V.var	a character-string that is the label of the latent variance process.
Latent.var	a character-string that is the label of the latent process in the state space representation for the variance process.
jump.variable	the jump variable.
time.variable	the time variable.
measure	Levy measure of jump variables.
measure.type	type specification for Levy measure.
XinExpr	a vector of expressions identyfying the starting conditions for Cogarch model.
startCogarch	Start condition for the Cogarch process
work	Internal Variable. In the final release this input will be removed.
...	Arguments to be passed to setCogarch such as the slots of the yuima.model-class

Details

We remark that yuima describes a Cogarch(p,q) model using the formulation proposed in Brockwell et al. (2006). This representation has the Cogarch(1,1) model introduced in Kluppelberg et al. (2004) as a special case. Indeed, by choosing beta = a0 b1, eta = b1 and phi = a1, we obtain the Cogarch(1,1) model proposed in Kluppelberg et al. (2004) defined as the solution of the SDEs:

dGt = sqrt(Vt)dZt

dVt = (beta - eta Vt) dt + phi Vt d[ZtZt]^{q}

Please refer to the vignettes and the examples.

An object of yuima.cogarch-class contains:

info: It is an object of cogarch.info-class which is a list of arguments that identifies the Cogarch(p,q) model

and the same slots in an object of yuima.model-class .

Value

model an object of yuima.cogarch-class.

Note

There may be missing information in the model description. Please contribute with suggestions and fixings.

Author(s)

The YUIMA Project Team

References

Brockwell, P., Chadraa, E. and Lindner, A. (2006) Continuous-time GARCH processes, *The Annals of Applied Probability*, **16**, 790-826.

Kluppelberg, C., Lindner, A., and Maller, R. (2004) A continuous-time GARCH process driven by a Levy process: Stationarity and second-order behaviour, *Journal of Applied Probability*, **41**, 601-622.

Stefano M. Iacus, Lorenzo Mercuri, Edit Rroji (2017) COGARCH(p,q): Simulation and Inference with the yuima Package, *Journal of Statistical Software*, **80**(4), 1-49.

Examples

```
# Ex 1. (Continuous time GARCH process driven by a compound poisson process)
prova<-setCogarch(p=1,q=3,work=FALSE,
                  measure=list(intensity="1", df=list("dnorm(z, 0, 1)")),
                  measure.type="CP",
                  Cogarch.var="y",
                  V.var="v",
                  Latent.var="x")
```

setData *Set and access data of an object of type "yuima.data" or "yuima".*

Description

setData constructs an object of yuima.data-class.

get.zoo.data returns the content of the zoo.data slot of a yuima.data-class object. (Note: value is a list of zoo objects).

plot plot method for object of yuima.data-class or yuima-class.

dim returns the dim of the zoo.data slot of a yuima.data-class object.

length returns the length of the time series in zoo.data slot of a yuima.data-class object. cbind.yuima bind yuima.data object.

Usage

```
setData(original.data, delta=NULL, t0=0)
get.zoo.data(x)
```

Arguments

original.data	some type of data, usually some sort of time series. The function always tries to convert to the input data into an object of zoo-type. See Details.
x	an object of type yuima.data-class or yuima-class.
delta	If there is the need to redefine on the fly the delta increment of the data to make it consistent to statistical theory. See Details.
t0	the time origin for the internal zoo.data slot, defaults to 0.

Details

Objects in the yuima.data-class contain two slots:

original.data**:** The slot original.data contains, as the name suggests, a copy of the original data passed to the function setData. It is intended for backup purposes.

zoo.data**:** the function setData tries to convert original.data into an object of class zoo. The coerced zoo data are stored in the slot zoo.data. If the conversion fails the function exits with an error. Internally, the **yuima** package stores and operates on zoo-type objects.

The function get.zoo.data returns the content of the slot zoo.data of x if x is of yuima.data-class or the content of x@data@zoo.data if x is of yuima-class.

Value

value	a list of object(s) of yuima.data-class for setData. The content of the zoo.data slot for get.zoo.data

Author(s)

The YUIMA Project Team

Examples

```
X <- ts(matrix(rnorm(200),100,2))
mydata <- setData(X)
str(get.zoo.data(mydata))
dim(mydata)
length(mydata)
plot(mydata)

# exactly the same output
mysde <- setYuima(data=setData(X))
str(get.zoo.data(mysde))
plot(mysde)
dim(mysde)
length(mysde)

# changing delta on the fly to 1/252
mysde2 <- setYuima(data=setData(X, delta=1/252))
str(get.zoo.data(mysde2))
plot(mysde2)
dim(mysde2)
length(mysde2)

# changing delta on the fly to 1/252 and shifting time to t0=1
mysde2 <- setYuima(data=setData(X, delta=1/252, t0=1))
str(get.zoo.data(mysde2))
plot(mysde2)
dim(mysde2)
length(mysde2)
```

---

setFunctional *Description of a functional associated with a perturbed stochastic differential equation*

Description

This function is used to give a description of the stochastic differential equation. The functional represent the price of the option in financial economics, for example.

Usage

```
setFunctional(model, F, f, xinit,e)
```

Arguments

model	yuima or yuima.model object.
F	function of X_t and $epsilon$
f	list of functions of X_t and $epsilon$
xinit	initial values of state variable.
e	epsilon parameter

Details

You should look at the vignette and examples.

The object foi contains several "slots". To see inside its structure we use the R command str. f and Fare R (list of) expressions which contains the functional of interest specification. e is a small parameter on which we conduct asymptotic expansion of the functional.

Value

yuima	an object of class 'yuima' containing object of class 'functional'. If yuima object was given as 'model' argument, the result is just added and the other slots of the object are maintained.

Note

There may be missing information in the model description. Please contribute with suggestions and fixings.

Author(s)

The YUIMA Project Team

Examples

```
set.seed(123)
# to the Black-Scholes economy:
# dXt^e = Xt^e * dt + e * Xt^e * dWt
diff.matrix <- matrix( c("x*e"), 1,1)
model <- setModel(drift = c("x"), diffusion = diff.matrix)
# call option is evaluated by averating
# max{ (1/T)*int_0^T Xt^e dt, 0}, the first argument is the functional of interest:
Terminal <- 1
xinit <- c(1)
f <- list( c(expression(x/Terminal)), c(expression(0)))
F <- 0
division <- 1000
e <- .3
yuima <- setYuima(model = model,sampling = setSampling(Terminal = Terminal, n = division))
yuima <- setFunctional( model = yuima, xinit=xinit, f=f,F=F,e=e)
# look at the model structure
str(yuima@functional)
```

setHawkes *Constructor of Hawkes model*

Description

'setHawkes' constructs an object of class yuima.Hawkes that is a mathematical description of a multivariate Hawkes model

Usage

```
setHawkes(lower.var = "0", upper.var = "t", var.dt = "s",
  process = "N", dimension = 1, intensity = "lambda",
  ExpKernParm1 = "c", ExpKernParm2 = "a", const = "nu",
  measure = NULL, measure.type = NULL)
```

Arguments

lower.var	Lower bound in the integral
upper.var	Upper bound in the integral
var.dt	Time variable
process	Counting process
dimension	An integer that indicates the components of the counting process
intensity	Intensity Process
ExpKernParm1	Kernel parameters
ExpKernParm2	Kernel parameters
const	Constant term in the intensity process
measure	Jump size. By default 1
measure.type	Type. By default code.

Details

By default the object is an univariate Hawkes process

Value

The function returns an object of class yuima.Hawkes.

Author(s)

YUIMA Team

Examples

```
## Not run:
# Definition of an univariate hawkes model

provaHawkes2<-setHawkes()
str(provaHawkes2)

# Simulation

true.par <- list(nu1=0.5, c11=3.5,  a11=4.5)

simprv1 <- simulate(object = provaHawkes2, true.parameter = true.par,
  sampling = setSampling(Terminal =70, n=7000))

plot(simprv1)

# Computation of intensity

lambda1 <- Intensity.PPR(simprv1, param = true.par)

plot(lambda1)

# qmle

res1 <- qmle(simprv1, method="Nelder-Mead", start = true.par)

summary(res1)

## End(Not run)
```

`setIntegral` *Integral of Stochastic Differential Equation*

Description

'`setIntegral`' is the constructor of an object of class yuima.Integral

Usage

```
setIntegral(yuima, integrand, var.dx, lower.var, upper.var,
 out.var = "", nrow = 1, ncol = 1)
```

Arguments

`yuima`	an object of class `yuima.model` that is the SDE.
`integrand`	A matrix or a vector of strings that describe each component of the integrand.
`var.dx`	A label that indicates the variable of integration

lower.var	A label that indicates the lower variable in the support of integration, by default lower.var = 0.
upper.var	A label that indicates the upper variable in the support of integration, by default upper.var = t.
out.var	Label for the output
nrow	Dimension of output if integrand is a vector of string.
ncol	Dimension of output if integrand is a vector of string.

Value

The constructor returns an object of class yuima.Integral.

Author(s)

The YUIMA Project Team

References

Yuima Documentation

Examples

```
## Not run:
# Definition Model

Mod1<-setModel(drift=c("a1"), diffusion = matrix(c("s1"),1,1),
  solve.variable = c("X"), time.variable = "s")

# In this example we define an integral of SDE such as
# \[
# I=\int^{t}_{0} b*exp(-a*(t-s))*(X_s-a1*s)dX_s
# \]

integ <- matrix("b*exp(-a*(t-s))*(X-a1*s)",1,1)

Integral <- setIntegral(yuima = Mod1,integrand = integ,
  var.dx = "X", lower.var = "0", upper.var = "t",
  out.var = "", nrow =1 ,ncol=1)

# Structure of slots

is(Integral)
# Function h in the above definition
Integral@Integral@Integrand@IntegrandList
# Dimension of Intgrand
Integral@Integral@Integrand@dimIntegrand

# all parameters are $\left(b,a,a1,s1\right)$
Integral@Integral@param.Integral@allparam

# the parameters in the integrand are $\left(b,a,a1\right)$ \newline
```

```
Integral@Integral@param.Integral@Integrandparam

# common parameters are $a1$
Integral@Integral@param.Integral@common

# integral variable dX_s
Integral@Integral@variable.Integral@var.dx
Integral@Integral@variable.Integral@var.time

# lower and upper vars
Integral@Integral@variable.Integral@lower.var
Integral@Integral@variable.Integral@upper.var


## End(Not run)
```

`setLaw` *Random variable constructor*

Description

Constructor of a random variable

Usage

```
setLaw(rng = function(n, ...) {
    NULL
}, density = function(x, ...) {
    NULL
}, cdf = function(q, ...) {
    NULL
}, quant = function(p, ...) {
    NULL
}, characteristic = function(u, ...) {
    NULL
}, time.var = "t", dim = NA)
```

Arguments

`rng`	function
`density`	function
`cdf`	function
`characteristic`	function
`quant`	function
`time.var`	label
`dim`	label

Details

Insert additional info

Value

object of class yuima.law

Note

Insert additional info

Author(s)

YUIMA TEAM

`setLaw_th` *Constructior of a t-Levy process.*

Description

`setLaw_th` constructs an object of class `yuima.th-class`.

Usage

```
setLaw_th(h = 1, method = "LAG", up = 7, low = -7, N = 180,
N_grid = 1000, regular_par = NULL, ...)
```

Arguments

`h`	a numeric object that is the time of the intervals
`method`	Method for the inversion of the characteristic function. Three methods are available: `cos`, `LAG`, and `FFT`.
`up`	Upper bound for the integration support.
`low`	Lower bound for the integration support.
`N`	Integration grid.
`N_grid`	Number of points in the support.
`regular_par`	A scalar for controlling the Gibbs effect for the inversion of the characteristic function
`...`	Additional arguments. See `setLaw` for more details.

Value

The function returns an object of class `yuima.th-class`.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

setLRM *A constructor of a t-Student Regression Model.*

Description

This function returns an object of yuima.LevyRM-class

Usage

```
setLRM(unit_Levy, yuima_regressors, LevyRM = "Y", coeff = c("mu", "sigma0"),
data = NULL, sampling = NULL, characteristic = NULL, functional = NULL, ...)
```

Arguments

unit_Levy	An object of yuima.th-class that describes the t - noise in the regression model.
yuima_regressors	An object of yuima.model-class that represents the regressors.
LevyRM	The label of the output variable. Default 'Y'.
coeff	Labels for the regressor coefficients and the scale parameter.
data	An object of yuima.data-class that contains simulated or real data.
sampling	An object of yuima.sampling-class.
characteristic	An object of yuima.characteristic-class.
functional	An object of class yuima.functional-class.
...	Additional arguments. See setYuima.

Value

An object of yuima.LevyRM-class.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

setMap *Map of a Stochastic Differential Equation*

Description

'setMap' is the constructor of an object of class yuima.Map that describes a map of a SDE

Usage

```
setMap(func, yuima, out.var = "", nrow = 1, ncol = 1)
```

Arguments

func	a matrix or a vector of strings that describe each component of the map.
yuima	an object of class yuima.model that is the SDE.
out.var	label for the output
nrow	dimension of Map if func is a vector of string.
ncol	dimension of output if func is a vector of string.

Value

The constructor returns an object of class yuima.Map.

Author(s)

The YUIMA Project Team

References

Yuima Documentation

Examples

```
## Not run:
# Definition of a yuima model
mod <- setModel(drift=c("a1", "a2"),
  diffusion = matrix(c("s1","0","0","s2"),2,2),
  solve.variable = c("X","Y"))

# Definition of a map
my.Map <- matrix(c("(X+Y)","-X-Y",
  "a*exp(X-a1*t)","b*exp(Y-a2*t)"),
  nrow=2,ncol=2)

# Construction of yuima.Map

yuimaMap <- setMap(func = my.Map, yuima = mod,
```

```
  out.var = c("f11","f21","f12","f22"))

# Simulation of a Map

set.seed(123)
samp <- setSampling(0, 100,n = 1000)
mypar <- list(a=1, b=1, s1=0.1, s2=0.2, a1=0.1, a2=0.1)
sim1 <- simulate(object = yuimaMap, true.parameter = mypar,
  sampling = samp)

# plot

plot(sim1, ylab = yuimaMap@Output@param@out.var,
  main = "simulation Map", cex.main = 0.8)


## End(Not run)
```

`setModel` *Basic description of stochastic differential equations (SDE)*

Description

'setModel' gives a description of stochastic differential equation with or without jumps of the following form:

`dXt = a(t,Xt, alpha)dt + b(t,Xt,beta)dWt + c(t,Xt,gamma)dZt, X0=x0`

All functions relying on the **yuima** package will get as much information as possible from the different slots of the `yuima-class` structure without replicating the same code twice. If there are missing pieces of information, some default values can be assumed.

Usage

```
setModel(drift = NULL, diffusion = NULL, hurst = 0.5, jump.coeff = NULL,
measure = list(), measure.type = character(), state.variable = "x",
jump.variable = "z", time.variable = "t", solve.variable, xinit)
```

Arguments

`drift`	a vector of `expressions` (the default value is 0 when `drift=NULL`).
`diffusion`	a matrix of `expressions` (the default value is 0 when `diffusion=NULL`).
`hurst`	the Hurst parameter of the gaussian noise. If `h=0.5`, the default, the process is Wiener otherwise it is fractional Brownian motion with that precise value of the Hurst index. Can be set to `NA` for further specification.
`jump.coeff`	a matrix of `expressions` for the jump component.
`measure`	Levy measure for jump variables.

measure.type	type specification for Levy measures.
state.variable	a vector of names of the state variables in the drift and diffusion coefficients.
jump.variable	a vector of names of the jump variables in the jump coefficient.
time.variable	the name of the time variable.
solve.variable	a vector of names of the variables in the left-hand-side of the equations in the model; solve.variable equals state.variable as long as we have no exogenous variable other than statistical parameters in the coefficients (drift and diffusion).
xinit	a vector of numbers identifying the initial value of the solve.variable.

Details

Please refer to the vignettes and the examples or to the **yuimadocs** package.

An object of yuima.model-class contains several slots:

drift: an R expression which specifies the drift coefficient (a vector).

diffusion: an R expression which specifies the diffusion coefficient (a matrix).

jump.coeff: coefficient of the jump term.

measure: the Levy measure of the driving Levy process.

measure.type: specifies the type of the measure, such as CP, code or density. See below.

parameter: a short name for "parameters". It is an object of model.parameter-class which is a list of vectors of names of parameters belonging to the single components of the model (drift, diffusion, jump and measure), the names of common parameters and the names of all parameters. For more details see model.parameter-class documentation page.

solve.variable: a vector of variable names, each element corresponds to the name of the solution variable (left-hand-side) of each equation in the model, in the corresponding order.

state.variable: identifies the state variables in the R expression. By default, it is assumed to be x.

jump.variable: the variable for the jump coefficient. By default, it is assumed to be z.

time: the time variable. By default, it is assumed to be t.

solve.variable: used to identify the solution variables in the R expression, i.e. the variable with respect to which the stochastic differential equation has to be solved. By default, it is assumed to be x, otherwise the user can choose any other model specification.

noise.number: denotes the number of sources of noise. Currently only for the Gaussian part.

equation.number: denotes the dimension of the stochastic differential equation.

dimension: the dimensions of the parameters in the parameter slot.

xinit: denotes the initial value of the stochastic differential equation.

The yuima.model-class structure assumes that the user either uses the default names for state.variable, jump.variable, solution.variable and time.variable or specifies his/her own names. All the rest of the terms in the R expressions are considered as parameters and identified accordingly in the parameter slot.

Value

model — an object of yuima.model-class.

Note

There may be missing information in the model description. Please contribute with suggestions and fixings.

Author(s)

The YUIMA Project Team

Examples

```
# Ex 1. (One-dimensional diffusion process)
# To describe
# dXt = -3*Xt*dt + (1/(1+Xt^2+t))dWt,
# we set
mod1 <- setModel(drift = "-3*x", diffusion = "1/(1+x^2+t)", solve.variable = c("x"))
# We may omit the solve.variable; then the default variable x is used
mod1 <- setModel(drift = "-3*x", diffusion = "1/(1+x^2+t)")
# Look at the model structure by
str(mod1)

# Ex 2. (Two-dimensional diffusion process with three factors)
# To describe
# dX1t = -3*X1t*dt + dW1t +X2t*dW3t,
# dX2t = -(X1t + 2*X2t)*dt + X1t*dW1t + 3*dW2t,
# we set the drift coefficient
a <- c("-3*x1","-x1-2*x2")
# and also the diffusion coefficient
b <- matrix(c("1","x1","0","3","x2","0"),2,3)
# Then set
mod2 <- setModel(drift = a, diffusion = b, solve.variable = c("x1","x2"))
# Look at the model structure by
str(mod2)
# The noise.number is automatically determined by inputting the diffusion matrix expression.
# If the dimensions of the drift differs from the number of the rows of the diffusion,
# the error message is returned.

# Ex 3. (Process with jumps (compound Poisson process))
# To describe
# dXt = -theta*Xt*dt+sigma*dZt
mod3 <- setModel(drift=c("-theta*x"), diffusion="sigma",
jump.coeff="1", measure=list(intensity="1", df=list("dnorm(z, 0, 1)")),
measure.type="CP", solve.variable="x")
# Look at the model structure by
str(mod3)

# Ex 4. (Process with jumps (stable process))
# To describe
# dXt = -theta*Xt*dt+sigma*dZt
```

```
mod4 <- setModel(drift=c("-theta*x"), diffusion="sigma",
jump.coeff="1", measure.type="code",measure=list(df="rstable(z,1,0,1,0)"), solve.variable="x")
# Look at the model structure by
str(mod4)
# See rng about other candidate of Levy noises.

# Ex 5. (Two-dimensional stochastic differenatial equation with Levy noise)
# To describe
# dX1t = (1 - X1t - X2t)*dt+dZ1t
# dX2t = (0.5 - X1t - X2t)*dt+dZ2t
beta<-c(.5,.5)
mu<-c(0,0)
Lambda<-matrix(c(1,0,0,1),2,2)
mod5 <- setModel(drift=c("1 - x1-x2",".5 - x1-x2"),
solve.variable=c("x1","x2"), jump.coeff=Lambda, measure.type="code",
measure=list(df="rNIG(z, alpha, beta, delta0, mu, Lambda)"))
# Look at the model structure by
str(mod5)

# Ex 6. (Process with fractional Gaussian noise)
# dYt = 3*Yt*dt + dWt^h
mod6 <- setModel(drift="3*y", diffusion=1, hurst=0.3, solve.variable=c("y"))
# Look at the model structure by
str(mod6)
```

`setPoisson` *Basic constructor for Compound Poisson processes*

Description

'setPoisson' construct a Compound Poisson model specification for a process of the form:

`Mt = m0+sum_{i=0}^Nt c*Y_{tau_i}, M0=m0`

where Nt is a homogeneous or time-inhomogeneous Poisson process, tau_i is the sequence of random times of Nt and Y is a sequence of i.i.d. random jumps.

Usage

```
setPoisson(intensity = 1, df = NULL, scale = 1, dimension=1, ...)
```

Arguments

`intensity`	either and expression or a numerical value representing the intensity function of the Poisson process Nt.
`df`	is the density of jump random variables Y.
`scale`	this is the scaling factor c.
`dimension`	this is the dimension of the jump component.
`...`	passed to `setModel`

Details

An object of yuima.model-class where the model slot is of class yuima.poisson-class.

Value

model an object of yuima.model-class.

Author(s)

The YUIMA Project Team

Examples

```
## Not run:
Terminal <- 10
samp <- setSampling(T=Terminal,n=1000)

# Ex 1. (Simple homogeneous Poisson process)
mod1 <- setPoisson(intensity="lambda", df=list("dconst(z,1)"))
set.seed(123)
y1 <- simulate(mod1, true.par=list(lambda=1),sampling=samp)
plot(y1)

# scaling the jumps
mod2 <- setPoisson(intensity="lambda", df=list("dconst(z,1)"),scale=5)
set.seed(123)
y2 <- simulate(mod2, true.par=list(lambda=1),sampling=samp)
plot(y2)

# scaling the jumps through the constant distribution
mod3 <- setPoisson(intensity="lambda", df=list("dconst(z,5)"))
set.seed(123)
y3 <- simulate(mod3, true.par=list(lambda=1),sampling=samp)
plot(y3)

# Ex 2. (Time inhomogeneous Poisson process)
mod4 <- setPoisson(intensity="beta*(1+sin(lambda*t))", df=list("dconst(z,1)"))
set.seed(123)
lambda <- 3
beta <- 5
y4 <- simulate(mod4, true.par=list(lambda=lambda,beta=beta),sampling=samp)
par(mfrow=c(2,1))
par(mar=c(3,3,1,1))
plot(y4)
f <- function(t) beta*(1+sin(lambda*t))
curve(f, 0, Terminal, col="red")

# Ex 2. (Time inhomogeneous Compound Poisson process with Gaussian Jumps)
mod5 <- setPoisson(intensity="beta*(1+sin(lambda*t))", df=list("dnorm(z,mu,sigma)"))
set.seed(123)
y5 <- simulate(mod5, true.par=list(lambda=lambda,beta=beta,mu=0, sigma=2),sampling=samp)
plot(y5)
```

```
f <- function(t)  beta*(1+sin(lambda*t))
curve(f, 0, Terminal, col="red")

## End(Not run)
```

`setPPR` *Point Process*

Description

Constructor of a Point Process Regression Model

Usage

```
setPPR(yuima, counting.var = "N", gFun, Kernel,
  var.dx = "s", var.dt = "s", lambda.var = "lambda",
  lower.var = "0", upper.var = "t", nrow = 1, ncol = 1)
```

Arguments

`yuima`	an object of `yuima.model-class` that describes the mathematical features of counting and covariates processes `Y[t]=(X[t],N[t])`.
`counting.var`	a label denoting the name of the counting process.
`gFun`	a vector string that is the mathematical expression of the vector function `g(t,Y[t-],theta)` in the intensity process.
`Kernel`	a matrix string that is the kernel `kappa(t-s,Y[s],theta)` in the definition of the intensity process.
`var.dx`	a string denoting the integration variable in the intensity process.
`var.dt`	a string denoting the integration time variable in the intensity process.
`lambda.var`	name of the intensity process.
`lower.var`	Lower bound of the support for the integral in the definition of the intensity process.
`upper.var`	Upper bound of the support for the integral in the definition of the intensity process.
`nrow`	number of rows in the kernel.
`ncol`	number of columns in the kernel.

Value

An object of `yuima.PPR`

Note

There may be missing information in the model description. Please contribute with suggestions and fixings.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

References

Insert Here References

Examples

```
## Not run:
## Hawkes process with power law kernel

# I. Law Definition:
my.rHwk2 <- function(n){
  as.matrix(rep(1,n))
  }
Law.Hwk2 <- setLaw(rng = my.rHwk2, dim = 1)

# II. Definition of the counting process N_t
mod.Hwk2 <- setModel(drift = c("0"), diffusion = matrix("0",1,1),
  jump.coeff = matrix(c("1"),1,1), measure = list(df = Law.Hwk2),
  measure.type = "code", solve.variable = c("N"),
  xinit=c("0"))

# III. Definition of g() and kappa()
g.Hwk2 <- "mu"
Kern.Hwk2 <- "alpha/(1+(t-s))^beta"

# IV. Construction of an yuima.PPR object
PPR.Hwk2 <- setPPR(yuima = mod.Hwk2, gFun=g.Hwk2,
  Kernel = as.matrix(Kern.Hwk2),var.dx = "N")

## End(Not run)
```

`setSampling` *Set sampling information and create a 'sampling' object.*

Description

`setSampling` is a constructor for `yuima.sampling-class`.

Usage

```
setSampling(Initial = 0, Terminal = 1, n = 100, delta,
 grid, random = FALSE, sdelta=as.numeric(NULL),
 sgrid=as.numeric(NULL), interpolation="pt" )
```

Arguments

Initial	Initial time of the grid.
Terminal	Terminal time of the grid.
n	number of time intervals.
delta	mesh size in case of regular time grid.
grid	a grid of times for the simulation, possibly empty.
random	specify if it is random sampling. See Details.
sdelta	mesh size in case of regular space grid.
sgrid	a grid in space for the simulation, possibly empty.
interpolation	a rule of interpolation in case of subsampling. By default, the previous tick interpolation. See Details.

Details

The function creates an object of type yuima.sampling-class with several slots.

Initial: initial time of the grid.

Terminal: terminal time fo the grid.

n: the number of observations - 1.

delta: in case of a regular time grid it is the mesh.

grid: the grid of times.

random: either FALSE or the distribution of the random times.

regular: indicator of whether the grid is regular or not. For internal use only.

sdelta: in case of a regular space grid it is the mesh.

sgrid: the grid in space.

oindex: in case of interpolation, a vector of indexes corresponding to the original observations used for the approximation.

interpolation: the name of the interpolation method used.

In case of subsampling, the observations are subsampled on some given grid/sgrid or according to some random times. When the original observations do not exist at a give point of the grid they are obtained by some approximation method. Available methods are "pt" or "previous tick" observation method, "nt" or "next tick" observation method, or by l"linear" interpolation. In case of interpolation, the slot oindex contains the vector of indexes corresponding to the original observations used for the approximation. For the linear method the index corresponds to the left-most observation.

The slot random is used as information in case a grid is already determined (e.g. n or delta, etc. ot the grid itself are given) or if some subsampling has occurred or if some particular method which causes a random grid is used in simulation (for example the space discretized Euler scheme). The slot random contains a list of two elements distr and scale, where distr is a the distribution of independent random times and scale is either a scaling constant or a scaling function. If the grid of times is deterministic, then random is FALSE.

If not specified and random=FALSE, the slot grid is filled automatically by the function. It is eventually modified or created after the call to the function simulate.

If delta is not specified, it is calculated as (Terminal-Initial)/n). If delta is specified, the Terminal is adjusted to be equal to Initial+n*delta.

The vectors delta, n, Initial and Terminal may have different lengths, but then they are extended to the maximal length to keep consistency. See examples.

If grid is specified, it takes precedence over all other arguments.

Value

An object of type yuima.sampling-class.

Author(s)

The YUIMA Project Team

Examples

```
samp <- setSampling(Terminal=1, n=1000)
str(samp)

samp <- setSampling(Terminal=1, n=1000, delta=0.3)
str(samp)


samp <- setSampling(Terminal=1, n=1000, delta=c(0.1,0.3))
str(samp)

samp <- setSampling(Terminal=1:3, n=1000)
str(samp)
```

---

setYuima — *Creates a "yuima" object by combining "model", "data", "sampling", "characteristic" and "functional"slots.*

Description

setYuima constructs an object of yuima-class.

Usage

```
setYuima(data, model, sampling, characteristic, functional)
```

Arguments

data	an object of yuima.data-class.
model	an object of yuima.model-class.
sampling	an object of yuima.sampling-class.
characteristic	an object of yuima.characteristic-class.
functional	an object of class yuima.functional-class.

Details

The yuima-class object is the main object of the **yuima** package. Some of the slots can be missing.

The slot data contains the data, either empirical or simulated.

The slot model contains the description of the (statistical) model which is used to generate the data via different simulation schemes, to draw inference from the data or both.

The sampling slot contains information on how the data have been collected or how they should be simulated.

The slot characteristic contains information on PLEASE FINISH THIS. The slot functional contains information on PLEASE FINISH THIS.

Please refer to the vignettes and the examples in the **yuimadocs** package for more informations.

Value

an object of yuima-class.

Author(s)

The YUIMA Project Team

Examples

```
# Creation of a yuima object with all slots for a
# stochastic differential equation
# dXt^e = -theta2 * Xt^e * dt + theta1 * dWt
diffusion <- matrix(c("theta1"), 1, 1)
drift <- c("-1*theta2*x")
ymodel <- setModel(drift=drift, diffusion=diffusion)
n <- 100
ysamp <- setSampling(Terminal=1, n=n)

yuima <- setYuima(model=ymodel, sampling=ysamp)

str(yuima)
```

simBmllag *Simulation of increments of bivariate Brownian motions with multi-scale lead-lag relationships*

Description

This function simulates increments of bivariate Brownian motions with multi-scale lead-lag relationships introduced in Hayashi and Koike (2018a) by the multi-dimensional circulant embedding method of Chan and Wood (1999).

Usage

```
simBmllag(n, J, rho, theta, delta = 1/2^(J + 1), imaginary = FALSE)
simBmllag.coef(n, J, rho, theta, delta = 1/2^(J + 1))
```

Arguments

n	the number of increments to be simulated.
J	a positive integer to determine the finest time resolution: 2^(-J-1) is regarded as the finest time resolution.
rho	a vector of scale-by-scale correlation coefficients. If length(rho) < J, zeros are appended to make the length equal to J.
theta	a vector of scale-by-scale lead-lag parameters. If length(theta) < J, zeros are appended to make the length equal to J.
delta	the step size of time increments. This must be smaller than or equal to 2^(-J-1).
imaginary	logical. See 'Details'.

Details

Let $B(t)$ be a bivariate Gaussian process with stationary increments such that its marginal processes are standard Brownian motions and its cross-spectral density is given by Eq.(14) of Hayashi and Koike (2018a). The function simBmllag simulates the increments $B(i\delta)-B((i-1)\delta), i = 1, \ldots, n$. The parameters R_j and $theta_j$ in Eq.(14) of Hayashi and Koike (2018a) are specified by rho and theta, while δ and n are specified by delta and n, respecitively.

Simulation is implemented by the multi-dimensional circulant embedding algorithm of Chan and Wood (1999). The last step of this algorithm returns a bivariate complex-valued sequence whose real and imaginary parts are independent and has the same law as $B(k\delta) - B((k-1)\delta)$, $k = 1, \ldots, n$; see Step 3 of Chan and Wood (1999, Section 3.2). If imaginary = TRUE, the function simBmllag directly returns this bivariate complex-valued sequence, so we obtain two sets of simulated increments of $B(t)$ by taking its real and complex parts. If imaginary = FALSE (default), the function returns only the real part of this sequence, so we directly obtain simulated increments of $B(t)$.

The function simBmllag.coef is internally used to compute the sequence of coefficient matrices $R(k)\Lambda(k)^{1/2}$ in Step 2 of Chan and Wood (1999, Section 3.2). This procedure can be implemented before generating random numbers. Since this step typically takes the most computational cost,

this function is useful to reduce computational time when we conduct a Monte Carlo simulation for $(B(k\delta) - B((k-1)\delta))_{k=1}^n$ with a fixed set of parameters. See 'Examples' for how to use this function to simulate $(B(k\delta) - B((k-1)\delta))_{k=1}^n$.

Value

`simBmllag` returns a n x 2 matrix if `imaginary = FALSE` (default). Otherwise, `simBmllag` returns a complex-valued n x 2 matrix.

`simBmllag.coef` returns a complex-valued m x 2 x 2 array, where m is an integer determined by the rule described at the end of Chan and Wood (1999, Section 2.3).

Note

There are typos in the first and second displayed equations in page 1221 of Hayashi and Koike (2018a): The j-th summands on their right hand sides should be multiplied by 2^j.

Author(s)

Yuta Koike with YUIMA project Team

References

Chan, G. and Wood, A. T. A. (1999). Simulation of stationary Gaussian vector fields, *Statistics and Computing*, **9**, 265–268.

Hayashi, T. and Koike, Y. (2018a). Wavelet-based methods for high-frequency lead-lag analysis, *SIAM Journal of Financial Mathematics*, **9**, 1208–1248.

Hayashi, T. and Koike, Y. (2018b). Multi-scale analysis of lead-lag relationships in high-frequency financial markets. doi:10.48550/arXiv.1708.03992.

See Also

`wllag`

Examples

```
## Not run:
## Example 1
## Simulation setting of Hayashi and Koike (2018a, Section 4).

n <- 15000
J <- 13

rho <- c(0.3,0.5,0.7,0.5,0.5,0.5,0.5,0.5)
theta <- c(-1,-1, -2, -2, -3, -5, -7, -10)/2^(J + 1)

set.seed(123)

dB <- simBmllag(n, J, rho, theta)
str(dB)
n/2^(J + 1) # about 0.9155
```

```
sum(dB[ ,1]^2) # should be close to n/2^(J + 1)
sum(dB[ ,2]^2) # should be close to n/2^(J + 1)

# Plot the sample path of the process
B <- apply(dB, 2, "diffinv") # construct the sample path
Time <- seq(0, by = 1/2^(J+1), length.out = n) # Time index
plot(zoo(B, Time), main = "Sample path of B(t)")

# Using simBmllag.coef to implement the same simulation
a <- simBmllag.coef(n, J, rho, theta)
m <- dim(a)[1]

set.seed(123)

z1 <- rnorm(m) + 1i * rnorm(m)
z2 <- rnorm(m) + 1i * rnorm(m)
y1 <- a[ ,1,1] * z1 + a[ ,1,2] * z2
y2 <- a[ ,2,1] * z1 + a[ ,2,2] * z2
dW <- mvfft(cbind(y1, y2))[1:n, ]/sqrt(m)
dB2 <- Re(dW)

plot(diff(dB - dB2)) # identically equal to zero


## Example 2
## Simulation Scenario 2 of Hayashi and Koike (2018b, Section 5).

# Simulation of Bm driving the log-price processes
n <- 30000
J <- 14

rho <- c(0.3,0.5,0.7,0.5,0.5,0.5,0.5,0.5)
theta <- c(-1,-1, -2, -2, -3, -5, -7, -10)/2^(J + 1)

dB <- simBmllag(n, J, rho, theta)

# Simulation of Bm driving the volatility processes
R <- -0.5 # leverage parameter
delta <- 1/2^(J+1) # step size of time increments
dW1 <- R * dB[ ,1] + sqrt(1 - R^2) * rnorm(n, sd = sqrt(delta))
dW2 <- R * dB[ ,2] + sqrt(1 - R^2) * rnorm(n, sd = sqrt(delta))

# Simulation of the model by the simulate function
dW <- rbind(dB[,1], dB[,2], dW1, dW2) # increments of the driving Bm

# defining the yuima object
drift <- c(0, 0, "kappa*(eta - x3)", "kappa*(eta - x4)")
diffusion <- diag(4)
diag(diffusion) <- c("sqrt(max(x3,0))", "sqrt(max(x4,0))",
                     "xi*sqrt(max(x3,0))", "xi*sqrt(max(x4,0))")
xinit <- c(0,0,"rgamma(1, 2*kappa*eta/xi^2,2*kappa/xi^2)",
           "rgamma(1, 2*kappa*eta/xi^2,2*kappa/xi^2)")
mod <- setModel(drift = drift, diffusion = diffusion,
```

```
                xinit = xinit, state.variable = c("x1","x2","x3","x4"))
samp <- setSampling(Terminal = n * delta, n = n)
yuima <- setYuima(model = mod, sampling = samp)

# simulation
result <- simulate(yuima, increment.W = dW,
                   true.parameter = list(kappa = 5, eta = 0.04, xi = 0.5))

plot(result)

## End(Not run)
```

---

simCIR *Simulation of the Cox-Ingersoll-Ross diffusion*

Description

This is a function to simulate a Cox-Ingersoll-Ross process given via the SDE

$\mathrm{d}X_t = (\alpha - \beta X_t)\mathrm{d}t + \sqrt{\gamma X_t}\mathrm{d}W_t$

with a Brownian motion $(W_t)_{t\geq 0}$ and parameters $\alpha, \beta, \gamma > 0$. We use an exact CIR simulator for $(X_{t_j})_{j=1,\ldots,n}$ through the non-central chi-squares distribution.

Usage

```
simCIR(time.points, n, h, alpha, beta, gamma, equi.dist=FALSE )
```

Arguments

alpha, beta, gamma	numbers given as in the SDE above.
equi.dist	a logical value indicating whether the sampling points are equidistant (default equi.dist=FALSE).
n	a number indicating the quantity of sampling points in the case equi.dist=TRUE.
h	a number indicating the step size in the case equi.dist=TRUE.
time.points	a numeric vector of sampling times (necessary if equi.dist=FALSE).

Value

A numeric matrix containing the realization of $(t_0, X_{t_0}), \ldots, (t_n, X_{t_n})$ with t_j denoting the j-th sampling times.

Author(s)

Nicole Hufnagel

Contacts: <nicole.hufnagel@math.tu-dortmund.de>

References

S. J. A. Malham and A. Wiese. Chi-square simulation of the CIR process and the Heston model. Int. J. Theor. Appl. Finance, 16(3):1350014, 38, 2013.

Examples

```
## You always need the parameters alpha, beta and gamma
## Additionally e.g. time.points
data <- simCIR(alpha=3,beta=1,gamma=1,
               time.points = c(0,0.1,0.2,0.25,0.3))
## or n, number of observations, h, distance between observations,
## and equi.dist=TRUE
data <- simCIR(alpha=3,beta=1,gamma=1,n=1000,h=0.1,equi.dist=TRUE)
plot(data[1,],data[2,], type="l",col=4)

## If you input every value and equi.dist=TRUE, time.points are not
## used for the simulations.

data <- simCIR(alpha=3,beta=1,gamma=1,n=1000,h=0.1,
               time.points = c(0,0.1,0.2,0.25,0.3),
               equi.dist=TRUE)

## If you leave equi.dist=FALSE, the parameters n and h are not
## used for the simulation.
data <- simCIR(alpha=3,beta=1,gamma=1,n=1000,h=0.1,
               time.points = c(0,0.1,0.2,0.25,0.3))
```

`simFunctional` *Calculate the value of functional*

Description

Calculate the value of functional associated with sde by Euler scheme.

Usage

```
simFunctional(yuima, expand.var="e")
Fnorm(yuima, expand.var="e")
F0(yuima, expand.var="e")
```

Arguments

`yuima`	a `yuima` object containing model, functional and data.
`expand.var`	default expand.var="e".

Details

Calculate the value of functional of interest. Fnorm returns normalized one, and F0 returns the value for the case small parameter epsilon = 0. In simFunctional and Fnorm, yuima MUST contains the 'data' slot (X in legacy version)

Value

Fe a real value

Note

we need to fix this routine.

Author(s)

YUIMA Project Team

Examples

```
set.seed(123)
# to the Black-Scholes economy:
# dXt^e = Xt^e * dt + e * Xt^e * dWt
diff.matrix <- matrix( c("x*e"), 1,1)
model <- setModel(drift = c("x"), diffusion = diff.matrix)
# call option is evaluated by averating
# max{ (1/T)*int_0^T Xt^e dt, 0}, the first argument is the functional of interest:
Terminal <- 1
xinit <- c(1)
f <- list( c(expression(x/Terminal)), c(expression(0)))
F <- 0
division <- 1000
e <- .3
samp <- setSampling(Terminal = Terminal, n = division)
yuima <- setYuima(model = model,sampling = samp)
yuima <- setFunctional( yuima, xinit=xinit, f=f,F=F,e=e)
# evaluate the functional value

yuima <- simulate(yuima,xinit=xinit,true.par=e)
Fe <- simFunctional(yuima)
Fe
Fenorm <- Fnorm(yuima)
Fenorm
```

---

simulate *Simulator function for multi-dimensional stochastic processes*

Description

Simulate multi-dimensional stochastic processes.

Usage

```
simulate(object, nsim=1, seed=NULL, xinit, true.parameter, space.discretized = FALSE,
 increment.W = NULL, increment.L = NULL, method = "euler", hurst, methodfGn = "WoodChan",
  sampling=sampling, subsampling=subsampling, ...)
```

Arguments

object	an yuima-class, yuima.model-class or yuima.carma-class object.
xinit	initial value vector of state variables.
true.parameter	named list of parameters.
space.discretized	flag to switch to space-discretized Euler Maruyama method.
increment.W	to specify Wiener increment for each time tics in advance.
increment.L	to specify Levy increment for each time tics in advance.
method	string Variable for simulation scheme. The default value method=euler uses the euler discretization for the simulation of a sample path.
nsim	Not used yet. Included only to match the standard genenirc in package stats.
seed	Not used yet. Included only to match the standard genenirc in package stats.
hurst	value of Hurst parameter for simulation of the fGn. Overrides the specified hurst slot.
methodfGn	simulation methods for fractional Gaussian noise.
...	passed to setSampling to create a sampling
sampling	a yuima.sampling-class object.
subsampling	a yuima.sampling-class object.

Details

simulate is a function to solve SDE using the Euler-Maruyama method. This function supports usual Euler-Maruyama method for multidimensional SDE, and space discretized Euler-Maruyama method for one dimensional SDE.

It simulates solutions of stochastic differential equations with Gaussian noise, fractional Gaussian noise awith/without jumps.

If a yuima-class object is passed as input, then the sampling information is taken from the slot sampling of the object. If a yuima.carma-class object, a yuima.model-class object or a yuima-class object with missing sampling slot is passed as input the sampling argument is used. If this argument is missing then the sampling structure is constructed from Initial, Terminal, etc. arguments (see setSampling for details on how to use these arguments).

For a COGARCH(p,q) process setting method=mixed implies that the simulation scheme is based on the solution of the state space process. For the case in which the underlying noise is a compound poisson Levy process, the trajectory is build firstly by simulation of the jump time, then the quadratic variation and the increments noise are simulated exactly at jump time. For the others Levy process, the simulation scheme is based on the discretization of the state space process solution.

Value

yuima	a yuima-class object.

Note

In the simulation of multi-variate Levy processes, the values of parameters have to be defined outside of simulate function in advance (see examples below).

Author(s)

The YUIMA Project Team

Examples

```
set.seed(123)

# Path-simulation for 1-dim diffusion process.
# dXt = -0.3*Xt*dt + dWt
mod <- setModel(drift="-0.3*y", diffusion=1, solve.variable=c("y"))
str(mod)

# Set the model in an `yuima' object with a sampling scheme.
T <- 1
n <- 1000
samp <- setSampling(Terminal=T, n=n)
ou <- setYuima(model=mod, sampling=samp)

# Solve SDEs using Euler-Maruyama method.
par(mfrow=c(3,1))
ou <- simulate(ou, xinit=1)
plot(ou)


set.seed(123)
ouB <- simulate(mod, xinit=1,sampling=samp)
plot(ouB)


set.seed(123)
ouC <- simulate(mod, xinit=1, Terminal=1, n=1000)
plot(ouC)

par(mfrow=c(1,1))


# Path-simulation for 1-dim diffusion process.
# dXt = theta*Xt*dt + dWt
mod1 <- setModel(drift="theta*y", diffusion=1, solve.variable=c("y"))
str(mod1)
ou1 <- setYuima(model=mod1, sampling=samp)

# Solve SDEs using Euler-Maruyama method.
ou1 <- simulate(ou1, xinit=1, true.p = list(theta=-0.3))
plot(ou1)

## Not run:

# A multi-dimensional (correlated) diffusion process.
# To describe the following model:
# X=(X1,X2,X3); dXt = U(t,Xt)dt + V(t)dWt
# For drift coeffcient
```

```
U <- c("-x1","-2*x2","-t*x3")
# For diffusion coefficient of X1
v1 <- function(t) 0.5*sqrt(t)
# For diffusion coefficient of X2
v2 <- function(t) sqrt(t)
# For diffusion coefficient of X3
v3 <- function(t) 2*sqrt(t)
# correlation
rho <- function(t) sqrt(1/2)
# coefficient matrix for diffusion term
V <- matrix( c( "v1(t)",
                "v2(t) * rho(t)",
                "v3(t) * rho(t)",
                "",
                "v2(t) * sqrt(1-rho(t)^2)",
                "",
                "",
                "",
                "v3(t) * sqrt(1-rho(t)^2)"
               ), 3, 3)
# Model sde using "setModel" function
cor.mod <- setModel(drift = U, diffusion = V,
state.variable=c("x1","x2","x3"),
solve.variable=c("x1","x2","x3") )
str(cor.mod)

# Set the `yuima' object.
cor.samp <- setSampling(Terminal=T, n=n)
cor <- setYuima(model=cor.mod, sampling=cor.samp)

# Solve SDEs using Euler-Maruyama method.
set.seed(123)
cor <- simulate(cor)
plot(cor)

# A non-negative process (CIR process)
# dXt= a*(c-y)*dt + b*sqrt(Xt)*dWt
 sq <- function(x){y = 0;if(x>0){y = sqrt(x);};return(y);}
 model<- setModel(drift="0.8*(0.2-x)",
  diffusion="0.5*sq(x)",solve.variable=c("x"))
 T<-10
 n<-1000
 sampling <- setSampling(Terminal=T,n=n)
 yuima<-setYuima(model=model, sampling=sampling)
 cir<-simulate(yuima,xinit=0.1)
 plot(cir)

# solve SDEs using Space-discretized Euler-Maruyama method
v4 <- function(t,x){
  return(0.5*(1-x)*sqrt(t))
}
mod_sd <- setModel(drift = c("0.1*x1", "0.2*x2"),
                     diffusion = c("v1(t)","v4(t,x2)"),
```

```
                    solve.var=c("x1","x2")
                    )
samp_sd <- setSampling(Terminal=T, n=n)
sd <- setYuima(model=mod_sd, sampling=samp_sd)
sd <- simulate(sd, xinit=c(1,1), space.discretized=TRUE)
plot(sd)


## example of simulation by specifying increments
## Path-simulation for 1-dim diffusion process
## dXt = -0.3*Xt*dt + dWt

mod <- setModel(drift="-0.3*y", diffusion=1,solve.variable=c("y"))
str(mod)

## Set the model in an `yuima' object with a sampling scheme.
Terminal <- 1
n <- 500
mod.sampling <- setSampling(Terminal=Terminal, n=n)
yuima.mod <- setYuima(model=mod, sampling=mod.sampling)

##use original increment
delta <- Terminal/n
my.dW <- rnorm(n * yuima.mod@model@noise.number, 0, sqrt(delta))
my.dW <- t(matrix(my.dW, nrow=n, ncol=yuima.mod@model@noise.number))

## Solve SDEs using Euler-Maruyama method.
yuima.mod <- simulate(yuima.mod,
                      xinit=1,
                      space.discretized=FALSE,
                      increment.W=my.dW)
if( !is.null(yuima.mod) ){
 dev.new()
 # x11()
  plot(yuima.mod)
}

## A multi-dimensional (correlated) diffusion process.
## To describe the following model:
## X=(X1,X2,X3); dXt = U(t,Xt)dt + V(t)dWt
## For drift coeffcient
U <- c("-x1","-2*x2","-t*x3")
## For process 1
diff.coef.1 <- function(t) 0.5*sqrt(t)
## For process 2
diff.coef.2 <- function(t) sqrt(t)
## For process 3
diff.coef.3 <- function(t) 2*sqrt(t)
## correlation
cor.rho <- function(t) sqrt(1/2)
## coefficient matrix for diffusion term
V <- matrix( c( "diff.coef.1(t)",
                "diff.coef.2(t) * cor.rho(t)",
```

```
                "diff.coef.3(t) * cor.rho(t)",
                "",
                "diff.coef.2(t)",
                "diff.coef.3(t) * sqrt(1-cor.rho(t)^2)",
                "diff.coef.1(t) * cor.rho(t)",
                "",
                "diff.coef.3(t)"
                ), 3, 3)
## Model sde using "setModel" function
cor.mod <- setModel(drift = U, diffusion = V,
                    solve.variable=c("x1","x2","x3") )
str(cor.mod)
## Set the `yuima' object.
set.seed(123)
obj.sampling <- setSampling(Terminal=Terminal, n=n)
yuima.obj <- setYuima(model=cor.mod, sampling=obj.sampling)

##use original dW
my.dW <- rnorm(n * yuima.obj@model@noise.number, 0, sqrt(delta))
my.dW <- t(matrix(my.dW, nrow=n, ncol=yuima.obj@model@noise.number))

## Solve SDEs using Euler-Maruyama method.
yuima.obj.path <- simulate(yuima.obj, space.discretized=FALSE,
 increment.W=my.dW)
if( !is.null(yuima.obj.path) ){
  dev.new()
#  x11()
  plot(yuima.obj.path)
}


##:: sample for Levy process ("CP" type)
## specify the jump term as c(x,t)dz
obj.model <- setModel(drift=c("-theta*x"), diffusion="sigma",
jump.coeff="1", measure=list(intensity="1", df=list("dnorm(z, 0, 1)")),
measure.type="CP", solve.variable="x")

##:: Parameters
lambda <- 3
theta <- 6
sigma <- 1
xinit <- runif(1)
N <- 500
h <- N^(-0.7)
eps <- h/50
n <- 50*N
T <- N*h

set.seed(123)
obj.sampling <- setSampling(Terminal=T, n=n)
obj.yuima <- setYuima(model=obj.model, sampling=obj.sampling)
X <- simulate(obj.yuima, xinit=xinit, true.parameter=list(theta=theta, sigma=sigma))
dev.new()
```

```
plot(X)


##:: sample for Levy process ("CP" type)
## specify the jump term as c(x,t,z)
## same plot as above example
obj.model <- setModel(drift=c("-theta*x"), diffusion="sigma",
jump.coeff="z", measure=list(intensity="1", df=list("dnorm(z, 0, 1)")),
measure.type="CP", solve.variable="x")

set.seed(123)
obj.sampling <- setSampling(Terminal=T, n=n)
obj.yuima <- setYuima(model=obj.model, sampling=obj.sampling)
X <- simulate(obj.yuima, xinit=xinit, true.parameter=list(theta=theta, sigma=sigma))
dev.new()
plot(X)




##:: sample for Levy process ("code" type)
## dX_{t} = -x dt + dZ_t
obj.model <- setModel(drift="-x", xinit=1, jump.coeff="1", measure.type="code",
measure=list(df="rIG(z, 1, 0.1)"))
obj.sampling <- setSampling(Terminal=10, n=10000)
obj.yuima <- setYuima(model=obj.model, sampling=obj.sampling)
result <- simulate(obj.yuima)
dev.new()
plot(result)

##:: sample for multidimensional Levy process ("code" type)
## dX = (theta - A X)dt + dZ,
##    theta=(theta_1, theta_2) = c(1,.5)
##    A=[a_ij], a_11 = 2, a_12 = 1, a_21 = 1, a_22=2
require(yuima)
x0 <- c(1,1)
beta <- c(.1,.1)
mu <- c(0,0)
delta0 <- 1
alpha <- 1
Lambda <- matrix(c(1,0,0,1),2,2)
cc <- matrix(c(1,0,0,1),2,2)
obj.model <- setModel(drift=c("1 - 2*x1-x2",".5-x1-2*x2"), xinit=x0,
solve.variable=c("x1","x2"), jump.coeff=cc, measure.type="code",
 measure=list(df="rNIG(z, alpha, beta, delta0, mu, Lambda)"))
obj.sampling <- setSampling(Terminal=10, n=10000)
obj.yuima <- setYuima(model=obj.model, sampling=obj.sampling)
result <- simulate(obj.yuima,true.par=list( alpha=alpha,
 beta=beta, delta0=delta0, mu=mu, Lambda=Lambda))
plot(result)


# Path-simulation for a Carma(p=2,q=1) model driven by a Brownian motion:
```

```
carma1<-setCarma(p=2,q=1)
str(carma1)

# Set the sampling scheme
samp<-setSampling(Terminal=100,n=10000)

# Set the values of the model parameters
par.carma1<-list(b0=1,b1=2.8,a1=2.66,a2=0.3)

set.seed(123)
sim.carma1<-simulate(carma1,
                     true.parameter=par.carma1,
                     sampling=samp)

plot(sim.carma1)



# Path-simulation for a Carma(p=2,q=1) model driven by a Compound Poisson process.
carma1<-setCarma(p=2,
                 q=1,
                 measure=list(intensity="1",df=list("dnorm(z, 0, 1)")),
                 measure.type="CP")

# Set Sampling scheme
samp<-setSampling(Terminal=100,n=10000)

# Fix carma parameters
par.carma1<-list(b0=1,
                 b1=2.8,
                 a1=2.66,
                 a2=0.3)

set.seed(123)
sim.carma1<-simulate(carma1,
                     true.parameter=par.carma1,
                     sampling=samp)

plot(sim.carma1)

## End(Not run)
```

---

snr *Calculating self-normalized residuals for SDEs.*

Description

Calculate self-normalized residuals based on the Gaussian quasi-likelihood estimator.

Usage

```
snr(yuima, start, lower, upper, withdrift)
```

Arguments

yuima	a yuima object.
lower	a named list for specifying lower bounds of parameters.
upper	a named list for specifying upper bounds of parameters.
start	initial values to be passed to the optimizer.
withdrift	use drift information for constructing self-normalized residuals. by default, withdrift = FALSE

Details

This function calculates the Gaussian quasi maximum likelihood estimator and associated self-normalized residuals.

Value

estimator	Gaussian quasi maximum likelihood estimator
snr	self-normalized residuals based on the Gaussian quasi maximum likelihood estimator

Author(s)

The YUIMA Project Team

Contacts: Yuma Uehara <y-uehara@ism.ac.jp>

References

Masuda, H. (2013). Asymptotics for functionals of self-normalized residuals of discretely observed stochastic processes. Stochastic Processes and their Applications 123 (2013), 2752–2778

Examples

```
## Not run:
# Test code (1. diffusion case)
yuima.mod <- setModel(drift="-theta*x",diffusion="theta1/sqrt(1+x^2)")
n <- 10000
ysamp <- setSampling(Terminal=n^(1/3),n=n)
yuima <- setYuima(model=yuima.mod, sampling=ysamp)
set.seed(123)
yuima <- simulate(yuima, xinit=0, true.parameter = list(theta=2,theta1=3))
start=list(theta=3,theta1=0.5)
lower=list(theta=1,theta1=0.3)
upper=list(theta=5,theta1=3)
res <- snr(yuima,start,lower,upper)
str(res)
```

```
# Test code (2.jump diffusion case)
a<-3
b<-5
mod <- setModel(drift="10-theta*x", #drift="10-3*x/(1+x^2)",
                diffusion="theta1*(2+x^2)/(1+x^2)",
                jump.coeff="1",
                # measure=list(intensity="10",df=list("dgamma(z, a, b)")),
                measure=list(intensity="10",df=list("dunif(z, a, b)")),
                measure.type="CP")

T <- 100 ## Terminal
n <- 10000 ## generation size
samp <- setSampling(Terminal=T, n=n) ## define sampling scheme
yuima <- setYuima(model = mod, sampling = samp)

yuima <- simulate(yuima, xinit=1,
                  true.parameter=list(theta=2,theta1=sqrt(2),a=a,b=b),
                  sampling = samp)
start=list(theta=3,theta1=0.5)
lower=list(theta=1,theta1=0.3)
upper=list(theta=5,theta1=3)
res <- snr(yuima,start,lower,upper)
str(res)

## End(Not run)
```

---

spectralcov *Spectral Method for Cumulative Covariance Estimation*

Description

This function implements the local method of moments proposed in Bibinger et al. (2014) to estimate the cummulative covariance matrix of a non-synchronously observed multi-dimensional Ito process with noise.

Usage

```
lmm(x, block = 20, freq = 50, freq.p = 10, K = 4, interval = c(0, 1),
    Sigma.p = NULL, noise.var = "AMZ", samp.adj = "direct", psd = TRUE)
```

Arguments

x	an object of yuima-class or yuima.data-class.
block	a positive integer indicating the number of the blocks which the observation interval is split into.
freq	a positive integer indicating the number of the frequencies used to compute the final estimator.

freq.p — a positive integer indicating the number of the frequencies used to compute the pilot estimator for the spot covariance matrix (corresponding to the number J_n in Eq.(29) from Altmeyer and Bibinger (2015)).

K — a positive integer indicating the number of the blocks used to compute the pilot estimator for the spot covariance matrix (corresponding to the number K_n in Eq.(29) from Altmeyer and Bibinger (2015)).

interval — a vector indicating the observation interval. The first component represents the initial value and the second component represents the terminal value.

Sigma.p — a block by dim(x) matrix giving the pilot estimates of the spot covariance matrix plugged into the optimal weight matrices. If NULL (the default), it is computed by using formula (29) from Altmeyer and Bibinger (2015).

noise.var — character string giving the method to estimate the noise variances. There are several options: "AMZ" (the default) uses equation (3.7) from Gatheral and Oomen (2010), i.e. the quasi-maximum likelihood estimator proposed by Ait-Sahalia et al. (2005) (see also Xiu (2010)). "BR" uses equation (3.9) from Gatheral and Oomen (2010), i.e. the sample average of the squared returns divided by 2, the estimator proposed by Bandi and Russel (2006). "O" uses equation (3.8) from Gatheral and Oomen (2010), i.e. another method-of-moments estimator proposed by Oomen (2006). It is also possible to directly specify the noise variances by setting this argument to a numeric vector. In this case the i-th component of noise.var must indicates the variance of the noise for the i-th component of the observation process.

samp.adj — character string giving the method to adjust the effect of the sampling times on the variances of the spectral statistics for the noise part. The default method "direct" uses the local sums of the squares of the one-skip differences of the sampling times divided by 2, which directly appears in the representation of the variances of the spectral statistics for the noise part. Another choice is "QVT", which uses the local quadratic variations of time as in Altmeyer and Bibinger (2015) and Bibinger et al. (2014).

psd — logical. If TRUE (the default), the estimated covariance matrix and variance-covariance matrix are converted to their spectral absolute values to ensure their positive semi-definiteness. This procedure does not matter in terms of the asymptotic theory.

Details

The default implementation is the adaptive version of the local method of moments estimator, which is only based on observation data. It is possible to implement oracle versions of the estimator by setting user-specified Sigma.p and/or noise.var. An example is given below.

Value

An object of class "yuima.specv", which is a list with the following elements:

covmat — the estimated covariance matrix

vcov — the estimated variance-covariance matrix of as.vector(covmat)

Sigma.p — the pilot estimates of the spot covariance matrix

Author(s)

Yuta Koike with YUIMA Project Team

References

Ait-Sahalia, Y., Mykland, P. A. and Zhang, L. (2005) How often to sample a continuous-time process in the presence of market microstructure noise, *The Review of Financial Studies*, **18**, 351–416.

Altmeyer, R. and Bibinger, M. (2015) Functional stable limit theorems for quasi-efficient spectral covolatility estimators, to appear in *Stochastic processes and their applications*, doi:10.1016/j.spa.2015.07.009.

Bandi, F. M. and Russell, J. R. (2006) Separating microstructure noise from volatility, *Journal of Financial Economics*, **79**, 655–692.

Bibinger, M., Hautsch, N., Malec, P. and Reiss, M. (2014) Estimating the quadratic covariation matrix from noisy observations: local method of moments and efficiency, *Annals of Statistics*, **42**, 80–114.

Gatheral J. and Oomen, R. C. A. (2010) Zero-intelligence realized variance estimation, *Finance Stochastics*, **14**, 249–283.

Oomen, R. C. A. (2006) Properties of realized variance under alternative sampling schemes, *Journal of Business and Economic Statistics*, **24**, 219–237.

Reiss, M. (2011) Asymptotic equivalence for inference on the volatility from noisy observations, *Annals of Statistics*, **39**, 772–802.

Xiu, D. (2010) Quasi-maximum likelihood estimation of volatility with high frequency data, *Journal of Econometrics*, **159**, 235–250.

See Also

cce, setData

Examples

```
# Example. One-dimensional and regular sampling case
# Here the simulated model is taken from Reiss (2011)

## Set a model
sigma <- function(t) sqrt(0.02 + 0.2 * (t - 0.5)^4)
modI <- setModel(drift = 0, diffusion = "sigma(t)")

## Generate a path of the process
set.seed(117)
n <- 12000
yuima.samp <- setSampling(Terminal = 1, n = n)
yuima <- setYuima(model = modI, sampling = yuima.samp)
yuima <- simulate(yuima, xinit = 0)

delta <- 0.01 # standard deviation of microstructure noise
yuima <- noisy.sampling(yuima, var.adj = delta^2) # generate noisy observations
plot(yuima)

## Estimation of the integrated volatility
```

```
est <- lmm(yuima)
est

## True integrated volatility and theoretical standard error
disc <- seq(0, 1, by = 1/n)
cat("true integrated volatility\n")
print(mean(sigma(disc[-1])^2))
cat("theoretical standard error\n")
print(sqrt(8*delta*mean(sigma(disc[-1])^3))/n^(1/4))

# Plotting the pilot estimate of the spot variance path
block <- 20
G <- seq(0,1,by=1/block)[1:block]
Sigma.p <- sigma(G)^2 # true spot variance
plot(zoo(Sigma.p, G), col = "blue",, xlab = "time",
     ylab = expression(sigma(t)^2))
lines(zoo(est$Sigma.p, G))

## "Oracle" implementation
lmm(yuima, block = block, Sigma.p = Sigma.p, noise.var = delta^2)

# Example. Multi-dimensional case
# We simulate noisy observations of a correlated bivariate Brownian motion
# First we examine the regular sampling case since in this situsation the theoretical standard
# error can easily be computed via the formulae given in p.88 of Bibinger et al. (2014)

## Set a model
drift <- c(0,0)

rho <- 0.5 # correlation

diffusion <- matrix(c(1,rho,0,sqrt(1-rho^2)),2,2)

modII <- setModel(drift=drift,diffusion=diffusion,
                  state.variable=c("x1","x2"),solve.variable=c("x1","x2"))

## Generate a path of the latent process
set.seed(123)

## We regard the unit interval as 6.5 hours and generate the path on it
## with the step size equal to 1 seconds

n <- 8000
yuima.samp <- setSampling(Terminal = 1, n = n)
yuima <- setYuima(model = modII, sampling = yuima.samp)
yuima <- simulate(yuima)

## Generate noisy observations
eta <- 0.05
yuima <- noisy.sampling(yuima, var.adj = diag(eta^2, 2))
plot(yuima)

## Estimation of the integrated covariance matrix
```

```
est <- lmm(yuima)
est

## Theoretical standard error
a <- sqrt(4 * eta * (sqrt(1 + rho) + sqrt(1 - rho)))
b <- sqrt(2 * eta * ((1 + rho)^(3/2) + (1 - rho)^(3/2)))
cat("theoretical standard error\n")
print(matrix(c(a,b,b,a),2,2)/n^(1/4))

## "Oracle" implementation
block <- 20
Sigma.p <- matrix(c(1,rho,rho,1),block,4,byrow=TRUE) # true spot covariance matrix
lmm(yuima, block = block, Sigma.p = Sigma.p, noise.var = rep(eta^2,2))

# Next we extract nonsynchronous observations from
# the path generated above by Poisson random sampling
psample <- poisson.random.sampling(yuima, rate = c(1/2,1/2), n = n)

## Estimation of the integrated covariance matrix
lmm(psample)

## "Oracle" implementation
lmm(psample, block = block, Sigma.p = Sigma.p, noise.var = rep(eta^2,2))

## Other choices of tuning parameters (estimated values are not varied so much)
lmm(psample, block = 25)
lmm(psample, freq = 100)
lmm(psample, freq.p = 15)
lmm(psample, K = 8)
```

`subsampling` *subsampling*

Description

subsampling

Usage

```
subsampling(x, sampling, ...)
```

Arguments

`x`	an `yuima-class` or `yuima.model-class` object.
`sampling`	a `yuima.sampling-class` object.
`...`	used to create a sampling structure

Details

When subsampling on some grid of times, it may happen that no data is available at the given grid point. In this case it is possible to use several techniques. Different options are avaiable specifying the argument, or the slot, `interpolation`:

`"none"` **or** `"exact"` no interpolation. If no data point exists at a given grid point, `NA` is returned in the subsampled data

`"pt"` **or** `"previous"` the first data on the left of the grid point instant is used.

`"nt"` **or** `"next"` the first data on the right of the grid point instant is used.

`"lin"` **or** `"linear"` the average of the values of the first data on the left and the first data to the right of the grid point instant is used.

Value

`yuima` a `yuima.data-class` object.

Author(s)

The YUIMA Project Team

Examples

```
## Set a model
diff.coef.1 <- function(t, x1=0, x2) x2*(1+t)
diff.coef.2 <- function(t, x1, x2=0) x1*sqrt(1+t^2)
cor.rho <- function(t, x1=0, x2=0) sqrt((1+cos(x1*x2))/2)
diff.coef.matrix <- matrix(c("diff.coef.1(t,x1,x2)",
"diff.coef.2(t,x1,x2)*cor.rho(t,x1,x2)", "",
"diff.coef.2(t,x1,x2)*sqrt(1-cor.rho(t,x1,x2)^2)"),2,2)
cor.mod <- setModel(drift=c("",""), diffusion=diff.coef.matrix,
solve.variable=c("x1", "x2"), xinit=c(3,2))
set.seed(111)

## We first simulate the two dimensional diffusion model
yuima.samp <- setSampling(Terminal=1, n=1200)
yuima <- setYuima(model=cor.mod, sampling=yuima.samp)
yuima.sim <- simulate(yuima)

plot(yuima.sim, plot.type="single")

## random sampling with exponential times
## one random sequence per time series
newsamp <- setSampling(
 random=list(rdist=c( function(x) rexp(x, rate=10),
  function(x) rexp(x, rate=20))) )
newdata <- subsampling(yuima.sim, sampling=newsamp)
points(get.zoo.data(newdata)[[1]],col="red")
points(get.zoo.data(newdata)[[2]],col="green")
```

```
plot(yuima.sim, plot.type="single")

## deterministic subsampling with different
## frequence for each time series
newsamp <- setSampling(delta=c(0.1,0.2))
newdata <- subsampling(yuima.sim, sampling=newsamp)
points(get.zoo.data(newdata)[[1]],col="red")
points(get.zoo.data(newdata)[[2]],col="green")
```

`toLatex` *Additional Methods for LaTeX Representations for Yuima objects*

Description

These methods convert `yuima-class`, `yuima.model-class`, `yuima.carma-class` or `yuima.cogarch-class` objects to character vectors with LaTeX markup.

Usage

```
## S3 method for class 'yuima'
toLatex(object,...)
## S3 method for class 'yuima.model'
toLatex(object,...)
## S3 method for class 'yuima.carma'
toLatex(object,...)
## S3 method for class 'yuima.cogarch'
toLatex(object,...)
```

Arguments

`object`	object of a class yuima, yuima.model or yuima.carma.
`...`	currently not used.

Details

This method tries to convert a formal description of the model slot of the yuima object into a LaTeX formula. This is just a simple proof of concept and probably further LaTex manipulations for use in papers. Copy and paste of the output of `toLatex` into a real LaTeX file should do the job.

Examples

```
# dXt = theta*Xt*dt + dWt
mod1 <- setModel(drift="theta*y", diffusion=1, solve.variable=c("y"))
str(mod1)
toLatex(mod1)

# A multi-dimensional (correlated) diffusion process.
# To describe the following model:
```

```
# X=(X1,X2,X3); dXt = U(t,Xt)dt + V(t)dWt
# For drift coeffcient
U <- c("-x1","-2*x2","-t*x3")
# For diffusion coefficient of X1
v1 <- function(t) 0.5*sqrt(t)
# For diffusion coefficient of X2
v2 <- function(t) sqrt(t)
# For diffusion coefficient of X3
v3 <- function(t) 2*sqrt(t)
# correlation
rho <- function(t) sqrt(1/2)
# coefficient matrix for diffusion term
V <- matrix( c( "v1(t)",
                "v2(t) * rho(t)",
                "v3(t) * rho(t)",
                "",
                "v2(t) * sqrt(1-rho(t)^2)",
                "",
                "",
                "",
                "v3(t) * sqrt(1-rho(t)^2)"
              ), 3, 3)
# Model sde using "setModel" function
cor.mod <- setModel(drift = U, diffusion = V,
state.variable=c("x1","x2","x3"),
solve.variable=c("x1","x2","x3") )
str(cor.mod)
toLatex(cor.mod)

# A CARMA(p=3,q=1) process.
carma1<-setCarma(p=3,q=1,loc.par="c",scale.par="s")
str(carma1)
toLatex(carma1)

# A COGARCH(p=3,q=5) process.
cogarch1<-setCogarch(p=3,q=5,
                     measure=list(df=list("rNIG(z, mu00, bu00, 1, 0)")),
                     measure.type="code")
str(cogarch1)
toLatex(cogarch1)
```

`variable.Integral` *Class for the mathematical description of integral of a stochastic process*

Description

Auxiliar class for definition of an object of class `yuima.Integral`. see the documentation of `yuima.Integral` for more details.

`wllag` *Scale-by-scale lead-lag estimation*

Description

This function estimates lead-lag parameters on a scale-by-scale basis from non-synchronously observed bivariate processes, using the estimatiors proposed in Hayashi and Koike (2018b).

Usage

```
wllag(x, y, J = 8, N = 10, tau = 1e-3, from = -to, to = 100,
      verbose = FALSE, in.tau = FALSE, tol = 1e-6)
```

Arguments

`x`	a zoo object for observation data of the first process.
`y`	a zoo object for observation data of the second process.
`J`	a positive integer. Scale-by scale lead-lag parameters are estimated up to the level `J`.
`N`	The number of vanishing moments of Daubechies' compactly supported wavelets. This should be an integer between 1 and 10.
`tau`	the step size of a finite grid on which objective functions are evaluated. Note that this value is identified with the finest time resolution of the underlying model. The default value `1e-3` corresponds to 1 mili-second if the unit time corresponds to 1 second.
`from`	a negative integer. `from*tau` gives the lower end of a finite grid on which objective functions are evaluated.
`to`	a positive integer. `to*tau` gives the upper end of a finite grid on which objective functions are evaluated.
`verbose`	a logical. If `FALSE` (default), the function returns only the estimated scale-by-scale lead-lag parameters. Otherwise, the function also returns some other statistics such as values of the signed objective functions. See 'Value'.
`in.tau`	a logical. If `TRUE`, the estimated lead-lag parameters are returned in increments of `tau`. That is, the estimated lead-lag parameters are divided by `tau`.
`tol`	tolelance parameter to avoid numerical errors in comparison of time stamps. All time stamps are divided by `tol` and rounded to integers. A reasonable choice of `tol` is the minimum unit of time stamps. The default value `1e-6` supposes that the minimum unit of time stamps is greater or equal to 1 micro-second.

Details

Hayashi and Koike (2018a) introduced a bivariate continuous-time model having different lead-lag relationships at different time scales. The wavelet cross-covariance functions of this model, computed based on the Littlewood-Paley wavelets, have unique maximizers in absolute values at

each time scale. These maximizer can be considered as lead-lag parameters at each time scale. To estimate these parameters from discrete observation data, Hayashi and Koike (2018b) constructed objective functions mimicking behavior of the wavelet cross-covariance functions of the underlying model. Then, estimates of the scale-by-scale lead-lag parameters can be obtained by maximizing these objective functions in absolute values.

Value

If `verbose` is `FALSE`, a numeric vector with length `J`, corresponding to the estimated scale-by-scale lead-lag parameters, is returned. Note that their positive values indicate that the first process leads the second process.

Otherwise, an object of class `"yuima.wllag"`, which is a list with the following components, is returned:

`lagtheta`	the estimated scale-by-scale lead-lag parameters. The j th component corresponds to the estimate at the level j. A positive value indicates that the first process leads the second process.
`obj.values`	the values of the objective functions evaluated at the estimated lead-lag parameters.
`obj.fun`	a list of values of the objective functions. The j th component of the list corresponds to a `zoo` object for values of the signed objective function at the level j indexed by the search grid.
`theta.hry`	the lead-lag parameter estimate in the sense of Hoffmann, Rosenbaum and Yoshida (2013).
`cor.hry`	the correltion coefficient in the sense of Hoffmann, Rosenbaum and Yoshida (2013), evaluated at the estimated lead-lag parameter.
`ccor.hry`	a `zoo` object for values of the cross correltion function in the sense of Hoffmann, Rosenbaum and Yoshida (2013) indexed by the search grid.

Note

Smaller levels correspond to finer time scales. In particular, the first level corresponds to the finest time resolution, which is defined by the argument `tau`.

If there are multiple maximizers in an objective function, `wllag` takes a maximizer farthest from zero (if there are two such values, the function takes the negative one). This behavior is different from `llag`.

The objective functions themselves do NOT consitently estimate the corresponding wavelet covariance functions. This means that values in `obj.values` and `obj.fun` cannot be interpreted as covaraince estimates (their scales depend on the degree of non-synchronicity of observation times).

Author(s)

Yuta Koike with YUIMA Project Team

References

Hayashi, T. and Koike, Y. (2018a). Wavelet-based methods for high-frequency lead-lag analysis, *SIAM Journal of Financial Mathematics*, **9**, 1208–1248.

Hayashi, T. and Koike, Y. (2018b). Multi-scale analysis of lead-lag relationships in high-frequency financial markets. doi:10.48550/arXiv.1708.03992.

Hoffmann, M., Rosenbaum, M. and Yoshida, N. (2013) Estimation of the lead-lag parameter from non-synchronous data, *Bernoulli*, **19**, no. 2, 426–461.

See Also

simBmllag, llag

Examples

```
## Not run:
## An example from a simulation setting of Hayashi and Koike (2018b)
set.seed(123)

# Simulation of Bm driving the log-price processes
n <- 15000
J <- 13
tau <- 1/2^(J+1)

rho <- c(0.3,0.5,0.7,0.5,0.5,0.5,0.5,0.5)
theta <- c(-1,-1, -2, -2, -3, -5, -7, -10) * tau

dB <- simBmllag(n, J, rho, theta)

Time <- seq(0, by = tau, length.out = n) # Time index
x <- zoo(diffinv(dB[ ,1]), Time) # simulated path of the first process
y <- zoo(diffinv(dB[ ,2]), Time) # simulated path of the second process

# Generate non-synchronously observed data
x <- x[as.logical(rbinom(n + 1, size = 1, prob = 0.5))]
y <- y[as.logical(rbinom(n + 1, size = 1, prob = 0.5))]

# Estimation of scale-by-scale lead-lag parameters (compare with theta/tau)
wllag(x, y, J = 8, tau = tau, tol = tau, in.tau = TRUE)
# Estimation with other information
out <- wllag(x, y, tau = tau, tol = tau, in.tau = TRUE, verbose = TRUE)
out

# Plot of the HRY cross-correlation function
plot(out$ccor.hry, xlab = expression(theta), ylab = expression(U(theta)))
dev.off()

# Plot of the objective functions
op <- par(mfrow = c(4,2))
plot(out)
par(op)
```

```
## End(Not run)
```

---

ybook *R code for the Yuima Book*

Description

Shows the R code corresponding to each chapter in the Yuima Book.

Usage

```
ybook(chapter)
```

Arguments

chapter	a number in 1:7

Details

This is an accessory function which open the R code corresponding to Chapter "chapter" in the Yuima Book so that the reader can replicate the code.

Examples

```
ybook(1)
```

---

yuima-class *Class for stochastic differential equations*

Description

The yuima S4 class is a class of the **yuima** package.

Details

The yuima-class object is the main object of the **yuima** package. Some of the slots may be missing.

The data slot contains the data, either empirical or simulated.

The model contains the description of the (statistical) model which is used to generate the data via different simulation schemes, to draw inference from the data or both.

The sampling slot contains information on how the data have been collected or how they should be generated.

The slot characteristic contains information on PLEASE FINISH THIS. The slot functional contains information on PLEASE FINISH THIS.

Slots

`data`: an object of class `yuima.data-class`

`model`: an object of class `yuima.model-class`

`sampling`: an object of class `yuima.sampling-class`

`characteristic`: an object of class `yuima.characteristic-class`

`functional`: an object of class `yuima.functional-class`

Methods

new `signature(x = "yuima", data = "yuima.data", model = "yuima.model", sampling = "yuima.sampling", characteristic = "yuima.characteristic")`: the function makes a copy of the prototype object from the class definition of `yuima-class`, then calls the `initialize` method passing as arguments the newly created object and the remaining arguments.

initialize `signature(x = "yuima", data = "yuima.data", model = "yuima.model", sampling = "yuima.sampling", characteristic = "yuima.characteristic")`: makes a copy of each argument in the corresponding slots of the object `x`.

get.data `signature(x = "yuima")`: returns the content of the slot `data`.

plot `signature(x = "yuima", ...)`: calls `plot` from the `zoo` package with argument `x@data@zoo.data`. Additional arguments `...` are passed as is to the `plot` function.

dim `signature(x = "yuima")`: the number of SDEs in the `yuima` object.

length `signature(x = "yuima")`: a vector of length of each SDE described in the `yuima` object.

cce `signature(x = "yuima")`: calculates the asyncronous covariance estimator on the data contained in `x@data@zoo.data`. For more details see `cce`.

llag `signature(x = "yuima")`: calculates the lead lag estimate r on the data contained in `x@data@zoo.data`. For more details see `llag`.

simulate simulation method. For more information see `simulate`.

cbind `signature(x = "yuima")`: bind yuima.data object.

Author(s)

The YUIMA Project Team

---

yuima.ae-class *Class for the asymptotic expansion of diffusion processes*

Description

The `yuima.ae` class is used to describe the output of the functions `ae` and `aeMarginal`.

Slots

`order` integer. The order of the expansion.

`var` character. The state variables.

`u.var` character. The variables of the characteristic function.

`eps.var` character. The perturbation variable.

`characteristic` expression. The characteristic function.

`density` expression. The probability density function.

`Z0` numeric. The solution to the deterministic process obtained by setting the perturbation to zero.

`Mu` numeric. The drift vector for the representation of Z1.

`Sigma` matrix. The diffusion matrix for the representation of Z1.

`c.gamma` list. The coefficients of the Hermite polynomials.

`h.gamma` list. Hermite polynomials.

---

yuima.carma-class *Class for the mathematical description of CARMA(p,q) model*

Description

The `yuima.carma` class is a class of the **yuima** package that extends the `yuima.model-class`.

Slots

`info`**:** is an `carma.info-class` object that describes the structure of the CARMA(p,q) model.

`drift`**:** is an R expression which specifies the drift coefficient (a vector).

`diffusion`**:** is an R expression which specifies the diffusion coefficient (a matrix).

`hurst`**:** the Hurst parameter of the gaussian noise. If `h=0.5`, the process is Wiener otherwise it is fractional Brownian motion with that precise value of the Hurst index. Can be set to `NA` for further specification.

`jump.coeff`**:** a vector of `expressions` for the jump component.

`measure`**:** Levy measure for jump variables.

`measure.type`**:** Type specification for Levy measures.

state.variable a vector of names identifying the names used to denote the state variable in the drift and diffusion specifications.

`parameter`**:** which is a short name for "parameters", is an object of class `model.parameter-class`. For more details see `model.parameter-class` documentation page.

`state.variable`**:** identifies the state variables in the R expression.

`jump.variable`**:** identifies the variable for the jump coefficient.

`time.variable`**:** the time variable.

`noise.number`**:** denotes the number of sources of noise. Currently only for the Gaussian part.

`equation.number`: denotes the dimension of the stochastic differential equation.

`dimension`: the dimensions of the parameter given in the `parameter` slot.

`solve.variable`: identifies the variable with respect to which the stochastic differential equation has to be solved.

`xinit`: contains the initial value of the stochastic differential equation.

`J.flag`: wheather jump.coeff include jump.variable.

Methods

simulate simulation method. For more information see `simulate`.

toLatex This method converts an object of `yuima.carma-class` to character vectors with LaTeX markup.

CarmaNoise Recovering underlying Levy. For more information see `CarmaNoise`.

qmle Quasi maximum likelihood estimation procedure. For more information see `qmle`.

Author(s)

The YUIMA Project Team

`yuima.carma.qmle-class`

Class for Quasi Maximum Likelihood Estimation of CARMA(p,q) model

---

Description

The `yuima.carma.qmle` class is a class of the **yuima** package that extends the `mle-class` of the **stats4** package.

Slots

`Incr.Lev`: is an object of class `zoo` that contains the estimated increments of the noise obtained using `CarmaNoise`.

`model`: is an object of of `yuima.carma-class`.

`logL.Incr`: is an object of class `numeric` that contains the value of the log-likelihood for estimated Levy increments.

`call`: is an object of class `language`.

`coef`: is an object of class `numeric` that contains estimated parameters.

`fullcoef`: is an object of class `numeric` that contains estimated and fixed parameters.

`vcov`: is an object of class `matrix`.

`min`: is an object of class `numeric`.

`minuslogl`: is an object of class `function`.

`method`: is an object of class `character`.

Methods

plot Plot method for estimated increment of the noise.

Methods mle All methods for `mle-class` are available.

Author(s)

The YUIMA Project Team

`yuima.carmaHawkes-class`

Class for the mathematical description of a Hawkes process with a CARMA(p,q) intensity

---

Description

The `yuima.carmaHawkes` class is a class of the **yuima** package that extends the `yuima.model-class`.

Slots

`info`**:** is an `carmaHawkes.info-class` object that describes the structure of the CARMA(p,q) model.

`drift`**:** is an R expression which specifies the drift coefficient (a vector).

`diffusion`**:** is an R expression which specifies the diffusion coefficient (a matrix).

`hurst`**:** the Hurst parameter of the gaussian noise. If `h=0.5`, the process is Wiener otherwise it is fractional Brownian motion with that precise value of the Hurst index. Can be set to `NA` for further specification.

`jump.coeff`**:** a vector of `expressions` for the jump component.

`measure`**:** Levy measure for jump variables.

`measure.type`**:** Type specification for Levy measures.

state.variable a vector of names identifying the names used to denote the state variable in the drift and diffusion specifications.

`parameter`**:** which is a short name for "parameters", is an object of class `model.parameter-class`. For more details see `model.parameter-class` documentation page.

`state.variable`**:** identifies the state variables in the R expression.

`jump.variable`**:** identifies the variable for the jump coefficient.

`time.variable`**:** the time variable.

`noise.number`**:** denotes the number of sources of noise. Currently only for the Gaussian part.

`equation.number`**:** denotes the dimension of the stochastic differential equation.

`dimension`**:** the dimensions of the parameter given in the `parameter` slot.

`solve.variable`**:** identifies the variable with respect to which the stochastic differential equation has to be solved.

`xinit`**:** contains the initial value of the stochastic differential equation.

`J.flag`**:** wheather jump.coeff include jump.variable.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

---

yuima.characteristic-class

Classe for stochastic differential equations characteristic scheme

---

Description

The yuima.characteristic class is a class of the **yuima** package.

Slots

equation.number: The number of equations modeled in the yuima object.

time.scale: The time scale assumed in the yuima object.

Author(s)

The YUIMA Project Team

---

yuima.cogarch-class

Class for the mathematical description of CoGarch(p,q) model

Description

The yuima.cogarch class is a class of the **yuima** package that extends the yuima.model-class.

Objects from the Class

Objects can be created by calls of the function setCogarch.

Slots

info: is an cogarch.info-class object that describes the structure of the Cogarch(p,q) model.

drift: is an R expression which specifies the drift coefficient (a vector).

diffusion: is an R expression which specifies the diffusion coefficient (a matrix).

hurst: the Hurst parameter of the gaussian noise.

jump.coeff: a vector of "expressions" for the jump component.

measure: Levy measure for the jump component.

measure.type: Type of specification for Levy measure

parameter: is an object of class model.parameter-class.

`state.variable`: the state variable.

`jump.variable`: the jump variable.

`time.variable`: the time variable.

`noise.number`: Object of class `"numeric"`

`equation.number`: dimension of the stochastic differential equation.

`dimension`: number of parameters.

`solve.variable`: the solve variable

`xinit`: Object of class `"expression"` that contains the starting function for the SDE.

`J.flag`: wheather jump.coeff include jump.variable.

Extends

Class `"yuima.model"`, directly.

Methods

simulate simulation method. For more information see `simulate`

toLatex This method converts an object of `yuima.cogarch-class` to character vectors with LaTeX markup.

qmle Quasi maximum likelihood estimation procedure. For more information see `qmle`.

Author(s)

The YUIMA Project Team

`yuima.CP.qmle-class` *Class for Quasi Maximum Likelihood Estimation of Compound Poisson-based and SDE models*

Description

The `yuima.CP.qmle` class is a class of the **yuima** package that extends the `mle-class` of the **stats4** package.

Slots

`Jump.times`: a vector which contains the estimated time of jumps.

`Jump.values`: a vector which contains the jumps.

`X.values`: the value of the process at the jump times.

`model`: is an object of of `yuima.model-class`.

`call`: is an object of class `language`.

`coef`: is an object of class `numeric` that contains estimated parameters.

`fullcoef`: is an object of class `numeric` that contains estimated and fixed parameters.

`vcov`: is an object of class `matrix`.

`min`: is an object of class `numeric`.

`minuslogl`: is an object of class `function`.

`method`: is an object of class `character`.

`model`: is an object of class `yuima.model-class`.

Methods

plot Plot method for plotting the jump times.

Methods mle All methods for `mle-class` are available.

Author(s)

The YUIMA Project Team

`yuima.data-class` *Class "yuima.data" for the data slot of a "yuima" class object*

Description

The `yuima.data-class` is a class of the **yuima** package used to store the data which are hold in the slot `data` of an object of the `yuima-class`.

Objects from this class contain either true data or simulated data.

Details

Objects in this class are created or initialized using the methods `new` or `initialize` or via the function `setData`. The preferred way to construct an object in this class is to use the function `setData`.

Objects in this class are used to store the data which are hold in the slot `data` of an object of the `yuima-class`.

Objects in this class contain two slots described here.

`original.data`: The slot `original.data` contains, as the name suggests, a copy of the original data passed by the user to methods `new` or `initialize` or to the function `setData`. It is intended for backup purposes.

`zoo.data`: When a new object of this class is created or initialized using the `original.data`, the package tries to convert `original.data` into an object of class `zoo`. Once coerced to `zoo`, the data are stored in the slot `zoo.data`.

If the conversion fails, the initialization or creation of the object fails.

Internally, the **yuima** package stores and operates on `zoo`-type objects.

If data are obtained by simulation, the `original.data` slot is usually empty.

Slots

`original.data`**:** The original data.

`zoo.data`**:** A list of zoo format data.

Methods

new `signature(x = "yuima.data", original.data)`: the function makes a copy of the prototype object from the class definition of `yuima.data-class`, then calls the `initialize` method passing as arguments the newly created object and the `original.data`.

initialize `signature(x = "yuima.data", original.data)`: makes a copy of `original.data` into the slot `original.data` of `x` and tries to coerce `original.data` into an object of class `zoo`. The result is put in the slot `zoo.data` of `x`. If coercion fails, the `intialize` method fails as well.

get.zoo.data `signature(x = "yuima.data")`: returns the content of the slot `zoo.data` of `x`.

plot `signature(x = "yuima.data", ...)`: calls `plot` from the `zoo` package with argument `x@zoo.data`. Additional arguments `...` are passed as is to the `plot` function.

dim `signature(x = "yuima.data")`: calls `dim` from the `zoo` package with argument `x@zoo.data`.

length `signature(x = "yuima.data")`: calls `length` from the `zoo` package with argument `x@zoo.data`.

cce `signature(x = "yuima.data")`: calculates asyncronous covariance estimator on the data contained in `x@zoo.data`. For more details see `cce`.

llag `signature(x = "yuima.data")`: calculates lead lag estimate on the data contained in `x@zoo.data`. For more details see `llag`.

cbind.yuima `signature(x = "yuima.data")`: bind yuima.data object.

Author(s)

The YUIMA Project Team

---

yuima.functional-class

Classes for stochastic differential equations data object

Description

The `yuima.functional` class is a class of the **yuima** package.

Author(s)

YUIMA Project

yuima.Hawkes *Class for a mathematical description of a Point Process*

Description

The yuima.Hawkes-class is a class of the **yuima** package that extends the yuima.PPR-class. The object of this class contains all the information about the Hawkes process with exponential kernel.

An object of this class can be created by calls of the function setHawkes.

yuima.Integral-class *Class for the mathematical description of integral of a stochastic process*

Description

The yuima.Integral class is a class of the **yuima** package that extends the yuima-class it represents a integral of a stochastic process

zt = int^{t}_0 h(theta, Xs, s) dXs

Slots

In the following we report the the additional slots of an object of class yuima.Integral with respect to the yuima-class:

Integral: It is an object of class Integral.sde and it is composed by the following slots:

- param.Integral: it is an object of class param.Integral and it is composed by the following slots:
  - allparam: labels of all parameters (model and integral).
  - common: common parameters.
  - Integrandparam: labels of all parameters only in the integral.
- variable.Integral: it is an object of class variable.Integral and it is composed by the following slots:
  - var.dx: integral variable.
  - lower.var: lower bound of support.
  - upper.var: upper bound of support.
  - out.var: labels of output.
  - var.time: label of time.
- Integrand: it is an object of class variable.Integral and it is composed by the following slots:
  - IntegrandList: It is a list that contains the components of integrand h(theta, Xs, s).
  - dimIntegrand: a numeric object that is the dimensions of the output.

Methods

simulate simulation method. For more information see simulate.

yuima.law-class yuima law-class: *A mathematical description for the noise.*

Description

A yuima class that contains all information on the noise. This class is a bridge between a yuima.model-class and a noise constructed by users.

Slots

rng A user defined function that generates the noise sample.

density A user defined function that is the density of the noise at time t.

cdf A user defined function that is the cumulative distribution function of the noise at time t.

quantile A user defined function that is the quantile of the noise at time t.

characteristic A user defined function that is the characteristic function of the noise at time t.

param.measure A character object that contains the parameters of the noise.

time.var the label of the time variable.

dim Dimension of the noise

Methods

rand signature(object = "yuima.law", n = "numeric", param = "list", ...): This method returns a sample of the noise, n is the sample size.

dens signature(object = "yuima.law", x = "numeric", param = "list", log = FALSE, ...): This method returns the density of the noise, x is the vector of the support.

cdf signature(object = "yuima.law", q = "numeric", param = "list", ...): This method returns the cdf of the noise, q is the vector of the support.

quant signature(object = "yuima.law", p = "numeric", param = "list", ...): This method returns the quantile of the noise, p is the vector of the support.

char signature(object = "yuima.law", u = "numeric", param = "list", ...): This method returns the characteristic function of the noise, u is the vector of the support.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

yuima.LevyRM-class — *yuima.LevyRM: A class for the mathematical description of the t-Student regression model.*

Description

A yuima class that contains all information on the regression model with t-student Levy process noise. This class extends yuima-class and contains information on the regressors used in the definition of the model. The regressors are represented by an object of yuima.model-class.

An object of this class can be created by calls of the function setLRM.

Methods

initialize Initialize method. It makes a copy of each argument.

simulate simulation method. For more information see simulate.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

yuima.Map-class — *Class for the mathematical description of function of a stochastic process*

Description

The yuima.Map class is a class of the **yuima** package that extends the yuima-class it represents a map of a stochastic process

`zt = g(theta, Xt, t) : R^{q x d x 1} -> R^{l1 x l2 x ...}`

or an operator between two independent stochasic process:

`zt = h(theta, Xt, Yt, t)`

where Xt and Yt are object of class yuima.model-class or yuima-class with the same dimension.

Slots

Here we report the additional slots of an object of class yuima.Map with respect to the yuima-class:

Output: It is an object of class info.Map and it is composed by the following slots:

- formula: It is a vector that contains the components of map g(theta, Xt, t) or the operator h(theta, Xt, Yt, t)
- dimension: a numeric object that is the dimensions of the Map.

`type`: If `type = "Maps"`, the Map is a map of stochastic process, If `type = "Operator"`, the result is an operator between two independent stochastic process

`param` it is an object of class `param.Map` and it is composed by the following slots:

`out.var`: labels for Map.

`allparam`: labels of all parameters (model and map/operators).

`allparamMap`: labels of map/operator parameters.

`common`: common parameters.

`Input.var`: labels for inputs.

`time.var`: label for time variable.

Methods

simulate simulation method. For more information see `simulate`.

Author(s)

The YUIMA Project Team

`yuima.model-class` *Classes for the mathematical description of stochastic differential equations*

Description

The `yuima.model` class is a class of the **yuima** package.

Slots

`drift`: is an R expression which specifies the drift coefficient (a vector).

`diffusion`: is an R expression which specifies the diffusion coefficient (a matrix).

`hurst`: the Hurst parameter of the gaussian noise. If `h=0.5`, the process is Wiener otherwise it is fractional Brownian motion with that precise value of the Hurst index. Can be set to `NA` for further specification.

`jump.coeff`: a matrix of `expressions` for the jump component.

`measure`: Levy measure for jump variables.

`measure.type`: Type specification for Levy measures.

state.variable a vector of names identifying the names used to denote the state variable in the drift and diffusion specifications.

`parameter`: which is a short name for "parameters", is an object of class `model.parameter-class`. For more details see `model.parameter-class` documentation page.

`state.variable`: identifies the state variables in the R expression.

`jump.variable`: identifies the variable for the jump coefficient.

`time.variable`: the time variable.

`noise.number`: denotes the number of sources of noise. Currently only for the Gaussian part.

`equation.number`: denotes the dimension of the stochastic differential equation.

`dimension`: the dimensions of the parameter given in the `parameter` slot.

`solve.variable`: identifies the variable with respect to which the stochastic differential equation has to be solved.

`xinit`: contains the initial value of the stochastic differential equation.

`J.flag`: wheather jump.coeff include jump.variable.

Author(s)

The YUIMA Project Team

`yuima.multimodel-class`

Class for the mathematical description of Multi dimensional Jump Diffusion processes

---

Description

The `yuima.multimodel` class is a class of the **yuima** package that extends the `yuima.model-class`.

Slots

`drift`: always `expression((0))`.

`diffusion`: a list of `expression((0))`.

`hurst`: always `h=0.5`, but ignored for this model.

`jump.coeff`: set according to `scale` in `setPoisson`.

`measure`: a list containting the intensity measure and the jump distribution.

`measure.type`: always `"CP"`.

state.variable a vector of names identifying the names used to denote the state variable in the drift and diffusion specifications.

`parameter`: which is a short name for "parameters", is an object of class `model.parameter-class`. For more details see `model.parameter-class` documentation page.

`state.variable`: identifies the state variables in the R expression.

`jump.variable`: identifies the variable for the jump coefficient.

`time.variable`: the time variable.

`noise.number`: denotes the number of sources of noise.

`equation.number`: denotes the dimension of the stochastic differential equation.

`dimension`: the dimensions of the parameter given in the `parameter` slot.

`solve.variable`: identifies the variable with respect to which the stochastic differential equation has to be solved.

`xinit`: contains the initial value of the stochastic differential equation.

`J.flag`: wheather jump.coeff include jump.variable.

Methods

simulate simulation method. For more information see simulate.

qmle Quasi maximum likelihood estimation procedure. For more information see qmle.

Author(s)

The YUIMA Project Team

Examples

```
## Not run:
# We define the density function of the underlying Levy

dmyexp <- function(z, sig1, sig2, sig3){
  rep(0,3)
}

# We define the random number generator

rmyexp <- function(z, sig1, sig2, sig3){
  cbind(rnorm(z,0,sig1), rgamma(z,1,sig2), rnorm(z,0,sig3))
}

# Model Definition: in this case we consider only a multi
# compound poisson process with a common intensity as underlying
# noise

mod <- setModel(drift = matrix(c("0","0","0"),3,1), diffusion = NULL,
  jump.coeff = matrix(c("1","0","0","0","1","-1","1","0","0"),3,3),
  measure = list( intensity = "lambda1", df = "dmyexp(z,sig1,sig2,sig3)"),
  jump.variable = c("z"), measure.type=c("CP"),
  solve.variable=c("X1","X2","X3"))

# Sample scheme

samp<-setSampling(0,100,n=1000)
param <- list(lambda1 = 1, sig1 = 0.1, sig2 = 0.1, sig3 = 0.1)

# Simulation

traj <- simulate(object = mod, sampling = samp,
  true.parameter = param)

# Plot

plot(traj, main = " driven noise. Multidimensional CP",
  cex.main = 0.8)

# We construct a multidimensional SDE driven by a multivariate
# levy process without CP components.

# Definition multivariate density
```

```
dmyexp1 <- function(z, sig1, sig2, sig3){
  rep(0,3)
}

# Definition of random number generator
# In this case user must define the delta parameter in order to
# control the effect of time interval in the simulation.

rmyexp1 <- function(z, sig1, sig2, sig3, delta){
  cbind(rexp(z,sig1*delta), rgamma(z,1*delta,sig2), rexp(z,sig3*delta))
}

# Model defintion

mod1 <- setModel(drift=matrix(c("0.1*(0.01-X1)",
  "0.05*(1-X2)","0.1*(0.1-X3)"),3,1), diffusion=NULL,
   jump.coeff = matrix(c("0.01","0","0","0","0.01",
                         "0","0","0","0.01"),3,3),
   measure = list(df="dmyexp1(z,sig1,sig2,sig3)"),
   jump.variable = c("z"), measure.type=c("code"),
   solve.variable=c("X1","X2","X3"),xinit=c("10","1.2","10"))

# Simulation sample paths

samp<-setSampling(0,100,n=1000)
param <- list(sig1 = 1, sig2 = 1, sig3 = 1)

# Simulation

set.seed(1)
traj1 <- simulate(object = mod1, sampling = samp,
  true.parameter = param)

# Plot

plot(traj1, main = "driven noise: multi Levy without CP",
  cex.main = 0.8)

# We construct a multidimensional SDE driven by a multivariate
# levy process.

# We consider a mixed situation where some
# noise are driven by a multivariate Compuond Poisson that
# shares a common intensity parameters.

### Multi Levy model

rmyexample2<-function(z,sig1,sig2,sig3, delta){
    if(missing(delta)){
      delta<-1
    }
    cbind(rexp(z,sig1*delta), rgamma(z,1*delta,sig2),
```

```
        rexp(z,sig3*delta), rep(1,z),
        rep(1,z))
}

dmyexample2<-function(z,sig1,sig2,sig3){
  rep(0,5)
}

# Definition Model

mod2 <- setModel(drift=matrix(c("0.1*(0.01-X1)",
  "0.05*(1-X2)","0.1*(0.1-X3)", "0", "0"),5,1), diffusion=NULL,
  jump.coeff = matrix(c("0.01","0","0","0","0",
                        "0","0.01","0","0","0",
                        "0","0","0.01","0","0",
                        "0","0","0","0.01","0",
                        "0","0","0","0","0.01"),5,5),
  measure = list(df = "dmyexample2(z,sig1,sig2,sig3)",
            intensity = "lambda1"),
  jump.variable = c("z"),
  measure.type=c("code","code","code","CP","CP"),
  solve.variable=c("X1","X2","X3","X4","X5"),
  xinit=c("10","1.2","10","0","0"))

# Simulation scheme
samp <- setSampling(0, 100, n = 1000)
param <- list(sig1 = 1, sig2 = 1, sig3 = 1, lambda1 = 1)

# Simulation

set.seed(1)
traj2 <- simulate(object = mod2, sampling = samp,
  true.parameter = param)

plot(traj2, main = "driven noise: general multi Levy", cex.main = 0.8)


## End(Not run)
```

`yuima.poisson-class` *Class for the mathematical description of Compound Poisson processes*

Description

The `yuima.poisson` class is a class of the **yuima** package that extends the `yuima.model-class`.

Slots

`drift:` always `expression((0))`.

`diffusion`: a list of `expression((0))`.

`hurst`: always `h=0.5`, but ignored for this model.

`jump.coeff`: set according to `scale` in `setPoisson`.

`measure`: a list containting the intensity measure and the jump distribution.

`measure.type`: always `"CP"`.

state.variable a vector of names identifying the names used to denote the state variable in the drift and diffusion specifications.

`parameter`: which is a short name for "parameters", is an object of class `model.parameter-class`. For more details see `model.parameter-class` documentation page.

`state.variable`: identifies the state variables in the R expression.

`jump.variable`: identifies the variable for the jump coefficient.

`time.variable`: the time variable.

`noise.number`: denotes the number of sources of noise.

`equation.number`: denotes the dimension of the stochastic differential equation.

`dimension`: the dimensions of the parameter given in the `parameter` slot.

`solve.variable`: identifies the variable with respect to which the stochastic differential equation has to be solved.

`xinit`: contains the initial value of the stochastic differential equation.

`J.flag`: wheather jump.coeff include jump.variable.

Methods

simulate simulation method. For more information see `simulate`.

qmle Quasi maximum likelihood estimation procedure. For more information see `qmle`.

Author(s)

The YUIMA Project Team

`yuima.PPR` *Class for a mathematical description of a Point Process*

Description

The `yuima.PPR` class is a class of the **yuima** package that extends the `yuima-class`. The object of this class contains all the information about the Point Process Regression Model.

Objects from the Class

Objects can be created by calls of the function `setPPR`.

Slots

PPR: is an object of class info.PPR.

gFun: is an object of class info.Map.

Kernel: is an object of class Integral.sde.

data: is an object of class yuima.data-class. The slot contain either true data or simulated data

model: is an object of class yuima.model-class. The slot contains all the information about the covariates

sampling: is an object of class yuima.sampling-class.

characteristic: is an object of class yuima.characteristic-class.

model: is an object of class yuima.functional-class.

Author(s)

The YUIMA Project Team

---

yuima.qmleLevy.incr *Class for Quasi Maximum Likelihood Estimation of Levy SDE model*

Description

The yuima.qmleLevy.incr-class is a class of the **yuima** package that extends the mle-class of the **stats4** package.

Slots

Incr.Lev: is an object of class yuima.data-class that contains the estimated increments of the noise.

logL.Incr: an numeric object that represents the value of the loglikelihood for the estimated Levy increments.

minusloglLevy: an R function that evaluates the loglikelihood of the estimated Levy increments. The function is used internally in qmleLevy for the estimation of the Levy measure parameters.

Levydetails: a list containing additional information about the optimization procedure in the estimation of the Levy measure parameters. See optim help for the meaning of the components of this list.

Data: is an object of yuima.data-class containing observation data.

model: is an object of of yuima.carma-class.

call: is an object of class language.

coef: is an object of class numeric that contains estimated parameters.

fullcoef: is an object of class numeric that contains estimated and fixed parameters.

vcov: is an object of class matrix.

min: is an object of class numeric.

minuslogl: is an object of class function.

nobs: an object of class numeric.

method: is an object of class character.

Methods

Methods mle All methods for `mle-class` are available.

Author(s)

The YUIMA Project Team

`yuima.sampling-class` *Classes for stochastic differential equations sampling scheme*

Description

The `yuima.sampling` class is a class of the **yuima** package.

Details

This object is created by `setSampling` or as a result of a simulation scheme by the `simulate` function or after subsampling via the function `subsampling`.

Slots

`Initial`**:** initial time of the grid.

`Terminal`**:** terminal time fo the grid.

`n`**:** the number of observations - 1.

`delta`**:** in case of a regular grid is the mesh.

`grid`**:** the grid of times.

`random`**:** either `FALSE` or the distribution of the random times.

`regular`**:** indicator of whether the grid is regular or not. For internal use only.

`sdelta`**:** in case of a regular space grid it is the mesh.

`sgrid`**:** the grid in space.

`oindex`**:** in case of interpolation, a vector of indexes corresponding to the original observations used for the approximation.

`interpolation`**:** the name of the interpolation method used.

Author(s)

The YUIMA Project Team

yuima.snr-class *Class "yuima.snr" for self-normalized residuals of SDE "yuima" class object*

Description

The yuima.snr-class is a class of the **yuima** package used to store the calculatied self-normalized residuals of an SDEs.

Slots

call: The original call.

coef: A numeric vector.

snr: A numeric vector of residuals.

model: A yuima.model.

Methods

show print method

Author(s)

The YUIMA Project Team

yuima.th-class *yuima.th-class: A mathematical description for the t-Levy process.*

Description

A yuima class that contains all information on the noise for t-Levy process. This class extends yuima.law-class and contains info on the numerical method used for the inversion of the characteristic function. Three inversion methods are available: cos, Laguerre and FFT.

An object of this class can be created by calls of the function setLaw_th.

Methods

rand signature(object = "yuima.th", n = "numeric", param = "list", ...): This method returns a sample of the noise, n is the sample size.

dens signature(object = "yuima.th", x = "numeric", param = "list", log = FALSE, ...): This method returns the density of the noise, x is the vector of the support.

cdf signature(object = "yuima.th", q = "numeric", param = "list", ...): This method returns the cdf of the noise, q is the vector of the support.

quant signature(object = "yuima.th", p = "numeric", param = "list", ...): This method returns the quantile of the noise, p is the vector of the support.

char signature(object = "yuima.th", u = "numeric", param = "list", ...): This method returns the characteristic function of the noise, u is the vector of the support.

Author(s)

The YUIMA Project Team

Contacts: Lorenzo Mercuri <lorenzo.mercuri@unimi.it>

Index