

Package ‘mixedside’

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Title Estimation Methods for Stochastic Differential Mixed Effects Models

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Depends R (>= 3.0.2), sde, moments, MASS, stats, graphics, methods

Imports plot3D, grDevices

Description Inference on stochastic differential models Ornstein-Uhlenbeck or Cox-Ingersoll-Ross, with one or two random effects in the drift function.

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URL <http://www.r-project.org>

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mixedsde-package	<i>Density estimation in mixed stochastic differential models</i>
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Description

This package proposes 3 methods for density estimation in the special context of stochastic differential equation with linear random effects in the drift.

Details

Package:	mixedsde
Type:	Package
Version:	1.0
Date:	2016-01-19
License:	What license is it under?

An overview of how to use the package, including the most important functions

Author(s)

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References

See Bidimensional random effect estimation in mixed stochastic differential model, C. Dion and V. Genon-Catalot, *Stochastic Inference for Stochastic Processes 2015*, Springer Netherlands **1–28**

Maximum likelihood estimation for stochastic differential equations with random effects, M. Delattre, V. Genon-Catalot and A. Samson, *Scandinavian Journal of Statistics* 2012, Vol 40, **322–343**

Bayesian Prediction of Crack Growth Based on a Hierarchical Diffusion Model. Hermann, S., Ickstadt, K. and C. Muller (2016)

Examples

```
# Frequentist estimation, two random effects

model = 'CIR'; M <- 200; T <- 10 ; delta <- 0.001; N <- floor(T/delta); sigma <- 0.01
random <- c(1,2); density.phi <- 'gammainvgamma2'
param<- c(1.8, 0.8, 8, 0.05);
simu <- mixedsde.sim(M=M,T=T,N=N,model=model,random=random,density.phi=density.phi,param=param,
                    sigma=sigma, invariant = 1)
X <- simu$X ; phi <- simu$phi; times <- simu$times
estim.method<- 'nonparam'
estim <- mixedsde.fit(times=times, X=X, model=model, random=random, estim.method= 'nonparam')
outputsNP <- out(estim)
plot(estim)
summary(estim)
print(estim)

validation <- valid(estim, numj=floor(runif(1,1,M)))

estim.method<-'paramML'
estim_param <- mixedsde.fit(times= times, X= X, model= model, random= random,
estim.method = 'paramML')
outputsP <- out(estim_param)
plot(estim_param)
summary(estim_param)

test1 <- pred(estim, invariant = 1)
test2 <- pred(estim_param, invariant = 1)

cutoff <- outputsNP$cutoff
phihat <- outputsNP$estimphi
phihat_trunc <- outputsNP$estimphi_trunc
par(mfrow=c(1,2))
plot.ts(phi[1,], phihat[1,], xlim=c(0, 15), ylim=c(0,15), pch=18); abline(0,1)
points(phi[1,]*(1-cutoff), phihat[1,]*(1-cutoff), xlim=c(0, 20), ylim=c(0,20), pch=18, col='red')
abline(0,1)
plot.ts(phi[2,], phihat[2,], xlim=c(0, 15), ylim=c(0,15),pch=18); abline(0,1)
points(phi[2,]*(1-cutoff), phihat[2,]*(1-cutoff), xlim=c(0, 20), ylim=c(0,20), pch=18, col='red')
abline(0,1)

# Parametric Bayesian estimation one random effect

model <- 'OU'; random <- 1; sigma <- 0.1; fixed <- 5
M <- 50 ; T <- 1; N <- 100
density.phi <- 'normal'; param <- c(3, 0.5)

simu <- mixedsde.sim(M, T = T, N = N, model= model, random = random, fixed = fixed,
                    density.phi= density.phi, param= param, sigma= sigma, X0 = 0)
X <- simu$X; phi <- simu$phi; times <- simu$times
plot(times, X[1,], ylim = range(X), type = 'l'); for(i in 2:M) lines(times, X[i,])
```

```

estim_Bayes_withoutprior <- mixedsde.fit(times, X= X, model = model, random = random,
  estim.method = 'paramBayes', nMCMC = 100) # nMCMC should be much larger
plot(estim_Bayes_withoutprior)

prior <- list(m = c(param[1], fixed), v = c(param[1], fixed), alpha.omega = 11,
  beta.omega = param[2]^2*10, alpha.sigma = 10, beta.sigma = sigma^2*9)
estim_Bayes <- mixedsde.fit(times, X = X, model = model, random = random,
  estim.method = 'paramBayes', prior = prior, nMCMC = 100)

plot(estim_Bayes)
outputBayes <- out(estim_Bayes)
summary(outputBayes)
(results_Bayes <- summary(estim_Bayes))
plot(estim_Bayes, style = 'cred.int', true.phi = phi)
plot(estim_Bayes_withoutprior, style = 'cred.int', true.phi = phi, reduced = TRUE)

plot2compare(estim_Bayes, estim_Bayes_withoutprior, names = c('with prior', 'without prior'))

print(estim_Bayes)

pred.result <- pred(estim_Bayes)
summary(out(pred.result))
plot(pred.result)

pred.result.trajectories <- pred(estim_Bayes, trajectories = TRUE)

validbayes <- valid(estim_Bayes, numj = 1)

```

ad.propSd

Adaptation For The Proposal Variance

Description

Calculation of new proposal standard deviation

Usage

```
ad.propSd(chain, propSd, iteration, lower = 0.3, upper = 0.6,
  delta.n = function(n) min(0.1, 1/sqrt(n)))
```

Arguments

chain	vector of Markov chain samples
propSd	old proposal standard deviation
iteration	number of current iteration
lower	lower bound
upper	upper bound
delta.n	function for adding/subtracting from the log propSd

References

Rosenthal, J. S. (2011). Optimal proposal distributions and adaptive MCMC. Handbook of Markov Chain Monte Carlo, 93-112.

ad.propSd_random	<i>Adaptation For The Proposal Variance</i>
------------------	---

Description

Calculation of new proposal standard deviation for the random effects

Usage

```
ad.propSd_random(chain, propSd, iteration, lower = 0.3, upper = 0.6,
  delta.n = function(n) min(0.1, 1/sqrt(n)))
```

Arguments

chain	matrix of Markov chain samples
propSd	old proposal standard deviation
iteration	number of current iteration
lower	lower bound
upper	upper bound
delta.n	function for adding/subtracting from the log propSd

References

Rosenthal, J. S. (2011). Optimal proposal distributions and adaptive MCMC. Handbook of Markov Chain Monte Carlo, 93-112.

Bayes.fit-class	<i>S4 class for the Bayesian estimation results</i>
-----------------	---

Description

S4 class for the Bayesian estimation results

Slots

sigma2	vector of posterior samples for σ^2
mu	matrix of posterior samples for μ
omega	matrix of posterior samples for ω
alpha	matrix of posterior samples for α
beta	matrix of posterior samples for β
random	1, 2 or c(1,2)
burnIn	proposal for the burn-in phase
thinning	proposal for the thinning rate
model	'OU' or 'CIR'
prior	list of prior values, input variable or calculated by the first 10% of series

times vector of observation times, storage of input variable
 X matrix of observations, storage of input variable
 ind.4.prior indices of series used for the prior parameter calculation, if prior knowledge is available it is set to M+1

Bayes.pred-class	<i>S4 class for the Bayesian prediction results</i>
------------------	---

Description

S4 class for the Bayesian prediction results

Slots

phi.pred matrix of predictive samples for the random effect
 Xpred matrix of predictive samples for observations
 coverage.rate amount of covering prediction intervals
 qu.u upper prediction interval bound
 qu.l lower prediction interval bound
 estim list of Bayes.fit object entries, storage of input variable

BayesianNormal	<i>Bayesian Estimation In Mixed Stochastic Differential Equations</i>
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Description

Gibbs sampler for Bayesian estimation of the random effects (α_j, β_j) in the mixed SDE $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma a(X_j(t))dW_j(t)$.

Usage

```
BayesianNormal(times, X, model = c("OU", "CIR"), prior, start, random,
  nMCMC = 1000, propSd = 0.2)
```

Arguments

times	vector of observation times
X	matrix of the M trajectories (each row is a trajectory with $N = T/\Delta$ column).
model	name of the SDE: 'OU' (Ornstein-Uhlenbeck) or 'CIR' (Cox-Ingersoll-Ross).
prior	list of prior parameters: mean and variance of the Gaussian prior on the mean mu, shape and scale of the inverse Gamma prior for the variances omega, shape and scale of the inverse Gamma prior for sigma
start	list of starting values: mu, sigma
random	random effects in the drift: 1 if one additive random effect, 2 if one multiplicative random effect or c(1,2) if 2 random effects.
nMCMC	number of iterations of the MCMC algorithm
propSd	proposal standard deviation of ϕ is $ \mu *propSd/\log(N)$ at the beginning, is adjusted when acceptance rate is under 30% or over 60%

Value

alpha	posterior samples (Markov chain) of α
beta	posterior samples (Markov chain) of β
mu	posterior samples (Markov chain) of μ
omega	posterior samples (Markov chain) of Ω
sigma2	posterior samples (Markov chain) of σ^2

References

- Hermann, S., Ickstadt, K. and C. Muller (2016). Bayesian Prediction of Crack Growth Based on a Hierarchical Diffusion Model.
- Rosenthal, J. S. (2011). 'Optimal proposal distributions and adaptive MCMC.' Handbook of Markov Chain Monte Carlo (2011): 93-112.

bx	<i>Computation Of The Drift Coefficient</i>
----	---

Description

Computation of the drift coefficient

Usage

`bx(x, fixed, random)`

Arguments

x	vector of data
fixed	drift constant in front of X (when there is one additive random effect), 0 otherwise
random	1 if there is one additive random effect, 2 one multiplicative random effect or c(1,2) for 2 random effects

Value

b
The drift is $b(x, \phi) = \phi_1 b_1(x) + \phi_2 b_2(x)$, the output is b_2 except when random c(1,2) then the output is the vector $(b_1, b_2)^t$

chain2samples	<i>Removing Of Burn-in Phase And Thinning</i>
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Description

Transfers class object Bayes.fit from the original to the thinned chains

Usage

```
chain2samples(res, burnIn, thinning)
```

Arguments

res	Bayes.fit class object
burnIn	number of burn-in samples
thinning	thinning rate

dcCIR2	<i>Likelihood Function For The CIR Model</i>
--------	--

Description

Likelihood

Usage

```
dcCIR2(x, t, x0, theta, log = FALSE)
```

Arguments

x	current observation
t	time of observation
x0	starting point, i.e. observation in time 0
theta	parameter (α, β, σ)
log	logical(1) if TRUE, log likelihood

References

Iacus, S. M. (2008). Simulation and Inference for Stochastic Differential Equations.

diagnostic

Calculation Of Burn-in Phase And Thinning Rate

Description

Proposal for burn-in and thin rate

Usage

```
diagnostic(results, random)
```

Arguments

results	Bayes.fit class object
random	one out of 1, 2, c(1,2)

discr

Simulation Of Random Variables

Description

Simulation of (discrete) random variables from a vector of probability (the nonparametrically estimated values of the density renormalised to sum at 1) and a vectors of real values (the grid of estimation)

Usage

```
discr(x, p)
```

Arguments

x	n real numbers
p	vector of probability, length n

Value

y a simulated value from the discrete distribution

eigenvaluesV	<i>Matrix Of Eigenvalues Of A List Of Symetric Matrices</i>
--------------	---

Description

Computation of the eigenvalues of each matrix V_j in the case of two random effects (random = c(1,2)), done via eigen

Usage

```
eigenvaluesV(V)
```

Arguments

V	list of matrices V_j
---	------------------------

Value

eigenvalues	Matrix of 2 rows and as much columns as matrices V
-------------	--

References

See Bidimensional random effect estimation in mixed stochastic differential model, C. Dion and V. Genon-Catalot, *Stochastic Inference for Stochastic Processes 2015*, Springer Netherlands, **1–28**

EstParamNormal	<i>Maximization Of The Log Likelihood In Mixed Stochastic Differential Equations</i>
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Description

Maximization of the loglikelihood of the mixed SDE with Normal distribution of the random effects $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma a(X_j(t))dW_j(t)$, done with [likelihoodNormal](#)

Usage

```
EstParamNormal(U, V, K, random, estim.fix, fixed = 0)
```

Arguments

U	matrix of M sufficient statistics U
V	list of the M sufficient statistics matrix V
K	number of times of observations
random	random effects in the drift: 1 if one additive random effect, 2 if one multiplicative random effect or c(1,2) if 2 random effects.
estim.fix	1 if the fixed parameter is estimated, when random 1 or 2 , 0 otherwise
fixed	value of the fixed parameter if known (not estimated)

Value

mu	estimated value of the mean
Omega	estimated value of the variance
BIChere	BIC indicator
AIChere	AIC indicator

Freq.fit-class	<i>S4 class for the frequentist estimation results</i>
----------------	--

Description

S4 class for the frequentist estimation results

Slots

model character 'OU' or 'CIR'

random numeric 1, 2, or c(1,2)

fixed numeric value of the fixed effect if there is one

gridf matrix of values on which the estimated is done

mu numeric MLE estimator for parametric approach

omega numeric MLE estimator for parametric approach

cutoff value of the cutoff if there is one

sigma2 numeric estimated value of σ^2

estimf.trunc matrix estimator of the density of ϕ for the truncated estimateur of the random effects

estimphi.trunc matrix truncated estimator of the random effects

index index of the used trajectories

estimphi matrix of the estimator of the random effects

estimf estimator of the density of ϕ

estim.fixed estimator of the fixed parameter if option estim.fix = 1

estim.fix 1 if the user asked for the estimation of fixed parameter

bic numeric bic

aic numeric aic

times vector of observation times, storage of input variable

X matrix of observations, storage of input variable

likelihoodNormal	<i>Computation Of The Log Likelihood In Mixed Stochastic Differential Equations</i>
------------------	---

Description

Computation of -2 loglikelihood of the mixed SDE with Normal distribution of the random effects $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma a(X_j(t))dW_j(t)$.

Usage

```
likelihoodNormal(mu, omega, U, V, estimphi, random)
```

Arguments

mu	current value of the mean of the normal distribution
omega	current value of the standard deviation of the normal distribution
U	vector of the M sufficient statistics U (see UV)
V	vector of the M sufficient statistics V (see UV)
estimphi	vector or matrix of estimators of the random effects
random	random effects in the drift: 1 if one additive random effect, 2 if one multiplicative random effect or c(1,2) if 2 random effects.

Value

L	value of -2 x loglikelihood
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References

Maximum likelihood estimation for stochastic differential equations with random effects, M. Delattre, V. Genon-Catalot and A. Samson, *Scandinavian Journal of Statistics* 2012, Vol 40, **322–343**

likelihoodNormalestimfix	<i>Likelihood Function When The Fixed Effect Is Estimated</i>
--------------------------	---

Description

Computation of -2 loglikelihood of the mixed SDE with Normal distribution of the random effects when the fixed effect is estimated for random 1 or 2 $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma a(X_j(t))dW_j(t)$.

Usage

```
likelihoodNormalestimfix(mu1, mu2, omega, U, V, estimphi, random)
```

Arguments

mu1	current value of the mean of the first effect
mu2	current value of the mean of the second effect
omega	current value of the standard deviation of the normal distribution
U	vector of the M sufficient statistics U (see UV)
V	vector of the M sufficient statistics V (see UV)
estimphi	vector or matrix of estimators of the random effects
random	random effects in the drift: 1 if one additive random effect, 2 if one multiplicative random effect or c(1,2) if 2 random effects.

Value

L	value of -2 x loglikelihood
---	-----------------------------

References

Maximum likelihood estimation for stochastic differential equations with random effects, M. Delattre, V. Genon-Catalot and A. Samson, *Scandinavian Journal of Statistics* 2012, Vol 40, **322–343**

mixedsde.fit	<i>Estimation Of The Random Effects In Mixed Stochastic Differential Equations</i>
--------------	--

Description

Estimation of the random effects (α_j, β_j) and of their density, parametrically or nonparametrically in the mixed SDE $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma \alpha(X_j(t))dW_j(t)$.

Usage

```
mixedsde.fit(times, X, model = c("OU", "CIR"), random, fixed = 0,
  estim.fix = 0, estim.method = c("nonparam", "paramML", "paramBayes"),
  gridf = NULL, prior, nMCMC = NULL)
```

Arguments

times	vector of observation times
X	matrix of the M trajectories (each row is a trajectory with as much columns as observations)
model	name of the SDE: 'OU' (Ornstein-Uhlenbeck) or 'CIR' (Cox-Ingersoll-Ross)
random	random effects in the drift: 1 if one additive random effect, 2 if one multiplicative random effect or c(1,2) if 2 random effects
fixed	fixed effect in the drift: value of the fixed effect when there is only one random effect and it is not estimated, 0 otherwise
estim.method	estimation method: 'paramML' for a Gaussian parametric estimation by maximum likelihood, 'paramBayes' for a Gaussian parametric Bayesian estimation or 'nonparam' for a non-parametric estimation

gridf	if nonparametric estimation: grid of values on which the density is estimated, a matrix with two rows if two random effects; NULL by default and then grid is chosen as a function of the estimated values of the random effects. For the plots this grid is used.
estim.fix	default 0, 1 if random = 1 or 2, method = 'paramML' and an estimator of the fixed parameter is needed (to lead the nonparametric estimation after for example)
prior	if method = 'paramBayes', list of prior parameters: mean and variance of the Gaussian prior on the mean mu, shape and scale of the inverse Gamma prior for the variances omega, shape and scale of the inverse Gamma prior for sigma
nMCMC	if method = 'paramBayes', number of iterations of the MCMC algorithm

Details

Estimation of the random effects density from M independent trajectories of the SDE (the Brownian motions W_j are independent), with linear drift. Two diffusions are implemented, with one or two random effects:

Ornstein-Uhlenbeck model (OU):

If random = 1, β is a fixed effect: $dX_j(t) = (\alpha_j - \beta X_j(t))dt + \sigma dW_j(t)$

If random = 2, α is a fixed effect: $dX_j(t) = (\alpha - \beta_j X_j(t))dt + \sigma dW_j(t)$

If random = c(1,2), $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma dW_j(t)$

Cox-Ingersoll-Ross model (CIR):

If random = 1, β is a fixed effect: $dX_j(t) = (\alpha_j - \beta X_j(t))dt + \sigma \sqrt{X_j(t)} dW_j(t)$

If random = 2, α is a fixed effect: $dX_j(t) = (\alpha - \beta_j X_j(t))dt + \sigma \sqrt{X_j(t)} dW_j(t)$

If random = c(1,2), $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma \sqrt{X_j(t)} dW_j(t)$

The nonparametric method estimates the density of the random effects with a kernel estimator (one-dimensional or two-dimensional density). The parametric method estimates the mean and standard deviation of the Gaussian distribution of the random effects.

Value

index	is the vector of subscript in $1, \dots, M$ where the estimation of ϕ has been done, most of the time $index = 1 : M$
estimphi	matrix of estimators of $\phi = \alpha$, or β , or (α, β) from the efficient statistics (see UV), matrix of two lines if random = c(1,2), numerical type otherwise
estim.fixed	if estim.fix is TRUE and random = 1 or 2, estimator of $\phi = \alpha$, or β from the efficient statistics (see UV), 0 otherwise
gridf	grid of values on which the estimated is done for the nonparametric method, otherwise, grid used for the plots, matrix form
estimf	estimator of the density of ϕ from a kernel estimator from package: stats, function: density, or package: MASS, function: kde2D. Matrix form: one line if one random effect or square matrix otherwise
If there is a truncation threshold in the estimator	
cutoff	the binary vector of cutoff, FALSE otherwise
estimphi.trunc	truncated estimator of ϕ , vector or matrix of 0 if we do not use truncation, matrix of two lines if random = c(1,2), numerical type otherwise

estimf.trunc truncated estimator of the density of ϕ , vector or matrix of 0 if we do not use truncation, matrix if random =c(1,2), numerical type otherwise

For the parametric maximum likelihood estimation

mu estimator of the mean of the random effects normal density, 0 if we do nonparametric estimation

omega estimator of the standard deviation of the random effects normal density, 0 if we do nonparametric estimation

bic BIC criterium, 0 if we do nonparametric estimation

aic AIC criterium, 0 if we do nonparametric estimation

model initial choice

random initial choice

fixed initial choice

times initial choice

X initial choice

For the parametric Bayesian estimation

alpha posterior samples (Markov chain) of α

beta posterior samples (Markov chain) of β

mu posterior samples (Markov chain) of μ

omega posterior samples (Markov chain) of Ω

sigma2 posterior samples (Markov chain) of σ^2

model initial choice

random initial choice

burnIn proposal for burn-in period

thinning proposal for thinning rate

prior initial choice or calculated by the first 10% of series

times initial choice

X initial choice

ind.4.prior in the case of calculation of prior parameters: the indices of used series

References

For the parametric estimation see: Maximum likelihood estimation for stochastic differential equations with random effects, M. Delattre, V. Genon-Catalot and A. Samson, *Scandinavian Journal of Statistics* 2012, Vol 40, **322–343**

For the nonparametric estimation see:

Nonparametric estimation for stochastic differential equations with random effects, F. Comte, V. Genon-Catalot and A. Samson, *Stochastic Processes and Their Applications* 2013, Vol 7, **2522–2551**

Estimation for stochastic differential equations with mixed effects, V. Genon-Catalot and C. Laredo 2014 *e-print: hal-00807258*

Bidimensional random effect estimation in mixed stochastic differential model, C. Dion and V. Genon-Catalot, *Stochastic Inference for Stochastic Processes* 2015, *Springer Netherlands*, **1–28**

Examples

```
# Frequentist estimation
# Two random effects
model = 'CIR'; M <- 200; T <- 10 ; delta <- 0.001; N <- floor(T/delta); sigma <- 0.01 ;
random <- c(1,2); density.phi <- 'gammainvgamma2'; param<- c(1.8, 0.8, 8, 0.05);
simu <- mixedsde.sim(M=M, T=T, N=N, model=model,random=random, density.phi=density.phi,
                    param=param, sigma=sigma, invariant = 1)
X <- simu$X ; phi <- simu$phi; times <- simu$times
estim.method<- 'nonparam'
estim <- mixedsde.fit(times=times, X=X, model=model, random=random, estim.method= 'nonparam')
#To stock the results of the function, use method \code{out}
#which put the outputs of the function on a list according to the frequentist or
# Bayesian approach.
outputsNP <- out(estim)
plot(estim)
# It represents the bidimensional density, the histogram of the first estimated random
# effect  $\alpha$  with the marginal of  $\hat{f}$  from the first coordinate which
# estimates the density of  $\alpha$ . And the same for the second random effect
#  $\beta$ . More, it plots a qq-plot for the sample of estimator of the random effects
# compared with the quantiles of a Gaussian sample with the same mean and standard deviation.

summary(estim)
print(estim)
# Validation
# If numj is fixed by the user: this function simulates Mrep =100 (by default) new
# trajectories with the value of the estimated random effect. Then it plots on the
# left graph the Mrep new trajectories  $X_{numj}^k(t_1), \dots, X_{numj}^k(t_N)$ ,
#  $k= 1, \dots, Mrep$  with in red the true trajectory  $X_{numj}(t_1), \dots, X_{numj}(t_N)$ .
#The right graph is a qq-plot of the quantiles of samples
#  $X_{numj}^1(t_i), \dots, X_{numj}^{Mrep}(t_i)$ 
# for each time  $t_i$  compared with the uniform quantiles. The outputs of the function
# are: a matrix Xnew dimension Mrep x N+1, vector of quantiles quantiles length
# N and the number of the trajectory for the plot plotnumj= numj
# If numj is not precised by the user, then, this function simulates Mrep =100 (by default)
# new trajectories for each estimated random effect. Then left graph is a plot of the Mrep
# new trajectories  $X_j^k(t_1), \dots, X_j^k(t_N)$ ,  $k= 1, \dots, Mrep$ 
#for a randomly chosen number j with in red the true trajectory  $X_j(t_1), \dots, X_j(t_N)$ .
#The right graph is a qq-plot of the quantiles of samples  $X_j^1(t_i), \dots, X_j^{Mrep}(t_i)$ ,
# for the same j and for each time  $t_i$ . The outputs of the function are: a list of
# matrices Xnew length M, matrix of quantiles quantiles dimension MxN
# and the number of the trajectory for the plot plotnumj

validation <- valid(estim, numj=floor(runif(1,1,M)))

# Parametric estimation
estim.method<-'paramML'
estim_param <- mixedsde.fit(times= times, X= X, model= model, random= random,
                          estim.method = 'paramML')
outputsP <- out(estim_param)
plot(estim_param)
summary(estim_param)

# Prediction for the frequentist approach
# This function uses the estimation of the density function to simulate a
# new sample of random effects according to this density. If plot.pred=1 (default)
# is plots on the top the predictive random effects versus the estimated random effects
```



```

# from the data. On the bottom, the left graph is the true trajectories, on the right
# the predictive trajectories and the empiric prediction intervals at level
# \code{level=0.05} (default). The function return on a list the prediction of phi
# \code{phipred}, the prediction of X \code{Xpred}, and the indexes of the
# corresponding true trajectories \code{indexpred}

test1 <- pred(estim, invariant = 1)
test2 <- pred(estim_param, invariant = 1)

# More graph
fhat <- outputsNP$estimf
fhat_trunc <- outputsNP$estimf.trunc
fhat_param <- outputsP$estimf

gridf <- outputsNP$gridf; gridf1 <- gridf[1,]; gridf2 <- gridf[2,]

marg1 <- ((max(gridf2)-min(gridf2))/length(gridf2))*apply(fhat,1,sum)
marg1_trunc <- ((max(gridf2)-min(gridf2))/length(gridf2))*apply(fhat_trunc,1,sum)
marg2 <- ((max(gridf1)-min(gridf1))/length(gridf1))*apply(fhat,2,sum)
marg2_trunc <- ((max(gridf1)-min(gridf1))/length(gridf1))*apply(fhat_trunc,2,sum)

marg1_param <- ((max(gridf2)-min(gridf2))/length(gridf2))*apply(fhat_param,1,sum)
marg2_param <- ((max(gridf1)-min(gridf1))/length(gridf1))*apply(fhat_param,2,sum)
f1 <- (gridf1^(param[1]-1))*exp(-gridf1/param[2])/((param[2])^param[1]*gamma(param[1]))
f2 <- (gridf2^(-param[3]-1)) * exp(-(1/param[4])*(1/gridf2)) *
  ((1/param[4])^param[3])*(1/gamma(param[3]))
par(mfrow=c(1,2))
plot(gridf1,f1,type='l', lwd=1, xlab='', ylab='')
lines(gridf1,marg1_trunc,col='blue', lwd=2)
lines(gridf1,marg1,col='blue', lwd=2, lty=2)
lines(gridf1,marg1_param,col='red', lwd=2, lty=2)
plot(gridf2,f2,type='l', lwd=1, xlab='', ylab='')
lines(gridf2,marg2_trunc,col='blue', lwd=2)
lines(gridf2,marg2,col='blue', lwd=2, lty=2)
lines(gridf2,marg2_param,col='red', lwd=2, lty=2)

cutoff <- outputsNP$cutoff
phi_hat <- outputsNP$estimphi
phi_hat_trunc <- outputsNP$estimphi.trunc
par(mfrow=c(1,2))
plot.ts(phi[1,], phi_hat[1,], xlim=c(0, 15), ylim=c(0,15), pch=18); abline(0,1)
points(phi[1,]*(1-cutoff), phi_hat[1,]*(1-cutoff), xlim=c(0, 20), ylim=c(0,20),pch=18, col='red');
abline(0,1)
plot.ts(phi[2,], phi_hat[2,], xlim=c(0, 15), ylim=c(0,15),pch=18); abline(0,1)
points(phi[2,]*(1-cutoff), phi_hat[2,]*(1-cutoff), xlim=c(0, 20), ylim=c(0,20),pch=18, col='red');
abline(0,1)

# one random effect:

model <- 'OU'
random <- 1
M <- 80; T <- 100 ; N <- 2000
sigma <- 0.1 ; X0 <- 0
density.phi <- 'normal'
fixed <- 2 ; param <- c(1, 0.2)
#-----
#- simulation

```

```

simu <- mixedsde.sim(M,T=T,N=N,model=model,random=random, fixed=fixed,density.phi=density.phi,
                    param=param, sigma=sigma, X0=X0)
X <- simu$X
phi <- simu$phi
times <-simu$times
plot(times, X[10,], type='l')

#- parametric estimation
estim.method<-'paramML'
estim_param <- mixedsde.fit(times, X=X, model=model, random=random, estim.fix= 1,
                           estim.method=estim.method)
outputsP <- out(estim_param)
estim.fixed <- outputsP$estim.fixed #to compare with fixed
#or
estim_param2 <- mixedsde.fit(times, X=X, model=model, random=random, fixed = fixed,
                           estim.method=estim.method)
outputsP2 <- out(estim_param2)
#- nonparametric estimation
estim.method <- 'nonparam'
estim <- mixedsde.fit(times, X, model=model, random=random, fixed = fixed,
                    estim.method=estim.method)
outputsNP <- out(estim)

plot(estim)
print(estim)
summary(estim)

plot(estim_param)
print(estim_param)
summary(estim_param)

valid1 <- valid(estim, numj=floor(runif(1,1,M)))
test1 <- pred(estim )
test2 <- pred(estim_param)

# Parametric Bayesian estimation
# one random effect
random <- 1; sigma <- 0.1; fixed <- 5; param <- c(3, 0.5)
sim <- mixedsde.sim(M = 50, T = 1, N = 100, model = 'OU', random = random, fixed = fixed,
                  density.phi = 'normal',param= param, sigma= sigma, X0 = 0, op.plot = 1)

# here: only 100 iterations for example - should be much more!
estim_Bayes_withoutprior <- mixedsde.fit(times = sim$times, X = sim$X, model = 'OU',
                                       random, estim.method = 'paramBayes', nMCMC = 100)
prior <- list( m = c(param[1], fixed), v = c(param[1], fixed), alpha.omega = 11,
              beta.omega = param[2]^2*10, alpha.sigma = 10, beta.sigma = sigma^2*9)
estim_Bayes <- mixedsde.fit(times = sim$times, X = sim$X, model = 'OU', random,
                          estim.method = 'paramBayes', prior = prior, nMCMC = 100)

validation <- valid(estim_Bayes, numj = 10)
plot(estim_Bayes)
outputBayes <- out(estim_Bayes)
summary(outputBayes)
(results_Bayes <- summary(estim_Bayes))
plot(estim_Bayes, style = 'cred.int', true.phi = sim$phi)
plot(estim_Bayes_withoutprior, style = 'cred.int', true.phi = sim$phi, reduced = TRUE)

```

```

plot2compare(estim_Bayes, estim_Bayes_withoutprior, names = c('with prior', 'without prior'))

print(estim_Bayes)

pred.result <- pred(estim_Bayes)
summary(out(pred.result))
plot(pred.result)

pred.result.trajectories <- pred(estim_Bayes, trajectories = TRUE)

# second example
## Not run:
random <- 2; sigma <- 0.2; fixed <- 5; param <- c(3, 0.5)
sim <- mixedside.sim(M = 20, T = 1, N = 100, model = 'CIR', random = random,
  fixed = fixed, density.phi = 'normal', param = param, sigma = sigma, X0 = 0.1, op.plot = 1)

prior <- list(m = c(fixed, param[1]), v = c(fixed, param[1]), alpha.omega = 11,
  beta.omega = param[2]^2*10, alpha.sigma = 10, beta.sigma = sigma^2*9)

estim_Bayes <- mixedside.fit(times = sim$times, X = sim$X, model = 'CIR', random = random,
  estim.method = 'paramBayes', prior = prior, nMCMC = 1000)
plot(estim_Bayes)
outputBayes <- out(estim_Bayes)
summary(outputBayes)
(results_Bayes <- summary(estim_Bayes))
plot(estim_Bayes, style = 'cred.int', true.phi = sim$phi, reduced = TRUE)

print(estim_Bayes)
pred.result <- pred(estim_Bayes)
summary(out(pred.result))
plot(pred.result)

## End(Not run)

# for two random effects
random <- c(1,2); sigma <- 0.1; param <- c(3, 0.5, 5, 0.2)

sim <- mixedside.sim(M = 20, T = 1, N = 100, model = 'OU', random = random,
  density.phi = 'normalnormal', param = param, sigma = sigma, X0 = 0, op.plot = 1)

# here: only 200 iterations for example - should be much more!
estim_Bayes_withoutprior <- mixedside.fit(times = sim$times, X = sim$X, model = 'OU',
  random = random, estim.method = 'paramBayes', nMCMC = 100)
plot(estim_Bayes_withoutprior, style = 'cred.int', true.phi = sim$phi, reduced = TRUE)

prior <- list(m = param[c(1,3)], v = param[c(1,3)], alpha.omega = c(11,11),
  beta.omega = param[c(2,4)]^2*10, alpha.sigma = 10, beta.sigma = sigma^2*9)
estim_Bayes <- mixedside.fit(times = sim$times, X = sim$X, model = 'OU', random = random,
  estim.method = 'paramBayes', prior = prior, nMCMC = 100)
outputBayes <- out(estim_Bayes)
summary(outputBayes)
summary(estim_Bayes)
plot(estim_Bayes)
plot(estim_Bayes, style = 'cred.int', true.phi = sim$phi)
print(estim_Bayes)

```

```

pred.result <- pred(estim_Bayes)

# invariant case

random <- 1; sigma <- 0.1; fixed <- 5; param <- c(3, 0.5)
sim <- mixedsde.sim(M = 50, T = 5, N = 100, model = 'OU', random = random, fixed = fixed,
  density.phi = 'normal', param = param, sigma = sigma, invariant = 1, op.plot = 1)

prior <- list(m = c(param[1], fixed), v = c(param[1], 1e-05), alpha.omega = 11,
  beta.omega = param[2]^2*10, alpha.sigma = 10, beta.sigma = sigma^2*9)
estim_Bayes <- mixedsde.fit(times = sim$times, X = sim$X, model = 'OU', random,
  estim.method = 'paramBayes', prior = prior, nMCMC = 100)
plot(estim_Bayes)

pred.result <- pred(estim_Bayes, invariant = 1)
pred.result.traj <- pred(estim_Bayes, invariant = 1, trajectories = TRUE)

```

mixedsde.sim

Simulation Of A Mixed Stochastic Differential Equation

Description

Simulation of M independent trajectories of a mixed stochastic differential equation (SDE) with linear drift and two random effects (α_j, β_j) $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma a(X_j(t))dW_j(t)$, for $j = 1, \dots, M$.

Usage

```

mixedsde.sim(M, T, N = 100, model, random, fixed = 0, density.phi, param,
  sigma, t0 = 0, X0 = 0.01, invariant = 0, delta = T/N, op.plot = 0,
  add.plot = FALSE)

```

Arguments

M	number of trajectories
T	horizon of simulation.
N	number of simulation steps, default $T \times 100$.
model	name of the SDE: 'OU' (Ornstein-Uhlenbeck) or 'CIR' (Cox-Ingersoll-Ross).
random	random effects in the drift: 1 if one additive random effect, 2 if one multiplicative random effect or c(1,2) if 2 random effects.
fixed	fixed effects in the drift: value of the fixed effect when there is only one random effect, 0 otherwise. If random =2, fixed can be 0 but β has to be a non negative random variable for the estimation.
density.phi	name of the density of the random effects.
param	vector of parameters of the distribution of the two random effects.
sigma	diffusion parameter
t0	time origin, default 0.
X0	initial value of the process, default $X_0=0$.

invariant	1 if the initial value is simulated from the invariant distribution, default 0.01 and X0 is fixed.
delta	time step of the simulation (T/N).
op.plot	1 if a plot of the trajectories is required, default 0.
add.plot	1 for add trajectories to an existing plot

Details

Simulation of M independent trajectories of the SDE (the Brownian motions W_j are independent), with linear drift. Two diffusions are implemented, with one or two random effects:

Ornstein-Uhlenbeck model (OU): If random = 1, β is a fixed effect: $dX_j(t) = (\alpha_j - \beta X_j(t))dt + \sigma dW_j(t)$

If random = 2, α is a fixed effect: $dX_j(t) = (\alpha - \beta_j X_j(t))dt + \sigma dW_j(t)$

If random = c(1,2), $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma dW_j(t)$

Cox-Ingersoll-Ross model (CIR): If random = 1, β is a fixed effect: $dX_j(t) = (\alpha_j - \beta X_j(t))dt + \sigma \sqrt{X_j(t)} dW_j(t)$

If random = 2, α is a fixed effect: $dX_j(t) = (\alpha - \beta_j X_j(t))dt + \sigma \sqrt{X_j(t)} dW_j(t)$

If random = c(1,2), $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma \sqrt{X_j(t)} dW_j(t)$

The initial value of each trajectory can be simulated from the invariant distribution of the process: Normal distribution with mean α/β and variance $\sigma^2/(2\beta)$ for the OU, a gamma distribution $\Gamma(2\alpha/\sigma^2, \sigma^2/(2\beta))$ for the C-I-R model.

Density of the random effects: Several densities are implemented for the random effects, depending on the number of random effects.

If two random effects, choice between

'normalnormal': Normal distributions for both α β and param=c(mean_α, sd_α, mean_β, sd_β)

'gammagamma': Gamma distributions for both α β and param=c(shape_α, scale_α, shape_β, scale_β)

'gammainvgamma': Gamma for α , Inverse Gamma for β and param=c(shape_α, scale_α, shape_β, scale_β)

'normalgamma': Normal for α , Gamma for β and param=c(mean_α, sd_α, shape_β, scale_β)

'normalinvgamma': Normal for α , Inverse Gamma for β and param=c(mean_α, sd_α, shape_β, scale_β)

'gammagamma2': Gamma +2 * σ^2 for α , Gamma +1 for β and param=c(shape_α, scale_α, shape_β, scale_β)

'gammainvgamma2': Gamma +2 * σ^2 for α , Inverse Gamma for β and param=c(shape_α, scale_α, shape_β, scale_β)

If only α is random, choice between

'normal': Normal distribution with param=c(mean, sd)

lognormal': logNormal distribution with param=c(mean, sd)

'mixture.normal': mixture of normal distributions $pN(\mu_1, \sigma_1^2) + (1-p)N(\mu_2, \sigma_2^2)$ with param=c(p, $\mu_1, \sigma_1, \mu_2, \sigma_2$)

'gamma': Gamma distribution with param=c(shape, scale)

'mixture.gamma': mixture of Gamma distribution $p\Gamma(shape_1, scale_1) + (1-p)\Gamma(shape_2, scale_2)$ with param=c(p, shape1, scale1, shape2, scale2)

'gamma2': Gamma distribution +2 * σ^2 with param=c(shape, scale)

'mixed.gamma2': mixture of Gamma distribution $p\Gamma(shape1, scale1) + (1-p)\Gamma(shape2, scale2) + 2 * \sigma^2$ with param=c(p, shape1, scale1, shape2, scale2)
If only β is random, choice between 'normal': Normal distribution with param=c(mean, sd)
 'gamma': Gamma distribution with param=c(shape, scale)
 'mixture.gamma': mixture of Gamma distribution $p\Gamma(shape1, scale1) + (1-p)\Gamma(shape2, scale2)$ with param=c(p, shape1, scale1, shape2, scale2)

Value

X	matrix (M x (N+1)) of the M trajectories.
phi	vector (or matrix) of the M simulated random effects.

References

This function mixedsde.sim is based on the package sde, function sde.sim. See Simulation and Inference for stochastic differential equation, S.Iacus, *Springer Series in Statistics 2008* Chapter 2

See Also

<http://cran.r-project.org/package=sde>

Examples

```
#Simulation of 5 trajectories of the OU SDE with random =1, and a Gamma distribution.

simuOU <- mixedsde.sim(M=5, T=10, N=1000, model='OU', random=1, fixed=0.5,
  density.phi='gamma', param=c(1.8, 0.8), sigma=0.1, op.plot=1)
X <- simuOU$X ;
phi <- simuOU$phi
hist(phi)
```

mixture.sim

Simulation Of A Mixture Of Two Normal Or Gamma Distributions

Description

Simulation of M random variables from a mixture of two Gaussian or Gamma distributions

Usage

```
mixture.sim(M, density.phi, param)
```

Arguments

M	number of simulated variables
density.phi	name of the chosen density 'mixture.normal' or 'mixture.gamma'
param	vector of parameters with the proportion of mixture of the two distributions and means and standard-deviations of the two normal or shapes and scales of the two Gamma distribution

Details

If 'mixture.normal', the distribution is $pN(\mu_1, \sigma_1^2) + (1 - p)N(\mu_2, \sigma_2^2)$

and param=c(p, μ_1 , σ_1 , μ_2 , σ_2)

If 'mixture.gamma', the distribution is $p\text{Gamma}(\text{shape1}, \text{scale1}) + (1 - p)\text{Gamma}(\text{shape2}, \text{scale2})$

and param=c(p, shape1, scale1, shape2, scale2)

Value

Y
vector of simulated variables

Examples

```
density.phi <- 'mixture.gamma'
param <- c(0.2, 1.8, 0.5, 5.05, 1); M <- 200
gridf <- seq(0, 8, length = 200)
f <- param[1] * 1/gamma(param[2]) * (gridf)^(param[2]-1) *
      exp(-(gridf) / param[3]) / param[3]^param[2] +
(1-param[1]) * 1/gamma(param[4]) * (gridf)^(param[4]-1) *
      exp(-(gridf) / param[5]) / param[5]^param[4]
Y <- mixture.sim(M, density.phi, param)
hist(Y)
lines(gridf, f)
```

neuronai.data

Trajectories Interspike Of A Single Neuron Of A Guinea Pig

Description

The neuronai.data data has 240 measurements of the membrane potential in volts for one single neuron of a pig between the spikes, along time, with 2000 points for each. The step time is $\delta t = 0.00015$ s.

Usage

```
neuronai.data
```

Format

This data frame has a list form of length 2. The first element in the matrix named Xreal. Each row is a trajectory, that one can model by a diffusion process with random effect. The realisation can be assumed independent. The second element is a vector of times of observations times

Source

The parameters of the stochastic leaky integrate-and-fire neuronal model. Lansky, P., Sanda, P. and He, J. (2006). *Journal of Computational Neuroscience* Vol 21, **211–223**

References

The parameters of the stochastic leaky integrate-and-fire neuronal model. Lansky, P., Sanda, P. and He, J. (2006). *Journal of Computational Neuroscience* Vol 21, **211–223**

Examples

```

require(plot3D)
model <- "OU"
random <- c(1,2)
M <- 240      # number of trajectories, number of rows of the matrix of the data
T <- 0.3      # width of the interval of observation
delta <- 0.00015 # step time
N <- T/delta  # number of points in the time interval 2000
# load ("data/neuronal.data.rda")
data(neuronal.data)
X <- neuronal.data[[1]]
times <- neuronal.data[[2]]

#plot(times,X[10, ], type = 'l', xlab = 'time', ylab='', col = 'blue', ylim=c(0,0.016))

random <- c(1,2)

#- nonparametric estimation
estim.method <- 'nonparam'
estim <- mixedside.fit(times=times, X=X, model=model, random=random, estim.method='nonparam')

#- parametric estimation
estim.method<-'paramML'
estim_param <- mixedside.fit(times=times, X=X, model=model, random= random, estim.method= 'paramML')

#- implemented methods
# plot(estim);
print(estim); #valid(estim)
print(estim_param); #plot(estim_param); valid(estim_param)

#test1 <- pred(estim, X, estim.method= 'nonparam',times = times)
#test2 <- pred(estim_param, X,estim.method= 'paramML', times = times)

#- Other possible plots
par(mfrow=c(1,2))

outputsNP <- out(estim)
outputsP <- out(estim_param)
fhat <- outputsNP$estidf
fhat_param <- outputsP$estidf

gridf <- outputsNP$gridf
gridf1 <- gridf[1,]; gridf2 <- gridf[2,]
marg1 <- ((max(gridf2)-min(gridf2))/length(gridf2))*apply(fhat,1,sum) #with cutoff
marg2 <- ((max(gridf1)-min(gridf1))/length(gridf1))*apply(fhat,2,sum)
marg1_param <- ((max(gridf2)-min(gridf2))/length(gridf2))*apply(fhat_param,1,sum)
marg2_param <- ((max(gridf1)-min(gridf1))/length(gridf1))*apply(fhat_param,2,sum)

plot(gridf1,marg1,type='l', col='red')
lines(gridf1,marg1_param, lwd=2, col='red')
plot(gridf2, marg2,type='l', col='red')
lines(gridf2,marg2_param, lwd=2, col='red')

# Bayesian
ind <- seq(1, 2000, by = 10)

```



```

estim_Bayes <- mixedside.fit(times[ind], X[,ind], model = "OU", random = 1,
                             estim.method = "paramBayes", nMCMC = 1000)
plot(estim_Bayes)
pred_Bayes1 <- pred(estim_Bayes)
pred_Bayes2 <- pred(estim_Bayes, trajectories = TRUE)

```

out

*Transfers the class object to a list***Description**

Method for the S4 classes

Usage

```
out(x)
```

Arguments

x Freq.fit, Bayes.fit or Bayes.pred class

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixedside: an R package to fit mixed stochastic differential equations.

```
plot,Bayes.fit,ANY-method
```

*Plot method for the Bayesian estimation class object***Description**

Plot method for the S4 class Bayes.fit

Usage

```

## S4 method for signature 'Bayes.fit,ANY'
plot(x, plot.priorMean = FALSE, reduced = FALSE,
     style = c("chains", "acf", "density", "cred.int"), level = 0.05, true.phi,
     newwindow = FALSE, ...)

```

Arguments

x	Bayes.fit class
plot.priorMean	logical(1), if TRUE, prior means are added to the plots
reduced	logical(1), if TRUE, the chains are reduced with the burn-in and thin rate
style	one out of 'chains', 'acf', 'density' or 'cred.int'
level	alpha for the credibility intervals, only for style 'cred.int', default = 0.05
true.phi	only for style 'cred.int', for the case of known true values, e.g. for simulation
newwindow	logical(1), if TRUE, a new window is opened for the plot
...	optional plot parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

`plot, Bayes.pred, ANY-method`

Plot method for the Bayesian prediction class object

Description

Plot method for the S4 class `Bayes.pred`

Usage

```
## S4 method for signature 'Bayes.pred,ANY'
plot(x, newwindow = FALSE, plot.legend = TRUE,
     ylim, xlab = "times", ylab = "X", col = 3, lwd = 2, ...)
```

Arguments

<code>x</code>	<code>Bayes.fit</code> class
<code>newwindow</code>	logical(1), if TRUE, a new window is opened for the plot
<code>plot.legend</code>	logical(1)
<code>ylim</code>	optional
<code>xlab</code>	optional, default 'times'
<code>ylab</code>	optional, default 'X'
<code>col</code>	color for the prediction intervals, default 3
<code>lwd</code>	linewidth for the prediction intervals, default 2
<code>...</code>	optional plot parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

plot,Freq.fit,ANY-method

Plot method for the frequentist estimation class object

Description

Plot method for the S4 class Freq.fit

Usage

```
## S4 method for signature 'Freq.fit,ANY'
plot(x, newwindow = FALSE, ...)
```

Arguments

x	Freq.fit class
newwindow	logical(1), if TRUE, a new window is opened for the plot
...	optional plot parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

plot2compare

Comparing plot method

Description

Method for classes

Usage

```
plot2compare(x, y, z, ...)
```

Arguments

x	Bayes.fit or Bayes.pred class
y	Bayes.fit or Bayes.pred class
z	Bayes.fit or Bayes.pred class (optional)
...	other parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

plot2compare,Bayes.fit-method

Comparing plot method plot2compare for three Bayesian estimation class objects

Description

Comparison of the posterior densities for up to three S4 class Bayes.fit objects

Usage

```
## S4 method for signature 'Bayes.fit'
plot2compare(x, y, z, names, true.values,
  reduced = TRUE, newwindow = FALSE)
```

Arguments

x	Bayes.fit class
y	Bayes.fit class
z	Bayes.fit class (optional)
names	character vector of names for x, y and z
true.values	list of parameters to compare with the estimations, if available
reduced	logical(1), if TRUE, the chains are reduced with the burn-in and thin rate
newwindow	logical(1), if TRUE, a new window is opened for the plot

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

plot2compare,Bayes.pred-method

Comparing plot method plot2compare for three Bayesian prediction class objects

Description

Comparison of the results for up to three S4 class Bayes.pred objects

Usage

```
## S4 method for signature 'Bayes.pred'
plot2compare(x, y, z, newwindow = FALSE,
  plot.legend = TRUE, names, ylim, xlab = "times", ylab = "X", ...)
```

Arguments

x	Bayes.pred class
y	Bayes.pred class
z	Bayes.pred class (optional)
newwindow	logical(1), if TRUE, a new window is opened for the plot
plot.legend	logical(1), if TRUE, a legend is added
names	character vector with names for the three objects appearing in the legend
ylim	optional
xlab	optional, default 'times'
ylab	optional, default 'X'
...	optional plot parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixedside: an R package to fit mixed stochastic differential equations.

pred	<i>Prediction method</i>
------	--------------------------

Description

Prediction

Usage

```
pred(x, ...)
```

Arguments

x	Freq.fit or Bayes.fit class
...	other optional parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixedside: an R package to fit mixed stochastic differential equations.

pred, Bayes.fit-method *Bayesian prediction method for a class object Bayes.fit*

Description

Bayesian prediction

Usage

```
## S4 method for signature 'Bayes.fit'
pred(x, invariant = FALSE, level = 0.05,
     newwindow = FALSE, plot.pred = TRUE, plot.legend = TRUE, burnIn,
     thinning, only.interval = TRUE, sample.length = 500, cand.length = 100,
     trajectories = FALSE, ylim, xlab = "times", ylab = "X", col = 3,
     lwd = 2, ...)
```

Arguments

x	Bayes.fit class
invariant	logical(1), if TRUE, the initial value is from the invariant distribution $X_t \sim N(\alpha/\beta, \sigma^2/2\beta)$ for the OU and $X_t \sim \Gamma(2\alpha/\sigma^2, \sigma^2/2\beta)$ for the CIR process, if FALSE (default) X_0 is fixed from the data starting points
level	alpha for the predicion intervals, default 0.05
newwindow	logical(1), if TRUE, a new window is opened for the plot
plot.pred	logical(1), if TRUE, the results are depicted grafically
plot.legend	logical(1), if TRUE, a legend is added to the plot
burnIn	optional, if missing, the proposed value of the mixeddsde.fit function is taken
thinning	optional, if missing, the proposed value of the mixeddsde.fit function is taken
only.interval	logical(1), if TRUE, only prediction intervals are calculated, much faster than sampling from the whole predictive distribution
sample.length	number of samples to be drawn from the predictive distribution, if only.interval = FALSE
cand.length	number of candidates for which the predictive density is calculated, i.e. the candidates to be drawn from
trajectories	logical(1), if TRUE, only trajectories are drawn from the point estimations instead of sampling from the predictive distribution, similar to the frequentist approach
ylim	optional
xlab	optional, default 'times'
ylab	optional, default 'X'
col	color for the prediction intervals, default 3
lwd	linewidth for the prediction intervals, default 3
...	optional plot parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

pred,Freq.fit-method *Prediction method for the Freq.fit class object*

Description

Frequentist prediction

Usage

```
## S4 method for signature 'Freq.fit'
pred(x, invariant = 0, level = 0.05,
     newwindow = FALSE, plot.pred = TRUE, ...)
```

Arguments

x	Freq.fit class
invariant	1 if the initial value is from the invariant distribution, default X0 is fixed from Xtrue
level	alpha for the predicion intervals, default 0.05
newwindow	logical(1), if TRUE, a new window is opened for the plot
plot.pred	logical(1), if TRUE, the results are depicted grafically
...	optional plot parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixedside: an R package to fit mixed stochastic differential equations.

print,Bayes.fit-method *Print of acceptance rates of the MH steps*

Description

Method for the S4 class Bayes.fit

Usage

```
## S4 method for signature 'Bayes.fit'
print(x)
```

Arguments

x	Bayes.fit class
---	-----------------

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixedside: an R package to fit mixed stochastic differential equations.

print, Freq.fit-method *Description of print*

Description

Method for the S4 class Freq.fit

Usage

```
## S4 method for signature 'Freq.fit'
print(x)
```

Arguments

x Freq.fit class

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

summary, Bayes.fit-method
Short summary of the results of class object Bayes.fit

Description

Method for the S4 class Bayes.fit

Usage

```
## S4 method for signature 'Bayes.fit'
summary(object, level = 0.05, burnIn, thinning)
```

Arguments

object	Bayes.fit class
level	default is 0.05
burnIn	optional
thinning	optional

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

summary,Freq.fit-method

Short summary of the results of class object Freq.fit

Description

Method for the S4 class Freq.fit

Usage

```
## S4 method for signature 'Freq.fit'
summary(object)
```

Arguments

object Freq.fit class

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

UV

Computation Of The Sufficient Statistics

Description

Computation of U and V, the two sufficient statistics of the likelihood of the mixed SDE $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma a(X_j(t))dW_j(t)$.

Usage

```
UV(X, model, random, fixed, times)
```

Arguments

X	matrix of the M trajectories.
model	name of the SDE: 'OU' (Ornstein-Uhlenbeck) or 'CIR' (Cox-Ingersoll-Ross).
random	random effects in the drift: 1 if one additive random effect, 2 if one multiplicative random effect or c(1,2) if 2 random effects.
fixed	fixed effects in the drift: value of the fixed effect when there is only one random effect, 0 otherwise.
times	times vector of observation times.

Details

Computation of U and V, the two sufficient statistics of the likelihood of the mixed SDE $dX_j(t) = (\alpha_j - \beta_j X_j(t))dt + \sigma a(X_j(t))dW_j(t) = (\alpha_j, \beta_j)b(X_j(t))dt + \sigma a(X_j(t))dW_j(t)$ with $b(x) = (1, -x)^t$:

$$U : U(Tend) = \int_0^{Tend} b(X(s))/a^2(X(s))dX(s)$$

$$V : V(Tend) = \int_0^{Tend} b(X(s))^2/a^2(X(s))ds$$

Value

U vector of the M statistics U(Tend)
V list of the M matrices V(Tend)

References

See Bidimensional random effect estimation in mixed stochastic differential model, C. Dion and V. Genon-Catalot, *Stochastic Inference for Stochastic Processes 2015*, Springer Netherlands **1–28**

valid	<i>Validation of the chosen model.</i>
-------	--

Description

Validation of the chosen model. For the index numj, Mrep=100 new trajectories are simulated with the value of the estimated random effect number numj. Two plots are given: on the left the simulated trajectories and the true one (red) and on the right the corresponding qq-plot for each time.

Usage

```
valid(x, ...)
```

Arguments

x Freq.fit or Bayes.fit class
... other optional parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixeddsde: an R package to fit mixed stochastic differential equations.

valid, Bayes.fit-method

Validation of the chosen model.

Description

Validation of the chosen model. For the index numj, Mrep=100 new trajectories are simulated with the value of the estimated random effect number numj. Two plots are given: on the left the simulated trajectories and the true one (red) and on the right the corresponding qq-plot for each time.

Usage

```
## S4 method for signature 'Bayes.fit'
valid(x, Mrep = 100, newwindow = FALSE,
      plot.valid = TRUE, numj, ...)
```

Arguments

x	Bayes.fit class
Mrep	number of trajectories to be drawn
newwindow	logical(1), if TRUE, a new window is opened for the plot
plot.valid	logical(1), if TRUE, the results are depicted grafically
numj	optional number of series to be validated
...	optional plot parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). MixedSDE: an R package to fit mixed stochastic differential equations.

valid, Freq.fit-method *Validation of the chosen model.*

Description

Validation of the chosen model. For the index numj, Mrep=100 new trajectories are simulated with the value of the estimated random effect number numj. Two plots are given: on the left the simulated trajectories and the true one (red) and on the right the corresponding qq-plot for each time.

Usage

```
## S4 method for signature 'Freq.fit'
valid(x, Mrep = 100, newwindow = FALSE,
      plot.valid = TRUE, numj, ...)
```

Arguments

<code>x</code>	Freq.fit class
<code>Mrep</code>	number of trajectories to be drawn
<code>newwindow</code>	logical(1), if TRUE, a new window is opened for the plot
<code>plot.valid</code>	logical(1), if TRUE, the results are depicted grafically
<code>numj</code>	optional number of series to be validated
<code>...</code>	optional plot parameters

References

Dion, C., Hermann, S. and Samson, A. (2016). Mixedside: an R package to fit mixed stochastic differential equations.

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