Package ‘lineqGPR’

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Type Package

Title Gaussian Process Regression with Linear Inequality Constraints

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Description Gaussian processes regression with linear inequality constraints (Lopez-Lopera et al., 2018) <doi:10.1137/17M1153157>.

License GPL-3

Depends utils, stats, broom, nloptr, purrr

Imports MASS, Matrix, quadprog, mvtnorm, TruncatedNormal, graphics, grDevices, ggplot2, plot3D

Suggests Rcpp, testthat, tmg, viridis, tikzDevice, foreach, doParallel

RoxygenNote 7.1.2

Encoding UTF-8

NeedsCompilation yes

R topics documented:

`lineqGPR-package` *Gaussian Processes with Linear Inequality Constraints*

Description

A package for Gaussian process interpolation, regression and simulation under linear inequality constraints based on (López-Lopera et al., 2018). Constrained models and constrained additive models are given as objects with "lineqGP" and "lineqAGP" S3 class, respectively. Implementations according to (Maatouk and Bay, 2017) are also provided as objects with "lineqDGP" S3 class.

Details

This package was not yet installed at build time.

Warning

lineqGPR may strongly evolve in the future in order to incorporate other packages for Gaussian process regression modelling (see, e.g., **kergp**, **DiceKriging**, **DiceDesign**). It could be also scaled to higher dimensions and for a large number of observations.

Note

This package was initially developed within the frame of the Chair in Applied Mathematics OQUAIDO, gathering partners in technological research (BRGM, CEA, IFPEN, IRSN, Safran, Storengy) and academia (CNRS, Ecole Centrale de Lyon, Mines Saint-Etienne, University of Grenoble, University of Nice, University of Toulouse) around advanced methods for Computer Experiments.

	Important functions or methods
`create`	Creation function of GP models under linear inequality constraints.
`augment`	Augmentation of GP models according to local and covariance parameters.
`lineqGPOptim`	Covariance parameter estimation via maximum likelihood.
`predict`	Prediction of the objective function at new points using a Kriging model under linear inequality constraints.
`simulate`	Simulation of kriging models under linear inequality constraints.
`plot`	Plot for a constrained Kriging model.
`ggplot`	GGPlot for a constrained Kriging model.

Author(s)

Andrés F. López-Lopera (UPHF, Valenciennes) with contributions from Olivier Roustant (INSA, Toulouse) and Yves Deville (Alpestat).

Maintainer: Andrés F. López-Lopera, <andres.lopezlopera@uphf.fr>

References

A. F. López-Lopera, F. Bachoc, N. Durrande and O. Roustant (2018), "Finite-dimensional Gaussian approximation with linear inequality constraints". *SIAM/ASA Journal on Uncertainty Quantification*, 6(3): 1224–1255. <doi:10.1137/17M1153157>

F. Bachoc, A. Lagnoux and A. F. López-Lopera (2019), "Maximum likelihood estimation for Gaussian processes under inequality constraints". *Electronic Journal of Statistics*, 13 (2): 2921-2969. <doi:10.1214/19-EJS1587>

F. Bachoc, A. F. López-Lopera and O. Roustant (2020), "Sequential construction and dimension reduction of Gaussian processes under inequality constraints". *SIAM Journal on Mathematics of Data Science*, 4(2): 772-800. <doi:10.1137/21M1407513>

A. F. López-Lopera, F. Bachoc and O. Roustant (2022), "High-dimensional additive Gaussian processes under monotonicity constraints". *NeurIPS* <arXiv:2009.04188>

H. Maatouk and X. Bay (2017), "Gaussian process emulators for computer experiments with inequality constraints". *Mathematical Geosciences*, 49(5): 557-582.

Roustant, O., Ginsbourger, D., and Deville, Y. (2012), "DiceKriging, DiceOptim: Two R Packages for the Analysis of Computer Experiments by Kriging-Based Metamodeling and Optimization". *Journal of Statistical Software*, 51(1): 1-55.

Examples

```
## ------------------------------------------------------------------
## Gaussian process regression modelling under boundedness constraint
## ------------------------------------------------------------------
library(lineqGPR)
```

```
#### generating the synthetic data ####
sigfun <- function(x) return(1/(1+exp(-7*(x-0.5))))
x <- seq(0, 1, 0.001)
y <- sigfun(x)
DoE <- splitDoE(x, y, DoE.idx = c(201, 501, 801))

#### GP with inactive boundedness constraints ####
# creating the "lineqGP" model
model <- create(class = "lineqGP", x = DoE$xdesign, y = DoE$ydesign,
                constrType = c("boundedness"), m = 100)
model$bounds <- c(-10,10)

# sampling from the model
sim.model <- simulate(model, DoE$xtest, nsim = 1e3, seed = 1)
plot(sim.model, xlab = "x", ylab = "y(x)", ylim = range(y),
     main = "Unconstrained GP model")
lines(x, y, lty = 2)
legend("topleft", c("ytrain","ytest","mean","confidence"),
       lty = c(NaN,2,1,NaN), pch = c(20,NaN,NaN,15),
       col = c("black","black","darkgreen","gray80"))

#### GP with active boundedness constraints ####
# creating the "lineqGP" model
model <- create(class = "lineqGP", x = DoE$xdesign, y = DoE$ydesign,
                constrType = c("boundedness"), m = 100)
model$bounds <- c(0,1)

# sampling from the model
sim.model <- simulate(model, DoE$xtest, nsim = 1e2, seed = 1)
plot(sim.model, bounds = model$bounds,
     xlab = "x", ylab = "y(x)", ylim = range(y),
     main = "Constrained GP model under boundedness conditions")
lines(x, y, lty = 2)
legend("topleft", c("ytrain","ytest","mean","confidence"),
       lty = c(NaN,2,1,NaN), pch = c(20,NaN,NaN,15),
       col = c("black","black","darkgreen","gray80"))


## ------------------------------------------------------------------
## Gaussian process regression modelling under multiple constraints
## ------------------------------------------------------------------
library(lineqGPR)

#### generating the synthetic data ####
sigfun <- function(x) return(1/(1+exp(-7*(x-0.5))))
x <- seq(0, 1, 0.001)
y <- sigfun(x)
DoE <- splitDoE(x, y, DoE.idx = c(201, 501, 801))

#### GP with boundedness and monotonicity constraints ####
# creating the "lineqGP" model
model <- create(class = "lineqGP", x = DoE$xdesign, y = DoE$ydesign,
                constrType = c("boundedness","monotonicity"), m = 30)
model$bounds[1, ] <- c(0,1)
model$varnoise <- 1e-5

# sampling from the model
```

```
sim.model <- simulate(model, DoE$xtest, nsim = 1e2, seed = 1)
plot(sim.model, bounds = model$bounds,
     xlab = "x", ylab = "y(x)", ylim = range(y),
     main = "Constrained GP model under boundedness & monotonicity conditions")
lines(x, y, lty = 2)
legend("topleft", c("ytrain","ytest","mean","confidence"),
       lty = c(NaN,2,1,NaN), pch = c(20,NaN,NaN,15),
       col = c("black","black","darkgreen","gray80"))


## ------------------------------------------------------------------
## Gaussian process regression modelling under linear constraints
## ------------------------------------------------------------------
library(lineqGPR)
library(Matrix)

#### generating the synthetic data ####
targetFun <- function(x){
  y <- rep(1, length(x))
  y[x <= 0.4] <- 2.5*x[x <= 0.4]
  return(y)
}
x <- seq(0, 1, by = 0.001)
y <- targetFun(x)
DoE <- splitDoE(x, y, DoE.idx = c(101, 301, 501, 701))

#### GP with predefined linear inequality constraints ####
# creating the "lineqGP" model
model <- create(class = "lineqGP", x = DoE$xdesign, y = DoE$ydesign,
                constrType = c("linear"), m = 100)
m <- model$localParam$m
model$localParam$sampler <- "HMC"

# building the predefined linear constraints
bounds1 <- c(0,Inf)
LambdaB1 <- diag(2*m/5)
LambdaM <- diag(2*m/5)
LambdaB2 <- diag(3*m/5)
lsys <- lineqGPSys(m = 2*m/5, constrType = "monotonicity",
                   l = bounds1[1], u = bounds1[2], lineqSysType = "oneside")
LambdaM[-seq(1),] <- lsys$M
model$Lambda <- as.matrix(bdiag(rbind(LambdaM,LambdaB1),LambdaB2))
model$lb <- c(-Inf, rep(0, 2*m/5-1), rep(0, 2*m/5), rep(0.85, 3*m/5))
model$ub <- c(rep(0.1, 2*m/5), rep(1.1, 2*m/5), rep(1.1, 3*m/5))

# sampling from the model
sim.model <- simulate(model, DoE$xtest, nsim = 1e2, seed = 1)
plot(sim.model, bounds = c(0,1.1),
     xlab = "x", ylab = "y(x)", ylim = c(0,1.1),
     main = "Constrained GP model under linear conditions")
lines(x, y, lty = 2)
abline(v = 0.4, lty = 2)
lines(c(0.4, 1), rep(0.85, 2), lty = 2)
legend("bottomright", c("ytrain","ytest","mean","confidence"),
       lty = c(NaN,2,1,NaN), pch = c(20,NaN,NaN,15),
       col = c("black","black","darkgreen","gray80"))
```

```
## ------------------------------------------------------------------
## Note:
## 1. More examples are given as demos (run: demo(package="lineqGPR")).
## 2. See also the examples from inner functions of the package
## (run: help("simulate.lineqGP")).
## ------------------------------------------------------------------
```

`AdditiveMaxMod` *MaxMod algorithm for* `"lineqGP"` *and* `"lineqAGP"` *Models*

Description

A wrapper function for the maximum Modification algorithm.

Usage

```
AdditiveMaxMod(
  model,
  xtest,
  tol = 1e-04,
  max_iter = 10 * ncol(model$x),
  reward_new_knot = tol,
  reward_new_dim = 1e-09,
  print_iter = FALSE,
  nClusters = 1,
  save_history = FALSE
)
```

Arguments

`model`	an object with class `lineqGP` or `lineqAGP`
`xtest`	test data for assessing the modification of the MAP estimate
`tol`	a number corresponding to the tolerance of algorithm. The algorithm stops if the (MaxMod criterion)/norm(pred_old) < tol
`max_iter`	an integer corresponding to number of iterations
`reward_new_knot`	a number corresponding to the reward of adding a new knot in an existing dimension
`reward_new_dim`	a number corresponding to the reward of adding a new dimension
`print_iter`	a logical variable to print results at each iteration
`nClusters`	an integer corresponding to the number of clusters
`save_history`	a logical variable to save the model at each iteration

Value

an object with class `lineqGP` or `lineqAGP` containing the resulting model

Author(s)

A. F. Lopez-Lopera

`augment.lineqAGP` *Augmenting Method for the* `"lineqAGP"` *S3 Class*

Description

Augmenting method for the `"lineqAGP"` S3 class.

Usage

```
## S3 method for class 'lineqAGP'
augment(x, ...)
```

Arguments

`x`	an object with class `lineqGP`
`...`	further arguments passed to or from other methods

Details

Some paramaters of the finite-dimensional GP with linear inequality constraints are computed. Here, $\boldsymbol{\xi}$ is a centred Gaussian vector with covariance $\boldsymbol{\Gamma}$, s.t. $\boldsymbol{\Phi}\boldsymbol{\xi} = \boldsymbol{y}$ (interpolation constraints) and $\boldsymbol{l} \leq \boldsymbol{\Lambda}\boldsymbol{\xi} \leq \boldsymbol{u}$ (inequality constraints).

Value

An expanded `"lineqGP"` object with the following additional elements

`Phi`	a matrix corresponding to the hat basis functions. The basis functions are indexed by rows
`Gamma`	the covariance matrix of the Gassian vector $\boldsymbol{\xi}$.
`(Lambda,lb,ub)`	the linear system of inequalities.
`...`	further parameters passed to or from other methods.

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera (2019), "Gaussian process modelling under inequality constraints". *PhD thesis, Mines Saint-Etienne* <https://tel.archives-ouvertes.fr/tel-02863891>

See Also

`create.lineqAGP`, `predict.lineqAGP`, `simulate.lineqAGP`

Examples

```
# creating the model
d <- 2
fun1 <- function(x) return(4*(x-0.5)^2)
fun2 <- function(x) return(2*x)
targetFun <- function(x) return(fun1(x[, 1]) + fun1(x[, 2]))
xgrid <- expand.grid(seq(0, 1, 0.01), seq(0, 1, 0.01))
ygrid <- targetFun(xgrid)
xdesign <- rbind(c(0.5, 0), c(0.5, 0.5), c(0.5, 1), c(0, 0.5), c(1, 0.5))
ydesign <- targetFun(xdesign)
model <- create(class = "lineqAGP", x = xdesign, y = ydesign,
                constrType = c("convexity", "monotonicity"), m = 50)

# updating and expanding the model
model$kernParam[[1]]$par <- c(1, 0.2)
model$kernParam[[2]]$par <- c(1, 0.2)
model$nugget <- 1e-9
model$varnoise <- 1e-5
model <- augment(model)
str(model)
```

`augment.lineqGP` *Augmenting Method for the* `"lineqGP"` *S3 Class*

Description

Augmenting method for the `"lineqGP"` S3 class.

Usage

```
## S3 method for class 'lineqGP'
augment(x, ...)
```

Arguments

`x`	an object with class `lineqGP`
`...`	further arguments passed to or from other methods

Details

Some paramaters of the finite-dimensional GP with linear inequality constraints are computed. Here, $\boldsymbol{\xi}$ is a centred Gaussian vector with covariance $\boldsymbol{\Gamma}$, s.t. $\boldsymbol{\Phi}\boldsymbol{\xi} = \boldsymbol{y}$ (interpolation constraints) and $\boldsymbol{l} \leq \boldsymbol{\Lambda}\boldsymbol{\xi} \leq \boldsymbol{u}$ (inequality constraints).

Value

An expanded `"lineqGP"` object with the following additional elements

`Phi`	a matrix corresponding to the hat basis functions The basis functions are indexed by rows
`Gamma`	the covariance matrix of the Gassian vector $\boldsymbol{\xi}$.
`(Lambda,lb,ub)`	the linear system of inequalities
`...`	further parameters passed to or from other methods

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera, F. Bachoc, N. Durrande and O. Roustant (2017), "Finite-dimensional Gaussian approximation with linear inequality constraints". *SIAM/ASA Journal on Uncertainty Quantification*, 6(3): 1224–1255. <doi:10.1137/17M1153157>

See Also

create.lineqGP, predict.lineqGP, simulate.lineqGP

Examples

```
# creating the model
sigfun <- function(x) return(1/(1+exp(-7*(x-0.5))))
x <- seq(0, 1, length = 5)
y <- sigfun(x)
model <- create(class = "lineqGP", x, y, constrType = "monotonicity")

# updating and expanding the model
model$localParam$m <- 30
model$kernParam$par <- c(1, 0.2)
model2 <- augment(model)
image(model2$Gamma, main = "covariance matrix")
```

---

basisCompute.lineqGP *Hat Basis Functions for* "lineqGP" *Models*

Description

Evaluate the hat basis functions for "lineqGP" models.

Usage

```
basisCompute.lineqGP(x, u, d = 1)
```

Arguments

x	a vector (or matrix) with the input data
u	a vector (or matrix) with the locations of the knots
d	a number corresponding to the dimension of the input space

Value

A matrix with the hat basis functions. The basis functions are indexed by rows

Comments

This function was tested mainly for 1D or 2D input spaces. It could change in future versions for higher dimensions.

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera, F. Bachoc, N. Durrande and O. Roustant (2017), "Finite-dimensional Gaussian approximation with linear inequality constraints". *SIAM/ASA Journal on Uncertainty Quantification*, 6(3): 1224–1255. <doi:10.1137/17M1153157>

Examples

```
x <- seq(0, 1, 1e-3)
m <- 5
u <- seq(0, 1, 1/(m-1))
Phi <- basisCompute.lineqGP(x, u, d = 1)
matplot(Phi, type = "l", lty = 2, main = "Hat basis functions with m = 5")
```

---

bounds2lineqSys *Linear Systems of Inequalities*

Description

Build the linear system of inequalities given specific bounds.

Usage

```
bounds2lineqSys(
  d = nrow(A),
  l = 0,
  u = 1,
  A = diag(d),
  lineqSysType = "twosides",
  rmInf = TRUE
)
```

Arguments

`d`	the number of linear inequality constraints.
`l`	the value (or vector) with the lower bound.
`u`	the value (or vector) with the upper bound.
`A`	a matrix containing the structure of the linear equations.
`lineqSysType`	a character string corresponding to the type of the linear system. Options: `twosides`, `oneside`. - `twosides` : Linear system given by $$\boldsymbol{l} \leq \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{u}.$$ - `oneside` : Extended linear system given by $$\boldsymbol{M}\boldsymbol{x} + \boldsymbol{g} \geq \boldsymbol{0} \quad \text{with} \quad \boldsymbol{M} = [\boldsymbol{A}, -\boldsymbol{A}]^\top \quad \text{and} \quad \boldsymbol{g} = [-\boldsymbol{l}, \boldsymbol{u}]^\top.$$
`rmInf`	If `TRUE`, inactive constraints are removed (e.g. $-\infty \leq x \leq \infty$).

Value

A list with the linear system of inequalities: `list(A,l,u)` (`twosides`) or `list(M,g)` (`oneside`).

Author(s)

A. F. Lopez-Lopera

Examples

```
n <- 5
A <- diag(n)
l <- rep(0, n)
u <- c(Inf, rep(1, n-1))
bounds2lineqSys(n, l, u, A, lineqSysType = "twosides")
bounds2lineqSys(n, l, u, A, lineqSysType = "oneside", rmInf = FALSE)
bounds2lineqSys(n, l, u, A, lineqSysType = "oneside", rmInf = TRUE)
```

`constrlogLikFun` *Log-Constrained-Likelihood of a Gaussian Process.*

Description

Compute the negative log-constrained-likelihood of a Gaussian Process conditionally to the inequality constraints (Lopez-Lopera et al., 2019).

Usage

```
constrlogLikFun(
  par = model$kernParam$par,
  model,
  parfixed = NULL,
  mcmc.opts = list(probe = c("Genz"), nb.mcmc = 1000),
  estim.varnoise = FALSE
)
```

Arguments

`par`	the values of the covariance parameters.
`model`	an object with `"lineqGP"` S3 class.
`parfixed`	not used.
`mcmc.opts`	mcmc options. `mcmc.opts$probe` A character string corresponding to the estimator for the orthant multinormal probabilities. Options: `"Genz"` (Genz, 1992), `"ExpT"` (Botev, 2017). If `probe == "ExpT"`, `mcmc.opts$nb.mcmc` is the number of MCMC samples used for the estimation.
`estim.varnoise`	If `true`, a noise variance is estimated.

Details

Orthant multinormal probabilities are estimated according to (Genz, 1992; Botev, 2017). See (Lopez-Lopera et al., 2017).

Value

The value of the negative log-constrained-likelihood.

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera, F. Bachoc, N. Durrande and O. Roustant (2017), "Finite-dimensional Gaussian approximation with linear inequality constraints". *SIAM/ASA Journal on Uncertainty Quantification*, 6(3): 1224–1255. <doi:10.1137/17M1153157>

F. Bachoc, A. Lagnoux and A. F. Lopez-Lopera (2019), "Maximum likelihood estimation for Gaussian processes under inequality constraints". *Electronic Journal of Statistics*, 13 (2): 2921-2969. <doi:10.1214/19-EJS1587>

A. Genz (1992), "Numerical computation of multivariate normal probabilities". *Journal of Computational and Graphical Statistics*, 1:141-150.

Z. I. Botev (2017), "The normal law under linear restrictions: simulation and estimation via minimax tilting". *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 79(1):125-148.

See Also

`constrlogLikGrad`, `logLikFun`, `logLikGrad`

`constrlogLikGrad` *Numerical Gradient of the Log-Constrained-Likelihood of a Gaussian Process.*

Description

Compute the gradient numerically of the negative log-constrained-likelihood of a Gaussian Process conditionally to the inequality constraints (Lopez-Lopera et al., 2019).

Usage

```
constrlogLikGrad(
  par = model$kernParam$par,
  model,
  parfixed = rep(FALSE, length(par)),
  mcmc.opts = list(probe = "Genz", nb.mcmc = 1000),
  estim.varnoise = FALSE
)
```

Arguments

`par`	the values of the covariance parameters.
`model`	an object with class `lineqGP`.
`parfixed`	indices of fixed parameters to do not be optimised.
`mcmc.opts`	mcmc options. `mcmc.opts$probe` A character string corresponding to the estimator for the orthant multinormal probabilities. Options: `"Genz"` (Genz, 1992), `"ExpT"` (Botev, 2017). If `probe == "ExpT"`, `mcmc.opts$nb.mcmc` is the number of MCMC samples used for the estimation.
`estim.varnoise`	If `true`, a noise variance is estimated.

Details

Orthant multinormal probabilities are estimated via (Genz, 1992; Botev, 2017).

Value

The gradient of the negative log-constrained-likelihood.

Comments

As orthant multinormal probabilities don't have explicit expressions, the gradient is implemented numerically based on `nl.grad`.

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera, F. Bachoc, N. Durrande and O. Roustant (2017), "Finite-dimensional Gaussian approximation with linear inequality constraints". *SIAM/ASA Journal on Uncertainty Quantification*, 6(3): 1224–1255. <doi:10.1137/17M1153157>

F. Bachoc, A. Lagnoux and A. F. Lopez-Lopera (2019), "Maximum likelihood estimation for Gaussian processes under inequality constraints". *Electronic Journal of Statistics*, 13 (2): 2921-2969. <doi:10.1214/19-EJS1587>

A. Genz (1992), "Numerical computation of multivariate normal probabilities". *Journal of Computational and Graphical Statistics*, 1:141-150.

Z. I. Botev (2017), "The normal law under linear restrictions: simulation and estimation via minimax tilting". *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 79(1):125-148.

See Also

`constrlogLikFun`, `logLikFun`, `logLikGrad` `create` *Model Creations*

Description

Wrapper function for creations of model functions. The function invokes particular methods which depend on the `class` of the first argument.

Usage

```
create(class, ...)
```

Arguments

`class`	a character string corresponding to the desired class.
`...`	further arguments passed to or from other methods. (see, e.g., `create.lineqGP`)

Value

A model object created according to its `class`.

Author(s)

A. F. Lopez-Lopera

See Also

`augment`, `predict`, `simulate`

Examples

```
## Not run:
model <- list()
model2 <- create(class = "ClassName", model)
model2
## End(Not run)
```

`create.lineqAGP` *Creation Method for the* `"lineqAGP"` *S3 Class*

Description

Creation method for the `"lineqAGP"` S3 class.

Usage

```
## S3 method for class 'lineqAGP'
create(x, y, constrType, m = NULL)
```

Arguments

x	a vector or matrix with the input data. The dimensions should be indexed by columns
y	a vector with the output data
constrType	a character string corresponding to the type of the inequality constraint
m	a scalar or vector corresponding to the number of knots per dimension. Options: "boundedness", "monotonicity", "convexity", "linear" Multiple constraints can be also defined, e.g. `constrType = c("boundedness","monotonicity")`

Value

A list with the following elements.

x,y,constrType	see **Arguments**
d	a number corresponding to the input dimension
constrIdx	for d > 1, a integer vector with the indices of active constrained dimensions
constrParam	constraint inequalities for each dimension
varnoise	a scalar with noise variance
localParam	a list with specific parameters required for `"lineqAGP"` models: `m` (number of basis functions), `sampler`, and `samplingParams`. See `simulate.lineqAGP`
kernParam	a list with the kernel parameters: `par` (kernel parameters), `type`, `nugget`. See `kernCompute`
bounds	the limit values if `constrType = "boundedness"`.
(Lambda,lb,ub)	the linear system of inequalities if `constrType = "linear"`

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera (2019), "Gaussian process modelling under inequality constraints". *PhD thesis, Mines Saint-Etienne* <https://tel.archives-ouvertes.fr/tel-02863891>

See Also

`augment.lineqAGP`, `predict.lineqAGP`, `simulate.lineqAGP`

Examples

```
# creating the model
d <- 2
fun1 <- function(x) return(4*(x-0.5)^2)
fun2 <- function(x) return(2*x)
targetFun <- function(x) return(fun1(x[, 1]) + fun1(x[, 2]))
xgrid <- expand.grid(seq(0, 1, 0.01), seq(0, 1, 0.01))
ygrid <- targetFun(xgrid)
xdesign <- rbind(c(0.5, 0), c(0.5, 0.5), c(0.5, 1), c(0, 0.5), c(1, 0.5))
ydesign <- targetFun(xdesign)
model <- create(class = "lineqAGP", x = xdesign, y = ydesign,
                constrType = c("convexity", "monotonicity"))
str(model)
```

create.lineqGP *Creation Method for the "lineqGP" S3 Class*

Description

Creation method for the "lineqGP" S3 class.

Usage

```
## S3 method for class 'lineqGP'
create(x, y, constrType, m = NULL)
```

Arguments

x	a vector or matrix with the input data. The dimensions should be indexed by columns
y	a vector with the output data
constrType	a character string corresponding to the type of the inequality constraint.
m	a scalar or vector corresponding to the number of knots per dimension. Options: "boundedness", "monotonicity", "convexity", "linear"; Multiple constraints can be also defined, e.g. `constrType = c("boundedness","monotonicity")`

Value

A list with the following elements

x,y,constrType	see **Arguments**
d	a number corresponding to the input dimension
constrIdx	for d > 1, a logical vector with the indices of active constrained dimensions.
localParam	a list with specific parameters required for "lineqGP" models: m (number of basis functions), sampler, and samplingParams. See simulate.lineqGP.
kernParam	a list with the kernel parameters: par (kernel parameters), type, nugget. See kernCompute
bounds	the limit values if constrType = "boundedness"
(Lambda,lb,ub)	the linear system of inequalities if constrType = "linear"

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera, F. Bachoc, N. Durrande and O. Roustant (2017), "Finite-dimensional Gaussian approximation with linear inequality constraints". *SIAM/ASA Journal on Uncertainty Quantification*, 6(3): 1224–1255. <doi:10.1137/17M1153157>

See Also

augment.lineqGP, predict.lineqGP, simulate.lineqGP

Examples

```
# creating the model
sigfun <- function(x) return(1/(1+exp(-7*(x-0.5))))
x <- seq(0, 1, length = 5)
y <- sigfun(x)
model <- create(class = "lineqGP", x, y, constrType = "monotonicity")
model
```

---

distAdditiveModes *Modification of the MAP estimate ("lineqAGP")*

Description

Compute the modification of the MAP estimate according to the MaxMod criterion

Usage

```
distAdditiveModes(u, model, pred, xtest, idx_add, reward_new_knot = 1e-06)
```

Arguments

`u`	an extended sequence corresponding to the values of the knots
`model`	an object with class `lineqAGP`
`pred`	an predictive model with class `lineqAGP`
`xtest`	test input data
`idx_add`	index of the dimension that will be activated
`reward_new_knot`	a number corresponding to the reward of adding a new knot in an existing dimension

Value

the modification of the MAP estimate after adding a new knot

Author(s)

A. F. Lopez-Lopera

References

F. Bachoc, A. F. Lopez-Lopera, and O. Roustant (2020), "Sequential construction and dimension reduction of Gaussian processes under inequality constraints". *ArXiv e-prints* <arXiv:2009.04188>

distMoides

`distModes` *Modification of the MAP estimate ("lineqGP")*

Description

Compute the modification of the MAP estimate according to the MaxMod criterion

Usage

```
distModes(u, model, pred, xtest, idx_add, reward_new_knot = 1e-06, Nscale = 1)
```

Arguments

u	an extended sequence corresponding to the values of the knots
model	an object with class lineqGP
pred	an predictive model with class lineqGP
xtest	test input data
idx_add	index of the dimension that will be activated
reward_new_knot	a number corresponding to the reward of adding a new knot in an existing dimension
Nscale	an integer corresponding to the number of new added knots

Value

the modification of the MAP estimate after adding a new knot

Author(s)

A. F. Lopez-Lopera

References

F. Bachoc, A. F. Lopez-Lopera, and O. Roustant (2020), "Sequential construction and dimension reduction of Gaussian processes under inequality constraints". *ArXiv e-prints* <arXiv:2009.04188>

errorMeasureRegress

`errorMeasureRegress` *Error Measures for GP Models.*

Description

Compute error measures for GP models: mean absulte error ("mae"), mean squared error ("mse"), standardised mse ("smse"), mean standardised log loss ("msll"), Q2 ("q2"), predictive variance adequation ("pva"), confidence interval accuracy ("cia").

Usage

```
errorMeasureRegress(
  y,
  ytest,
  mu,
  varsigma,
  type = "all",
  control = list(nsigma = 1.96)
)
```

Arguments

`y`	a vector with the output observations used for training.
`ytest`	a vector with the output observations used for testing.
`mu`	a vector with the posterior mean.
`varsigma`	a vector with the posterior variances.
`type`	a character string corresponding to the type of the measure.
`control`	an optional list with parameters to be passed (e.g. cia: "nsigma").

Value

The values of the error measures.

Author(s)

A. F. Lopez-Lopera

References

C. E. Rasmussen, and C. K. I. Williams (2005), "Gaussian Processes for Machine Learning (Adaptive Computation and Machine Learning)". *The MIT Press*.

F. Bachoc (2013), "Cross validation and maximum likelihood estimations of hyper-parameters of Gaussian processes with model misspecification". *Computational Statistics & Data Analysis*, 66:55-69.

See Also

`errorMeasureRegressMC`

Examples

```
# generating the toy example
n <- 100
w <- 4*pi
x <- seq(0, 1, length = n)
y <- sin(w*x)

# results with high-level noises generating the toy example
nbsamples <- 100
set.seed(1)
ynoise <- y + matrix(rnorm(n*nbsamples, 0, 10), ncol = nbsamples)
mu <- apply(ynoise, 1, mean)
```

```
sigma <- apply(ynoise, 1, sd)
matplot(x, ynoise, type = "l", col = "gray70")
lines(x, y, lty = 2, col = "red")
lines(x, mu, col = "blue")
lines(x, mu+1.98*sigma, lty = 2)
lines(x, mu-1.98*sigma, lty = 2)
legend("topright", c("target", "mean", "confidence", "samples"),
       lty = c(2,1,2,1), col = c("red", "blue", "black", "gray70"))
t(errorMeasureRegress(y, y, mu, sigma^2))

# results with low-level noises generating the toy example
set.seed(1)
ynoise <- y + matrix(rnorm(n*nbsamples, 0, 0.05), ncol = nbsamples)
mu <- apply(ynoise, 1, mean)
sigma <- apply(ynoise, 1, sd)
matplot(x, ynoise, type = "l", col = "gray70")
lines(x, y, lty = 2, col = "red")
lines(x, mu, col = "blue")
lines(x, mu+1.98*sigma, lty = 2)
lines(x, mu-1.98*sigma, lty = 2)
legend("topright", c("target", "mean", "confidence", "samples"),
       lty = c(2,1,2,1), col = c("red", "blue", "black", "gray70"))
t(errorMeasureRegress(y, y, mu, sigma^2))
```

`errorMeasureRegressMC` *Error Measures for GP Models using Monte Carlo Samples.*

Description

Compute error measures for GP models using Monte Carlo samples: mean absulte error (`"mae"`), mean squared error (`"mse"`), standardised mse (`"smse"`), Q2 (`"q2"`), predictive variance adequation (`"pva"`), confidence interval accuracy (`"cia"`).

Usage

```
errorMeasureRegressMC(
  y,
  ytest,
  ysamples,
  type = "all",
  control = list(probs = c(0.05, 0.95))
)
```

Arguments

`y`	a vector with the output observations used for training.
`ytest`	a vector with the output observations used for testing.
`ysamples`	a matrix with posterior sample paths. Samples are indexed by columns.
`type`	a character string corresponding to the type of the measure.
`control`	an optional list with parameters to be passed (cia: "probs").

Value

The values of the error measures.

Author(s)

A. F. Lopez-Lopera

See Also

errorMeasureRegress

Examples

```
# generating the toy example
n <- 100
w <- 4*pi
x <- seq(0, 1, length = n)
y <- sin(w*x)

# results with high-level noises generating the toy example
nbsamples <- 100
set.seed(1)
ynoise <- y + matrix(rnorm(n*nbsamples, 0, 10), ncol = nbsamples)
matplot(x, ynoise, type = "l", col = "gray70")
lines(x, y, lty = 2, col = "red")
legend("topright", c("target", "samples"), lty = c(2,1), col = c("red", "gray70"))
t(errorMeasureRegressMC(y, y, ynoise))

# results with low-level noises generating the toy example
set.seed(1)
ynoise <- y + matrix(rnorm(n*nbsamples, 0, 0.05), ncol = nbsamples)
matplot(x, ynoise, type = "l", col = "gray70")
lines(x, y, lty = 2, col = "red")
legend("topright", c("target", "samples"), lty = c(2,1), col = c("red", "gray70"))
t(errorMeasureRegressMC(y, y, ynoise))
```

---

ggplot.lineqGP *GGPlot for the "lineqGP" S3 Class*

Description

GGPlot for the "lineqGP" S3 class.

Usage

```
## S3 method for class 'lineqGP'
ggplot(
  data,
  mapping,
  ytest = NULL,
  probs = c(0.05, 0.95),
  bounds = NULL,
```

```
    addlines = TRUE,
    nblines = 5,
    fillbackground = TRUE,
    alpha.qtls = 0.4,
    xlab = "",
    ylab = "",
    main = "",
    xlim = NULL,
    ylim = NULL,
    lwd = 1,
    cex = 1.5,
    ...
  )
```

Arguments

`data`	an object with `"lineqGP"` S3 class.
`mapping`	not used.
`ytest`	the values of the test observations. `If !is.null(ytest)`, ytest is drawn.
`probs`	the values of the confidence intervals evaluated at probs.
`bounds`	the values of the bounds of a constrained model. If `!is.null(bounds)`, bounds are drawn.
`addlines`	an optional Logical. If `TRUE`, some samples are drawn.
`nblines`	if `addlines`. The number of samples to be drawn.
`fillbackground`	an optional logical. If `TRUE`, fill gray background.
`alpha.qtls`	a number indicating the transparency of the quantiles.
`xlab`	a character string corresponding to the title for the x axis.
`ylab`	a character string corresponding to the title for the y axis.
`main`	a character string corresponding to the overall title for the plot.
`xlim`	the limit values for the x axis.
`ylim`	the limit values for the y axis.
`lwd`	a number indicating the line width.
`cex`	a number indicating the amount by which plotting text and symbols should be scaled.
`...`	further arguments passed to or from other methods.

Value

GGPlot with the `"lineqGP"` model.

Author(s)

A. F. Lopez-Lopera

See Also

`ggplot`, `plot.lineqGP`

`GramMatrixPhi` *Gram matrix of the basis functions ("`lineqGP`")*

Description

Compute the Gram matrix of the basis functions for "`lineqGP`" models

Usage

```
GramMatrixPhi(u)
```

Arguments

`u`	a sequence corresponding to the values of the knots

Value

Gram matrix of the basis functions

Author(s)

A. F. Lopez-Lopera

References

F. Bachoc, A. F. Lopez-Lopera, and O. Roustant (2020), "Sequential construction and dimension reduction of Gaussian processes under inequality constraints". *ArXiv e-prints* <arXiv:2009.04188>

`GramMatrixPhiAdditive` *Gram matrix of the basis functions ("`lineqAGP`")*

Description

Compute the Gram matrix of the basis functions for "`lineqAGP`" models

Usage

```
GramMatrixPhiAdditive(u)
```

Arguments

`u`	a sequence corresponding to the values of the knots

Value

Gram matrix of the basis functions

Author(s)

A. F. Lopez-Lopera

References

F. Bachoc, A. F. Lopez-Lopera, and O. Roustant (2020), "Sequential construction and dimension reduction of Gaussian processes under inequality constraints". *ArXiv e-prints* <arXiv:2009.04188>

---

k1exponential — *1D Exponential Kernel Matrix for* "lineqGP" *Models.*

Description

Compute the 1D Exponential kernel for "lineqGP" models. attr: "gradient".

Usage

```
k1exponential(x1, x2, par, d = 1)
```

Arguments

x1	a vector with the first input locations.
x2	a vector with the second input locations.
par	the values of the kernel parameters (variance, lengthscale).
d	a number corresponding to the dimension of the input space.

Value

Kernel matrix $K(x_1, x_2)$ (or $K(x_1, x_1)$ if x_2 is not defined).

Author(s)

A. F. Lopez-Lopera

Examples

```
x <- seq(0, 1, 0.01)
K <- k1exponential(x, x, par =  c(1, 0.1))
image(K, main = "covariance matrix using a Exponential kernel")
```

`k1gaussian` *1D Gaussian Kernel Matrix for* `"lineqGP"` *Models.*

Description

Compute the 1D Gaussian kernel matrix for `"lineqGP"` models. attr: "gradient", "derivative".

Usage

```
k1gaussian(x1, x2, par, d = 1)
```

Arguments

`x1`	a vector with the first input locations.
`x2`	a vector with the second input locations.
`par`	the values of the kernel parameters (variance, lengthscale).
`d`	a number corresponding to the dimension of the input space.

Value

Kernel matrix $K(x_1, x_2)$ (or $K(x_1, x_1)$ if x_2 is not defined).

Author(s)

A. F. Lopez-Lopera

Examples

```
x <- seq(0, 1, 0.01)
K <- k1gaussian(x, x, par =  c(1, 0.1))
image(K, main = "covariance matrix using a Squared Exponential kernel")
```

`k1matern32` *1D Matern 3/2 Kernel Matrix for* `"lineqGP"` *Models.*

Description

Compute the 1D Matern 3/2 kernel for `"lineqGP"` models. attr: "gradient", "derivative".

Usage

```
k1matern32(x1, x2, par, d = 1)
```

Arguments

`x1`	a vector with the first input locations.
`x2`	a vector with the second input locations.
`par`	the values of the kernel parameters (variance, lengthscale).
`d`	a number corresponding to the dimension of the input space.

Value

Kernel matrix $K(x_1, x_2)$ (or $K(x_1, x_1)$ if x_2 is not defined).

Author(s)

A. F. Lopez-Lopera

Examples

```
x <- seq(0, 1, 0.01)
K <- k1matern32(x, x, par =  c(1, 0.1))
image(K, main = "covariance matrix using a Matern 3/2 kernel")
```

---

k1matern52 *1D Matern 5/2 Kernel Matrix for* `"lineqGP"` *Models.*

Description

Compute the 1D Matern 5/2 kernel for `"lineqGP"` models. attr: "gradient", "derivative".

Usage

```
k1matern52(x1, x2, par, d = 1)
```

Arguments

`x1`	A vector with the first input locations.
`x2`	A vector with the second input locations.
`par`	Values of the kernel parameters (variance, lengthscale).
`d`	A number corresponding to the dimension of the input space.

Value

Kernel matrix $K(x_1, x_2)$ (or $K(x_1, x_1)$ if x_2 is not defined).

Author(s)

A. F. Lopez-Lopera

Examples

```
x <- seq(0, 1, 0.01)
K <- k1matern52(x, x, par =  c(1, 0.1))
image(K, main = "covariance matrix using a Matern 5/2 kernel")
```

k2gaussian — *2D Gaussian Kernel Matrix for "lineqGP" Models.*

Description

Compute the 2D Gaussian kernel matrix for "lineqGP" models. attr: "gradient".

Usage

```
k2gaussian(x1, x2, par, d = 2)
```

Arguments

x1	a matrix with the first couple of input locations.
x2	a matrix with the second couple of input locations.
par	the values of the kernel parameters (variance, lengthscales).
d	a number corresponding to the dimension of the input space.

Value

Kernel matrix $K(x_1, x_2)$ (or $K(x_1, x_1)$ if x_2 is not defined).

Author(s)

A. F. Lopez-Lopera

Examples

```
xgrid <- seq(0, 1, 0.1)
x <- as.matrix(expand.grid(xgrid, xgrid))
K <- k2gaussian(x, x, par =  c(1, 0.1))
image(K, main = "covariance matrix using a 2D Gaussian kernel")
```

kernCompute — *Kernel Matrix for "lineqGP" Models.*

Description

Compute the kernel matrix for "lineqGP" models. attr: "gradient".

Usage

```
kernCompute(x1, x2 = NULL, type, par, d = 1L)
```

Arguments

x1	a vector with the first input locations.
x2	a vector with the second input locations.
type	a character string corresponding to the type of the kernel. Options: "gaussian", "matern32", "matern52", "exponential".
par	the values of the kernel parameters (variance, lengthscale).
d	a number corresponding to the dimension of the input space.

Value

Kernel matrix $K(x_1, x_2)$ (or $K(x_1, x_1)$ if x_2 is not defined).

Author(s)

A. F. Lopez-Lopera

Examples

```
x <- seq(0, 1, 0.01)
K <- kernCompute(x, type = "gaussian", par =  c(1, 0.1))
image(K, main = "covariance matrix")
```

---

lineqGPOptim *Gaussian Process Model Optimizations*

Description

Function for optimizations of "lineqGP" S3 class objects.

Usage

```
lineqGPOptim(
  model,
  x0 = model$kernParam$par,
  eval_f = "logLik",
  lb = rep(0.01, length(x0)),
  ub = rep(Inf, length(x0)),
 opts = list(algorithm = "NLOPT_LD_MMA", print_level = 0, ftol_abs = 0.001, maxeval =
    50, check_derivatives = FALSE, parfixed = rep(FALSE, length(x0))),
  seed = 1,
  estim.varnoise = FALSE,
  bounds.varnoise = c(0, Inf),
  add.constr = FALSE,
  additive = FALSE,
  mcmc.opts = list(probe = "Genz", nb.mcmc = 1000),
  max.trials = 10,
  ...
)
```

Arguments

model	a list with the structure of the constrained Kriging model.
x0	the initial values for the parameters to be optimized over.
eval_f	a function to be minimized, with first argument the vector of parameters over which minimization is to take place. It should return a scalar result.
lb	a vector with lower bounds of the params. The params are forced to be positive. See nloptr.
ub	a vector with upper bounds of the params. See nloptr.
opts	see nl.opts. Parameter parfixed indices of fixed parameters to do not be optimised. If estim.varnoise is true, the noise variance is estimated.
seed	an optional number. Set a seed to replicate results.
estim.varnoise	an optional logical. If TRUE, a noise variance is estimated.
bounds.varnoise	a vector with bounds of noise variance.
add.constr	an optional logical. If TRUE, the inequality constraints are taken into account in the optimization.
additive	an optional logical. If TRUE, the likelihood of an additive GP model is computed in the optimization.
mcmc.opts	if add.constr, mcmc options passed to methods.
max.trials	the value of the maximum number of trials when errors are produced by instabilities.
...	further arguments passed to or from other methods.

Value

An optimized lineqGP model.

Comments

This function has to be improved in the future for more stable procedures. Cros-validation (CV) methods could be implemented in future versions.

Author(s)

A. F. Lopez-Lopera

See Also

nloptr

lineqGPSys *Linear Systems of Inequalities for* "lineqGP" *Models*

Description

Build the linear system of inequalities for "lineqGP" models.

Usage

```
lineqGPSys(
  m = nrow(A),
 constrType = c("boundedness", "monotonicity", "decreasing", "convexity", "linear",
    "none"),
  l = -Inf,
  u = Inf,
  A = diag(m),
  d = length(m),
  lineqSysType = c("twosides", "oneside"),
  constrIdx = seq(length(m)),
  rmInf = TRUE
)
```

Arguments

m	the number of linear inequality constraints
constrType	a character string corresponding to the type of the inequality constraint Options: "boundedness", "monotonicity", "convexity", "linear"
l	the value (or vector) with the lower bound
u	the value (or vector) with the upper bound
A	a matrix containing the structure of the linear equations
d	the value with the input dimension
lineqSysType	a character string corresponding to the type of the linear system. Options: twosides, oneside (see bounds2lineqSys for more details)
constrIdx	for d > 1, a logical vector with the indices of active constrained dimensions
rmInf	If TRUE, inactive constraints are removed (e.g. $-\infty \leq x \leq \infty$).

Value

A list with the linear system of inequalities: list(A,l,u) (twosides) or list(M,g) (oneside).

Comments

This function could change in future versions for more types of inequality constraints in higher dimensions.

Author(s)

A. F. Lopez-Lopera

See Also

bounds2lineqSys

Examples

```
linSys1 <- lineqGPSys(m = 5, constrType = "boundedness", l = 0, u = 1, lineqSysType = "twosides")
linSys1
linSys2 <- lineqGPSys(m = 5, constrType = "boundedness", l = 0, u = 1, lineqSysType = "oneside")
linSys2
```

---

logLikAdditiveFun *Log-Likelihood of a Additive Gaussian Process.*

Description

Compute the negative log-likelihood of an Additive Gaussian Process.

Usage

```
logLikAdditiveFun(
  par = unlist(purrr::map(model$kernParam, "par")),
  model,
  parfixed = NULL,
  mcmc.opts = NULL,
  estim.varnoise = FALSE
)
```

Arguments

par	the values of the covariance parameters.
model	an object with "lineqAGP" S3 class.
parfixed	not used.
mcmc.opts	not used.
estim.varnoise	If true, a noise variance is estimated.

Value

The value of the negative log-likelihood.

Author(s)

A. F. Lopez-Lopera

See Also

logLikAdditiveGrad

`logLikAdditiveGrad` *Gradient of the Log-Likelihood of a Additive Gaussian Process.*

Description

Compute the gradient of the negative log-likelihood of an Additive Gaussian Process.

Usage

```
logLikAdditiveGrad(
  par = unlist(purrr::map(model$kernParam, "par")),
  model,
  parfixed = rep(FALSE, model$d * length(par)),
  mcmc.opts = NULL,
  estim.varnoise = FALSE
)
```

Arguments

`par`	the values of the covariance parameters.
`model`	an object with `"lineqAGP"` S3 class.
`parfixed`	indices of fixed parameters to do not be optimised.
`mcmc.opts`	not used.
`estim.varnoise`	If `true`, a noise variance is estimated.

Value

the gradient of the negative log-likelihood.

Author(s)

A. F. Lopez-Lopera

See Also

`logLikAdditiveFun`

`logLikFun` *Log-Likelihood of a Gaussian Process.*

Description

Compute the negative log-likelihood of a Gaussian Process.

Usage

```
logLikFun(
  par = model$kernParam$par,
  model,
  parfixed = NULL,
  mcmc.opts = NULL,
  estim.varnoise = FALSE
)
```

Arguments

par	the values of the covariance parameters.
model	an object with "lineqGP" S3 class.
parfixed	not used.
mcmc.opts	not used.
estim.varnoise	If true, a noise variance is estimated.

Value

The value of the negative log-likelihood.

Author(s)

A. F. Lopez-Lopera

References

Rasmussen, C. E. and Williams, C. K. I. (2005), "Gaussian Processes for Machine Learning (Adaptive Computation and Machine Learning)". *The MIT Press*.

See Also

logLikGrad, constrlogLikFun, constrlogLikGrad

logLikGrad — *Gradient of the Log-Likelihood of a Gaussian Process.*

Description

Compute the gradient of the negative log-likelihood of a Gaussian Process.

Usage

```
logLikGrad(
  par = model$kernParam$par,
  model,
  parfixed = rep(FALSE, length(par)),
  mcmc.opts = NULL,
  estim.varnoise = FALSE
)
```

Arguments

`par`	the values of the covariance parameters.
`model`	an object with `"lineqGP"` S3 class.
`parfixed`	indices of fixed parameters to do not be optimised.
`mcmc.opts`	not used.
`estim.varnoise`	If `true`, a noise variance is estimated.

Value

the gradient of the negative log-likelihood.

Author(s)

A. F. Lopez-Lopera

References

Rasmussen, C. E. and Williams, C. K. I. (2005), "Gaussian Processes for Machine Learning (Adaptive Computation and Machine Learning)". *The MIT Press*.

See Also

`logLikFun`, `constrlogLikFun`, `constrlogLikGrad`

MaxMod — *MaxMod algorithm for* `"lineqGP"` *and* `"lineqAGP"` *Models*

Description

A wrapper function for the maximum Modification algorithm.

Usage

```
MaxMod(
  model,
  xtest,
  tol = 1e-04,
  max_iter = 10 * ncol(model$x),
  reward_new_knot = tol,
  reward_new_dim = 1e-09,
  print_iter = FALSE,
  nClusters = 1,
  save_history = FALSE
)
```

Arguments

- `model` — an object with class `lineqGP` or `lineqAGP`
- `xtest` — test data for assessing the modification of the MAP estimate
- `tol` — a number corresponding to the tolerance of algorithm. The algorithm stops if the MaxMod criterion < tol
- `max_iter` — an integer corresponding to number of iterations
- `reward_new_knot` — a number corresponding to the reward of adding a new knot in an existing dimension
- `reward_new_dim` — a number corresponding to the reward of adding a new dimension
- `print_iter` — a logical variable to print results at each iteration
- `nClusters` — an integer corresponding to the number of clusters
- `save_history` — a logical variable to save the model at each iteration

Value

an object with class `lineqGP` or `lineqAGP` containing the resulting model

Author(s)

A. F. Lopez-Lopera

`MaxModCriterion` *MaxMod criterion for* `"lineqGP"` *Models*

Description

MaxMod criterion used to add a new knot or a new active dimension (see Bachoc et al., 2020)

Usage

```
MaxModCriterion(
  model,
  ulist,
  xtest,
  activeDim,
  activeDim_IdxSeq,
  idx_add,
  reward_new_dim = 1e-06,
  reward_new_knot = 1e-06,
  iter = 1,
  pred
)
```

Arguments

`model`	an object with class `lineqGP`
`ulist`	a list with the location of the knots
`xtest`	test data for assessing the modification of the MAP estimate
`activeDim`	a sequence containing the active dimensions
`activeDim_IdxSeq`	a sequence containing the indices of the actived input dimensions
`idx_add`	index of the dimension to be activated
`reward_new_dim`	a number corresponding to the reward of adding a new dimension
`reward_new_knot`	a number corresponding to the reward of adding a new knot in an existing dimension
`iter`	an integer corresponding to the iteration of the MaxMod algorithm
`pred`	an object with class `lineqGP` containing the predictive model

Value

the value of the knot that minimize the MaxMod criterion and the value of the objective function

Author(s)

A. F. Lopez-Lopera

References

F. Bachoc, A. F. Lopez-Lopera, and O. Roustant (2020), "Sequential construction and dimension reduction of Gaussian processes under inequality constraints". *ArXiv e-prints* <arXiv:2009.04188>

`MaxModCriterion.lineqAGP`

MaxMod criterion for "`lineqAGP`" *Models*

Description

MaxMod criterion used to add a new knot or a new active dimension (see Bachoc et al., 2020)

Usage

```
MaxModCriterion.lineqAGP(
  model,
  ulist,
  xtest,
  activeDim,
  activeDim_IdxSeq,
  idx_add,
  reward_new_dim,
  reward_new_knot,
  iter,
  pred
)
```

Arguments

`model`	an object with class `lineqAGP`
`ulist`	a list with the location of the knots
`xtest`	test data for assessing the modification of the MAP estimate
`activeDim`	a sequence containing the active dimensions
`activeDim_IdxSeq`	a sequence containing the indices of the actived input dimensions
`idx_add`	index of the dimension to be activated
`reward_new_dim`	a number corresponding to the reward of adding a new dimension
`reward_new_knot`	a number corresponding to the reward of adding a new knot in an existing dimension
`iter`	an integer corresponding to the iteration of the MaxMod algorithm
`pred`	an object with class `lineqAGP` containing the predictive model

Value

the value of the knot that minimize the MaxMod criterion and the value of the objective function

Author(s)

A. F. Lopez-Lopera

References

F. Bachoc, A. F. Lopez-Lopera, and O. Roustant (2022), "Sequential construction and dimension reduction of additive Gaussian processes under inequality constraints".

`MaxModCriterion.lineqGP`

MaxMod criterion for `"lineqGP"` *Models*

Description

MaxMod criterion used to add a new knot or a new active dimension (see Bachoc et al., 2020)

Usage

```
MaxModCriterion.lineqGP(
  model,
  ulist,
  xtest,
  activeDim,
  activeDim_IdxSeq,
  idx_add,
  reward_new_dim,
  reward_new_knot,
  iter,
  pred
)
```

Arguments

model	an object with class lineqGP
ulist	a list with the location of the knots
xtest	test data for assessing the modification of the MAP estimate
activeDim	a sequence containing the active dimensions
activeDim_IdxSeq	a sequence containing the indices of the actived input dimensions
idx_add	index of the dimension to be activated
reward_new_dim	a number corresponding to the reward of adding a new dimension
reward_new_knot	a number corresponding to the reward of adding a new knot in an existing dimension
iter	an integer corresponding to the iteration of the MaxMod algorithm
pred	an object with class lineqGP containing the predictive model

Value

the value of the knot that minimize the MaxMod criterion and the value of the objective function

Author(s)

A. F. Lopez-Lopera

References

F. Bachoc, A. F. Lopez-Lopera, and O. Roustant (2020), "Sequential construction and dimension reduction of Gaussian processes under inequality constraints". *ArXiv e-prints* <arXiv:2009.04188>

---

plot.lineqAGP *Plot for the "lineqAGP" S3 Class*

Description

Plot for the "lineqAGP" S3 class. See plot.lineqGP for more details.

Usage

```
## S3 method for class 'lineqAGP'
plot(x, y, ...)
```

Arguments

x	an object with "lineqAGP" S3 class.
y	not used.
...	further arguments passed to or from other methods.

Value

Plot with the "lineqAGP" model.

Author(s)

A. F. Lopez-Lopera

See Also

ggplot.lineqGP, plot

---

plot.lineqGP *Plot for the "lineqGP" S3 Class*

Description

Plot for the "lineqGP" S3 class.

Usage

```
## S3 method for class 'lineqGP'
plot(
  x,
  y,
  ytest = NULL,
  probs = c(0.025, 0.975),
  bounds = NULL,
  addlines = TRUE,
  nblines = 5,
  ...
)
```

Arguments

x	an object with "lineqGP" S3 class.
y	not used.
ytest	the values of the test observations. If !is.null(ytest), ytest is drawn.
probs	the values of the confidence intervals evaluated at probs.
bounds	the values of the bounds of a constrained model. If !is.null(bounds), bounds are drawn.
addlines	pptional Logical. If TRUE, some samples are drawn.
nblines	if addlines. The number of samples to be drawn.
...	further arguments passed to or from other methods.

Value

Plot with the "lineqGP" model.

Author(s)

A. F. Lopez-Lopera

See Also

plot, ggplot.lineqGP

predict.lineqAGP *Prediction Method for the* "lineqAGP" *S3 Class*

Description

Prediction method for the "lineqAGP" S3 class.

Usage

```
## S3 method for class 'lineqAGP'
predict(object, xtest, return_model = FALSE, ...)
```

Arguments

object	an object with class "lineqAGP".
xtest	a vector (or matrix) with the test input design
return_model	If TRUE, the augmented model is returned (see augment.lineqAGP).
...	further arguments passed to or from other methods

Details

The posterior paramaters of the finite-dimensional GP with linear inequality constraints are computed. Here, $\boldsymbol{\xi}$ is a centred Gaussian vector with covariance $\boldsymbol{\Gamma}$, s.t. $\boldsymbol{\Phi}\boldsymbol{\xi} = \boldsymbol{y}$ (interpolation constraints) and $\boldsymbol{l} \leq \boldsymbol{\Lambda}\boldsymbol{\xi} \leq \boldsymbol{u}$ (inequality constraints).

Value

A "lineqAGP" object with the following elements.

Lambda	a matrix corresponding to the linear set of inequality constraints
lb	the lower bound vector of the inequalities constraints
ub	the upper bound vector of the inequalities constraints
Phi.test	a matrix corresponding to the hat basis functions evaluated at xtest. The basis functions are indexed by rows
mu	the unconstrained GP mean predictor
Sigma	the unconstrained GP prediction conditional covariance matrix
xi.map	the GP maximum a posteriori (MAP) predictor given the inequality constraints

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera (2019), "Gaussian process modelling under inequality constraints". *PhD thesis, Mines Saint-Etienne* <https://tel.archives-ouvertes.fr/tel-02863891>

See Also

create.lineqAGP, augment.lineqAGP, simulate.lineqAGP

Examples

```
library(plot3D)
# creating the model
d <- 2
fun1 <- function(x) return(4*(x-0.5)^2)
fun2 <- function(x) return(2*x)
targetFun <- function(x) return(fun1(x[, 1]) + fun2(x[, 2]))
xgrid <- expand.grid(seq(0, 1, 0.01), seq(0, 1, 0.01))
ygrid <- targetFun(xgrid)
xdesign <- rbind(c(0.5, 0), c(0.5, 0.5), c(0.5, 1), c(0, 0.5), c(1, 0.5))
ydesign <- targetFun(xdesign)
model <- create(class = "lineqAGP", x = xdesign, y = ydesign,
                constrType = c("convexity", "monotonicity"), 10)

# updating and expanding the model
model$kernParam[[1]]$type <- "matern52"
model$kernParam[[2]]$type <- "matern52"
model$kernParam[[1]]$par <- c(1, 0.2)
model$kernParam[[2]]$par <- c(1, 0.3)
model$nugget <- 1e-9
model$varnoise <- 1e-5

# predictions from the model
ntest <- 25
xtest  <- cbind(seq(0, 1, length = ntest), seq(0, 1, length = ntest))
ytest <- targetFun(xtest)
pred <- predict(model, xtest)
persp3D(x = unique(xtest[, 1]), y = unique(xtest[, 2]),
        z = outer(c(pred$Phi.test[[1]] %*% pred$xi.map[[1]]),
                  c(pred$Phi.test[[2]] %*% pred$xi.map[[2]]), "+"),
        xlab = "x1", ylab = "x2", zlab = "mode(x1,x2)", zlim = c(0, 3),
        phi = 20, theta = -30, alpha = 1, colkey = FALSE)
points3D(x = xdesign[,1], y = xdesign[,2], z = ydesign, col = "black", pch = 19, add = TRUE)
```

---

predict.lineqGP — *Prediction Method for the "lineqGP" S3 Class*

Description

Prediction method for the "lineqGP" S3 class.

Usage

```
## S3 method for class 'lineqGP'
predict(object, xtest, return_model = FALSE, ...)
```

Arguments

object	an object with class "lineqGP"
xtest	a vector (or matrix) with the test input design
return_model	If TRUE, the augmented model is returned (see augment.lineqGP).
...	further arguments passed to or from other methods

Details

The posterior paramaters of the finite-dimensional GP with linear inequality constraints are computed. Here, $\boldsymbol{\xi}$ is a centred Gaussian vector with covariance $\boldsymbol{\Gamma}$, s.t. $\boldsymbol{\Phi}\boldsymbol{\xi} = \boldsymbol{y}$ (interpolation constraints) and $\boldsymbol{l} \leq \boldsymbol{\Lambda}\boldsymbol{\xi} \leq \boldsymbol{u}$ (inequality constraints).

Value

A "lineqGP" object with the following elements

Lambda	a matrix corresponding to the linear set of inequality constraints
lb	the lower bound vector of the inequalities constraints
ub	the upper bound vector of the inequalities constraints
Phi.test	a matrix corresponding to the hat basis functions evaluated at xtest. The basis functions are indexed by rows
mu	the unconstrained GP mean predictor
Sigma	the unconstrained GP prediction conditional covariance matrix
xi.map	the GP maximum a posteriori (MAP) predictor given the inequality constraints

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera, F. Bachoc, N. Durrande and O. Roustant (2017), "Finite-dimensional Gaussian approximation with linear inequality constraints". *SIAM/ASA Journal on Uncertainty Quantification*, 6(3): 1224–1255. <doi:10.1137/17M1153157>

See Also

create.lineqGP, augment.lineqGP, simulate.lineqGP

Examples

```
# creating the model
sigfun <- function(x) return(1/(1+exp(-7*(x-0.5))))
x <- seq(0, 1, length = 5)
y <- sigfun(x)
model <- create(class = "lineqGP", x, y, constrType = "monotonicity", m = 30)

# modifying the covariance parameters
model$kernParam$par <- c(1, 0.2)

# predictions from the model
xtest <- seq(0, 1, length = 100)
ytest <- sigfun(xtest)
pred <- predict(model, xtest)
plot(xtest, ytest, type = "l", lty = 2, main = "Kriging predictions")
lines(xtest, pred$Phi.test %*% pred$mu, type = "l", col = "blue")
lines(xtest, pred$Phi.test %*% pred$xi.map, type = "l", col = "red")
legend("right", c("ytest", "mean", "mode"), lty = c(2,1,1),
       col = c("black", "blue", "red"))
```

`simulate.lineqAGP` *Simulation Method for the* `"lineqAGP"` *S3 Class*

Description

Simulation method for the `"lineqAGP"` S3 class.

Usage

```
## S3 method for class 'lineqAGP'
simulate(object, nsim = 1, seed = NULL, xtest, ...)
```

Arguments

`object`	an object with class `"lineqAGP"`
`nsim`	the number of simulations
`seed`	see `simulate`
`xtest`	a vector (or matrix) with the test input design
`...`	further arguments passed to or from other methods

Details

The posterior sample-path of the finite-dimensional GP with linear inequality constraints are computed. Here, $\boldsymbol{\xi}$ is a centred Gaussian vector with covariance $\boldsymbol{\Gamma}$, s.t. $\boldsymbol{\Phi}\boldsymbol{\xi} = \boldsymbol{y}$ (interpolation constraints) and $\boldsymbol{l} \leq \boldsymbol{\Lambda}\boldsymbol{\xi} \leq \boldsymbol{u}$ (inequality constraints).

Value

A `"lineqAGP"` object with the following elements

`x`	a vector (or matrix) with the training input design
`y`	the training output vector at `x`
`xtest`	a vector (or matrix) with the test input design
`Phi.test`	a matrix corresponding to the hat basis functions evaluated at `xtest`. The basis functions are indexed by rows.
`xi.sim`	the posterior sample-path of the finite-dimensional Gaussian vector
`ysim`	the posterior sample-path of the observed GP Note: `ysim` = `Phi.test %*% xi.sim`

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera (2019), "Gaussian process modelling under inequality constraints". *PhD thesis, Mines Saint-Etienne* <https://tel.archives-ouvertes.fr/tel-02863891>

See Also

`create.lineqAGP`, `augment.lineqAGP`, `predict.lineqAGP`

Examples

```
library(plot3D)
# creating the model
d <- 2
fun1 <- function(x) return(4*(x-0.5)^2)
fun2 <- function(x) return(2*x)
targetFun <- function(x) return(fun1(x[, 1]) + fun2(x[, 2]))
xgrid <- expand.grid(seq(0, 1, 0.01), seq(0, 1, 0.01))
ygrid <- targetFun(xgrid)
xdesign <- rbind(c(0.5, 0), c(0.5, 0.5), c(0.5, 1), c(0, 0.5), c(1, 0.5))
ydesign <- targetFun(xdesign)
model <- create(class = "lineqAGP", x = xdesign, y = ydesign,
                constrType = c("convexity", "monotonicity"), m = 10)

# updating and expanding the model
model$kernParam[[1]]$type <- "matern52"
model$kernParam[[2]]$type <- "matern52"
model$kernParam[[1]]$par <- c(1, 0.2)
model$kernParam[[2]]$par <- c(1, 0.3)
model$nugget <- 1e-9
model$varnoise <- 1e-5

# sampling from the model
ntest <- 25
xtest  <- cbind(seq(0, 1, length = ntest), seq(0, 1, length = ntest))
ytest <- targetFun(xtest)
sim.model <- simulate(model, nsim = 1e3, seed = 1, xtest = xtest)
PhiAll.test <- cbind(sim.model$Phi.test[[1]][rep(1:ntest, times = ntest), ],
                     sim.model$Phi.test[[2]][rep(1:ntest, each = ntest), ])
persp3D(x = unique(xtest[, 1]), y = unique(xtest[, 2]),
        z = matrix(rowMeans(PhiAll.test %*% sim.model$xiAll.sim), ntest, ntest),
        xlab = "x1", ylab = "x2", zlab = "mode(x1,x2)", zlim = c(0, 3),
        phi = 20, theta = -30, alpha = 1, colkey = FALSE)
points3D(x = xdesign[,1], y = xdesign[,2], z = ydesign, col = "black", pch = 19, add = TRUE)
```

---

simulate.lineqGP — *Simulation Method for the* "lineqGP" *S3 Class*

Description

Simulation method for the "lineqGP" S3 class.

Usage

```
## S3 method for class 'lineqGP'
simulate(object, nsim = 1, seed = NULL, xtest, ...)
```

Arguments

object	an object with class "lineqGP"
nsim	the number of simulations
seed	see simulate

xtest	a vector (or matrix) with the test input design
...	further arguments passed to or from other methods

Details

The posterior sample-path of the finite-dimensional GP with linear inequality constraints are computed. Here, $\boldsymbol{\xi}$ is a centred Gaussian vector with covariance $\boldsymbol{\Gamma}$, s.t. $\boldsymbol{\Phi}\boldsymbol{\xi} = \boldsymbol{y}$ (interpolation constraints) and $\boldsymbol{l} \leq \boldsymbol{\Lambda}\boldsymbol{\xi} \leq \boldsymbol{u}$ (inequality constraints).

Value

A "lineqGP" object with the following elements

x	a vector (or matrix) with the training input design
y	the training output vector at x
xtest	a vector (or matrix) with the test input design
Phi.test	a matrix corresponding to the hat basis functions evaluated at xtest. The basis functions are indexed by rows
xi.sim	the posterior sample-path of the finite-dimensional Gaussian vector
ysim	the posterior sample-path of the observed GP Note: ysim = Phi.test %*% xi.sim

Author(s)

A. F. Lopez-Lopera

References

A. F. Lopez-Lopera, F. Bachoc, N. Durrande and O. Roustant (2017), "Finite-dimensional Gaussian approximation with linear inequality constraints". *SIAM/ASA Journal on Uncertainty Quantification*, 6(3): 1224–1255. <doi:10.1137/17M1153157>

See Also

create.lineqGP, augment.lineqGP, predict.lineqGP

Examples

```
# creating the model
sigfun <- function(x) return(1/(1+exp(-7*(x-0.5))))
x <- seq(0, 1, length = 5)
y <- sigfun(x)
model <- create(class = "lineqGP", x, y, constrType = "monotonicity", m = 30)

# modifying the covariance parameters
model$kernParam$par <- c(1, 0.2)

# sampling from the model
xtest <- seq(0, 1, length = 100)
ytest <- sigfun(xtest)
sim.model <- simulate(model, xtest, nsim = 50, seed = 1)
mu <- apply(sim.model$ysim, 1, mean)
qtls <- apply(sim.model$ysim, 1, quantile, probs = c(0.05, 0.95))
matplot(xtest, t(qtls), type = "l", lty = 1, col = "gray90",
        main = "Constrained Kriging model")
```

```
polygon(c(xtest, rev(xtest)), c(qtls[2,], rev(qtls[1,])), col = "gray90", border = NA)
lines(xtest, ytest, lty = 2)
lines(xtest, mu, type = "l", col = "darkgreen")
points(x, y, pch = 20)
legend("right", c("ytrain", "ytest", "mean", "confidence"), lty = c(NaN,2,1,NaN),
       pch = c(20,NaN,NaN,15), col = c("black", "black", "darkgreen", "gray80"))
```

`splitDoE` *Training/test data generator according to a given Design of Experiment (DoE)*

Description

Split the data in training/test sets according to a given DoE.

Usage

```
splitDoE(
  x,
  y,
  DoE.idx = NULL,
  DoE.type = c("rand", "regs"),
  ratio = 0.3,
  seed = NULL
)
```

Arguments

`x`	a vector (or matrix) with the input locations.
`y`	a vector with the output observations.
`DoE.idx`	the numeric indices of the training data used in the design.
`DoE.type`	if `is.null(DoE.idx)`, a character string corresponding to the type of DoE. Options: `rand` (random desings), `regs` (regular-spaced desings).
`ratio`	if `is.null(DoE.idx)`, a number with the ratio nb_train/nb_total (by default, ratio = 0.3).
`seed`	an optional value corresponding to the seed for random methods.

Value

A list with the DoE: `list(xdesign,ydesign,xtest,ytest)`.

Comments

This function is in progress. Other types of DoEs will be considered using the `DiceDesign` package.

Author(s)

A. F. Lopez-Lopera

Examples

```
# generating the toy example
x <- seq(0, 1, length = 100)
y <- sin(4*pi*x)

# regular DoE
DoE <- splitDoE(x, y, DoE.type = "regs", ratio = 0.3)
plot(x,y)
points(DoE$xdesign, DoE$ydesign, col = "red", pch = 20)
points(DoE$xtest, DoE$ytest, col = "blue", pch = 20)
legend("topright", c("training data", "test data"),
       pch = rep(20, 2), col = c("red", "blue"))

# random DoE
DoE <- splitDoE(x, y, DoE.type = "rand", ratio = 0.3, seed = 1)
plot(x,y)
points(DoE$xdesign, DoE$ydesign, col = "red", pch = 20)
points(DoE$xtest, DoE$ytest, col = "blue", pch = 20)
legend("topright", c("training data", "test data"),
       pch = rep(20, 2), col = c("red", "blue"))
```

`tmvrnorm` *Sampling Methods of Truncated Multivariate Normal Distributions*

Description

Wrapper function with a collection of Monte Carlo and Markov Chain Monte Carlo samplers for truncated multivariate normal distributions. The function invokes particular samplers which depend on the class of the first argument.

Usage

```
tmvrnorm(object, nsim, ...)
```

Arguments

`object`	an object with: `mu` (mean vector), `Sigma` (covariance matrix), `lb` (lower bound vector), `ub` (upper bound vector).
`nsim`	an integer corresponding to the number of simulations.
`...`	further arguments passed to or from other methods.

Value

A matrix with the sample path. Samples are indexed by columns.

Author(s)

A. F. Lopez-Lopera

See Also

`tmvrnorm.RSM`, `tmvrnorm.HMC`, `tmvrnorm.ExpT` tmvrnorm.ExpT "tmvrnorm" *Sampler for* "ExpT" *(Exponential Tilting) S3 Class*

Description

Sampler for truncated multivariate normal distributions via exponential tilting using the package TruncatedNormal (Botev, 2017).

Usage

```
## S3 method for class 'ExpT'
tmvrnorm(object, nsim, control = NULL, ...)
```

Arguments

object	an object with "ExpT" S3 class containing: mu (mean vector), Sigma (covariance matrix) lb (lower bound vector), ub (upper bound vector)
nsim	an integer corresponding to the number of simulations
control	extra parameters required for the MC/MCMC sampler
...	further arguments passed to or from other methods

Value

A matrix with the simulated samples. Samples are indexed by columns

Author(s)

A. F. Lopez-Lopera

References

Z. I. Botev (2017), "The normal law under linear restrictions: simulation and estimation via minimax tilting". *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 79(1):125-148.

See Also

tmvrnorm.RSM, tmvrnorm.HMC

Examples

```
n <- 100
x <- seq(0, 1, length = n)
Sigma <- kernCompute(x1 = x, type = "gaussian", par = c(1,0.2))
tmgPar <- list(mu = rep(0,n), Sigma = Sigma + 1e-9*diag(n), lb = rep(-1,n), ub = rep(1,n))
class(tmgPar) <- "ExpT"
y <- tmvrnorm(tmgPar, nsim = 10)
matplot(x, y, type = 'l', ylim = c(-1,1),
        main = "Constrained samples using exponential tilting")
abline(h = c(-1,1), lty = 2)
```

tmvrnorm.HMC *"tmvrnorm" Sampler for "HMC" (Hamiltonian Monte Carlo) S3 Class*

Description

Sampler for truncated multivariate normal distributions via Hamiltonian Monte Carlo using the package tmg (Pakman and Paninski, 2014).

Usage

```
## S3 method for class 'HMC'
tmvrnorm(object, nsim, control = list(burn.in = 100), ...)
```

Arguments

object	an object with "HMC" S3 class containing: mu (mean vector), Sigma (covariance matrix) lb (lower bound vector), ub (upper bound vector)
nsim	an integer corresponding to the number of simulations
control	extra parameters required for the MC/MCMC sampler
...	further arguments passed to or from other methods

Value

A matrix with the simulated samples. Samples are indexed by columns

Author(s)

A. F. Lopez-Lopera

References

A. Pakman and L. Paninski (2014), "Exact Hamiltonian Monte Carlo for truncated multivariate Gaussians". *Journal of Computational and Graphical Statistics*, 23(2):518-542.

See Also

tmvrnorm.RSM, tmvrnorm.ExpT

Examples

```
n <- 100
x <- seq(0, 1, length = n)
Sigma <- kernCompute(x1 = x, type = "gaussian", par = c(1,0.2))
tmgPar <- list(mu = rep(0,n), Sigma = Sigma + 1e-9*diag(n), lb = rep(-1,n), ub = rep(1,n))
class(tmgPar) <- "HMC"
y <- tmvrnorm(tmgPar, nsim = 10)
matplot(x, y, type = 'l', ylim = c(-1,1),
        main = "Constrained samples using Hamiltonian MC")
abline(h = c(-1,1), lty = 2)
```

tmvrnorm.RSM *"tmvrnorm" Sampler for "RSM" (Rejection Sampling from the Mode) S3 Class*

Description

Sampler for truncated multivariate normal distributions via RSM according to (Maatouk and Bay, 2017).

Usage

```
## S3 method for class 'RSM'
tmvrnorm(object, nsim, control = NULL, ...)
```

Arguments

object	an object with "RSM" S3 class containing: mu (mean vector), Sigma (covariance matrix) lb (lower bound vector), ub (upper bound vector)
nsim	an integer corresponding to the number of simulations
control	extra parameters required for the MC/MCMC sampler
...	further arguments passed to or from other methods

Value

A matrix with the simulated samples. Samples are indexed by columns

Author(s)

A. F. Lopez-Lopera

References

H. Maatouk and X. Bay (2017), "Gaussian process emulators for computer experiments with inequality constraints". *Mathematical Geosciences*, 49(5):557-582.

See Also

tmvrnorm.HMC, tmvrnorm.ExpT

Examples

```
n <- 100
x <- seq(0, 1, length = n)
Sigma <- kernCompute(x1 = x, type = "gaussian", par = c(1,0.2))
tmgPar <- list(mu = rep(0,n), Sigma = Sigma + 1e-9*diag(n), lb = rep(-1,n), ub = rep(1,n))
class(tmgPar) <- "RSM"
y <- tmvrnorm(tmgPar, nsim = 10)
matplot(x, y, type = 'l', ylim = c(-1,1),
        main = "Constrained samples using RSM")
abline(h = c(-1,1), lty = 2)
```

Index