Package ‘KrigInv’

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Type Package

Title Kriging-Based Inversion for Deterministic and Noisy Computer Experiments

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Depends DiceKriging

Imports randtoolbox, rgenoud, pbivnorm, anMC, mvtnorm

Suggests testthat

Description Criteria and algorithms for sequentially estimating level sets of a multivariate numerical function, possibly observed with noise.

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LazyLoad yes

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R topics documented:

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Kriging-based sequential algorithms, meant to identify the excursion set of a real valued function. The algorithms can also identify one or several level sets.

Details

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Note

Important functions are \texttt{EGI} and \texttt{EGIparallel}. The last 1.4 version allows to handle multiple thresholds \( T \), stored in an array and implements conservative excursion set strategies.

A first prototype of this package was originally developed by D. Ginsbourger in the frame of a collaboration with IRSN (Institut de Radioprotection et de Surete Nucleaire), acting through Yann Richet. The three main authors thank IRSN for sponsoring open source research, and allowing them to spread the present package and publish it on CRAN. They also would like to warmly thank Yann Richet for numerous discussions concerning this package, and more!

Author(s)

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References


Ranjan P., Bingham D., Michailidis G. (2008) \textit{Sequential experiment design for contour estimation from complex computer codes} Technometrics 50(4), pp 527-541
bichon_optim

Bichon et al.’s Expected Feasibility criterion

Description

Evaluation of Bichon’s Expected Feasibility criterion. To be used in optimization routines, like in `max_infill_criterion`.

Usage

```
bichon_optim(x, model, T, method.param = 1)
```

Arguments

- `x` Input vector at which one wants to evaluate the criterion. This argument can be either a vector of size d (for an evaluation at a single point) or a p*d matrix (for p simultaneous evaluations of the criterion at p different points).
- `model` An object of class `km` (Kriging model).
- `T` Target value (scalar).
- `method.param` Scalar tolerance around the target T. Default value is 1.

Value

Bichon EF criterion. When the argument `x` is a vector, the function returns a scalar. When the argument `x` is a p*d matrix, the function returns a vector of size p.

Author(s)

- Victor Picheny (INRA, Toulouse, France)
- David Ginsbourger (IDIAP Martigny and University of Bern, Switzerland)
- Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

`EGI.max_infill_criterion`
Examples

```r
cbichon_optim

set.seed(9)
N <- 20  # number of observations
T <- 80  # threshold
testfun <- branin

# a 20 points initial design
design <- data.frame(matrix(runif(2*N), ncol=2))
response <- testfun(design)

# km object with matern3_2 covariance
params estimated by ML from the observations
model <- km(formula=~ , design = design,
response = response, covtype="matern3_2")

x <- c(0.5, 0.4)  # one evaluation of the bichon criterion
bichon_optim(x=x, T=T, model=model)

n.grid <- 20  # resolution. You may use a larger value.
x.grid <- y.grid <- seq(0, 1, length=n.grid)
x <- expand.grid(x.grid, y.grid)
bichon.grid <- bichon_optim(x=x, T=T, model=model)
z.grid <- matrix(bichon.grid, n.grid, n.grid)

# plots: contour of the criterion, DOE points and new point
image(x=x.grid, y=y.grid, z=z.grid, col=grey.colors(10))
contour(x=x.grid, y=y.grid, z=z.grid, add=TRUE)
points(design, col="black", pch=17, lwd=4, cex=2)

i.best <- which.max(bichon.grid)
ponts(x[i.best, ], col="blue", pch=17, lwd=4, cex=3)

# plots the real (unknown in practice) curve f(x)=T

testfun.grid <- apply(x, 1, testfun)
z.grid.2 <- matrix(testfun.grid, n.grid, n.grid)
contour(x.grid, y.grid, z.grid.2, levels=T, col="blue", add=TRUE, lwd=5)
title("Contour lines of Bichon criterion (black) and of f(x)=T (blue)")
```

**computeQuickKrigcov**

Quick computation of kriging covariances

**Description**

Computes kriging covariances between some new points and many integration points, using pre-computed data.
computeQuickKrigcov

Usage

computeQuickKrigcov(model, integration.points, X.new, precalc.data, F.newdata, c.newdata)

Arguments

model A Kriging model of km class.
integration.points p*d matrix of fixed integration points in the X space.
X.new q*d matrix of new points. The calculated covariances are the covariances between these new point and the integration points.
precalc.data List containing precalculated data. This list is generated using the function precomputeUpdateData.
F.newdata The value of the kriging trend basis function at point X.new.
c.newdata The (unconditional) covariance between X.new and the design points.

Details

This function requires to use another function in order to generate the proper arguments. The argument precalc.data can be generated using precomputeUpdateData. The arguments F.newdata and c.newdata can be obtained using predict_nobias_km.

Value

Matrix of size p*q containing kriging covariances

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

precomputeUpdateData, predict_nobias_km
**computeRealVolumeConstant**

A constant used to calculate the expected excursion set’s volume variance.

**Examples**

```r
#computeQuickKrigcov

set.seed(9)
N <- 20  # number of observations
testfun <- branin

da 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfun(design)

#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=~., design = design,
             response = response,covtype="matern3_2")

#the integration.points are the points where we want to
#compute predictions/covariances if a point new.x is added
#to the DOE
x.grid <- seq(0,1,length=20)
integration.points <- expand.grid(x.grid,x.grid)
integration.points <- as.matrix(integration.points)

#precalculation
precalc.data <- precomputeUpdateData(model=model,
                                      integration.points=integration.points)

#now we can compute quickly kriging covariances
#between these data and any other points.
#example if 5 new points are added:
X.new <- matrix(runif(10),ncol=2)
pred <- predict_nobias_km(object=model,
                           newdata=X.new,type="UK",se.compute=TRUE)

kn <- computeQuickKrigcov(model=model,
                           integration.points=integration.points,X.new=X.new,
                           precalc.data=precalc.data,
                           F.newdata=pred$F.newdata,
                           c.newdata=pred$c)
```

**Description**

This function computes a constant used to calculate exactly the value of the “jn” criterion. Computing this constant does NOT change the optimum of the “jn” criterion. Therefore, its calculation is indicative only and is only necessary to know exactly (in expectation) the excursion set’s volume variance.
computeRealVolumeConstant

Usage

computeRealVolumeConstant(model, integration.points,
 integration.weights=NULL, T)

Arguments

model A Kriging model of km class.
integration.points p*d matrix of points for numerical integration in the X space.
integration.weights (Optional) Vector of size p corresponding to the weights of these integration points. If not provided, all weights are set to 1.
T Target threshold.

Details

Note that, even if the "jn" criterion can be used with more than one threshold, the computation of this constant is implemented only when the number of threshold is equal to 1.

Value

a scalar

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

precomputeUpdateData, predict_nobias_km

Examples

#computeRealVolumeConstant

set.seed(9)
N <- 20 #number of observations
testfun <- branin
T <- 80

# a 20 points initial design
design <- data.frame( matrix(runif(2*N), ncol=2) )
response <- testfun(design)
Description

Sequential sampling based on the optimization of a kriging-based criterion, with model update after each iteration. The criterias aim at identifying an excursion set or one/many level sets. At each iteration batchsize = 1 new locations are evaluated. Different criteria are available for selecting experiments. The pointwise criteria are “bichon”, “ranjan”, “tmse”, “tsee” and are fast to compute. In addition, integral criteria require numerical integration and can potentially deliver more than one new location per iteration. Available integral criteria are “imse”, “timse”, “sur”, “jn”, “vorob”, “vorobCons”, “vorobVol”. The use of the integral criteria is implemented in the \texttt{EGIparallel} function.

Usage

\texttt{EGI(T, model, method = NULL, method.param = NULL,}
\texttt{fun, iter, lower, upper, new.noise.var = 0,}
\texttt{optimcontrol = NULL, kmcontrol = NULL, integcontrol = NULL, ...)}

Arguments

\begin{itemize}
\item \texttt{T} Array containing one or several thresholds. The criteria which can be used with multiple thresholds are “tmse”, “timse”, “sur”, “jn”.
\item \texttt{model} A Kriging model of \texttt{km} class.
\item \texttt{method} Criterion used for choosing observations.
\item \texttt{method.param} Optional method parameters. For methods\end{itemize}
- "ranjan", "bichon", "tmse" and "timse": the tolerance value (scalar). If not provided, default value is used (1 for ranjan and bichon, 0 for tmse and timse).
- "vorobev": a list containing penalization (scalar, default=1), type I penalization, and typeExEx (character, default=">") either "<" or ">" denoting the type of excursion.
- "vorobCons" and "vorobVol": a list containing penalization (scalar, default), typeExEx (character, default=">"), consLevel (scalar, default=0.95), n_discrete_design (scalar, default=500*model@d), design (data.frame, default=as.data.frame(sobol (n = method.param$'n_discrete_design', dim = model@d))), pred (list resulting from predict.km). See also the arguments alpha, pred, design, type from the function conservativeEstimate, package anMC, for more details.

fun
Objective function.

iter
Number of iterations (i.e. number of additional sampling points).

lower
Vector containing the lower bounds of the design space.

upper
Vector containing the upper bounds of the design space.

new.noise.var
Optional scalar value of the noise variance of the new observations.

optimcontrol
Optional list of control parameters for the optimization of the sampling criterion. The field method defines which optimization method is used: it can be either "genoud" (default) for an optimisation using the genoud algorithm, or "discrete" for an optimisation over a specified discrete set. If the field method is set to "genoud", one can set some parameters of this algorithm: pop.size (default: 50*d), max.generations (default: 10*d), wait.generations (2), BFGSburnin (2) and the mutations P1, P2, up to P9 (see genoud). Numbers into brackets are the default values. If the field method is set to "discrete", one can set the field optim.points: p * d matrix corresponding to the p points where the criterion will be evaluated. If nothing is specified, 100*d points are chosen randomly.

kmcontrol
Optional list representing the control variables for the re-estimation of the kriging model once new points are sampled. The items are the same as in km.

integcontrol
Optional list specifying the procedure to build the integration points and weights, relevant only for the sampling criteria based on numerical integration: ("imse", "timse", "sur" or "jn"). Many options are possible. A) If nothing is specified, 100*d points are chosen using the Sobol sequence. B) One can directly set the field integration.points (a p * d matrix) for prespecified integration points. In this case these integration points and the corresponding vector integration.weights will be used for all the iterations of the algorithm. C) If the field integration.points is not set then the integration points are renewed at each iteration. In that case one can control the number of integration points n.points (default: 100*d) and a specific distribution distrib. Possible values for distrib are: "sobol", "MC", "timse", "imse", "sur" and "jn" (default: "sobol"). C.1) The choice "sobol" corresponds to integration points chosen with the Sobol sequence in dimension d (uniform weight). C.2) The choice "MC" corresponds to points chosen randomly, uniformly on the domain. C.3) The choices "timse", "imse", "sur" and "jn" correspond to importance
sampling distributions (unequal weights). It is strongly recommended to use
the importance sampling distribution corresponding to the chosen sampling cri-
terion. When important sampling procedures are chosen, n.points points are
chosen using importance sampling among a discrete set of n.candidates points
(default: n.points*10) which are distributed according to a distribution
init.distrib (default: "sobol"). Possible values for init.distrib are the
space filling distributions "sobol" and "MC" or an user defined distribution
"spec". The "sobol" and "MC" choices correspond to quasi random and ran-
dom points in the domain. If the "spec" value is chosen the user must fill in
manually the field init.distrib.spec to specify himself a n.candidates * d
matrix of points in dimension d.

... Other arguments of the target function fun.

Details

The function used to build the integration points and weights (based on the options specified in
integcontrol) is the function integration_design

Value

A list with components:

<table>
<thead>
<tr>
<th>Component</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>par</td>
<td>The added observations (ite * d matrix)</td>
</tr>
<tr>
<td>value</td>
<td>The value of the function fun at the added observations (vector of size &quot;ite&quot;)</td>
</tr>
<tr>
<td>nsteps</td>
<td>The number of added observations (=ite).</td>
</tr>
<tr>
<td>lastmodel</td>
<td>The current (last) kriging model of km class.</td>
</tr>
<tr>
<td>lastvalue</td>
<td>The value of the criterion at the last added point.</td>
</tr>
<tr>
<td>allvalues</td>
<td>If an optimization on a discrete set of points is chosen, the value of the criterion at all these points, for the last iteration.</td>
</tr>
</tbody>
</table>

If method="vorobCons" or method="vorobVol" the list also has components:

<table>
<thead>
<tr>
<th>Component</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>current.CE</td>
<td>Conservative estimate computed on lastmodel.</td>
</tr>
<tr>
<td>allCE_lvs</td>
<td>The conservative estimate levels computed at each iteration.</td>
</tr>
</tbody>
</table>

Author(s)

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Dario Azzimonti (IDSIA, Switzerland)
References


See Also

EGIparallel,max_infill_criterion

Examples

#EGI

set.seed(9)
N <- 20 #number of observations
T <- 80 #threshold
testfun <- branin
lower <- c(0,0)
upper <- c(1,1)

#a 20 points initial design
design <- data.frame(matrix(runif(2*N),ncol=2) )
response <- testfun(design)

#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=-., design = design,
response = response,covtype="matern3_2")

optimcontrol <- list(method="genoud",pop.size=50)
ingegcontrol <- list(distrib="sur",n.points=50)
iter <- 1

## Not run:
obj1 <- EGI(T=T,model=model,method="sur",fun=testfun,iter=iter,
lower=lower,upper=upper,optimcontrol=optimcontrol,
ingegcontrol=ingegcontrol)

obj2 <- EGI(T=T,model=model,method="ranjan",fun=testfun,iter=iter,
lower=lower,upper=upper,optimcontrol=optimcontrol,
ingegcontrol=ingegcontrol)
lower=lower,upper=upper,optimcontrol=optimcontrol)

par(mfrow=c(1,3))
print_uncertainty_2d(model=model,T=T,main="probability of excursion", type="pn",new.points=0,cex.points=2)

print_uncertainty_2d(model=obj1$lastmodel,T=T, main="updated probability of excursion, sur sampling", type="pn",new.points=iter, col.points.end="red",cex.points=2)

print_uncertainty_2d(model=obj2$lastmodel,T=T, main="updated probability of excursion, ranjan sampling", type="pn",new.points=iter, col.points.end="red",cex.points=2)

## End(Not run)

#same example with noisy initial observations and noisy new observations
branin.noise <- function(x) return(branin(x)+rnorm(n=1, sd=30))

set.seed(9)
N <- 20; T <- 80
testfun <- branin.noise
lower <- c(0,0); upper <- c(1,1)

design <- data.frame( matrix(runif(2*N),ncol=2) )
response.noise <- apply(design,1,testfun)
response.noise - response

model.noise <- km(formula=-., design = design, response = response.noise, covtype="matern3_2",noise.var=rep(30*30, times=N))

optimcontrol <- list(method="genoud",pop.size=50)
integcontrol <- list(distrib="sur",n.points=50)
iter <- 1

## Not run:
obj1 <- EGI(T=T,model=model.noise,method="sur",fun=testfun,iter=iter, lower=lower,upper=upper,optimcontrol=optimcontrol, integcontrol=integcontrol,new.noise.var=30*30)

obj2 <- EGI(T=T,model=model.noise,method="ranjan",fun=testfun,iter=iter, lower=lower,upper=upper,optimcontrol=optimcontrol, new.noise.var=30*30)

par(mfrow=c(1,3))
print_uncertainty_2d(model=model.noise,T=T, main="probability of excursion, noisy obs.", type="pn",new.points=0,cex.points=2)

print_uncertainty_2d(model=obj1$lastmodel,T=T, main="probability of excursion, sur sampling, noisy obs.",
type="pn", new.points=iter, col.points.end="red", cex.points=2)

print_uncertainty_2d(model=object$lastmodel, T=T, main="probability of excursion, ranjan sampling, noisy obs.", type="pn", new.points=iter, col.points.end="red", cex.points=2)

## End(Not run)


####
# Conservative estimates with non-noisy initial observations
## Not run:

testfun <- branin

## Minimize Type II error sampling

# The list method.param contains all parameters for the
# conservative estimate and the conservative sequential
# strategy. Below are parameters for a type II strategy
# with conservative estimates at 0.95
method.param = list(penalization=0, # Type II strategy
typeEx=">", consLevel = 0.95,
 n_discrete_design=500*model@d)

# If the CE for the initial model is already computed
# it is possible to pass the conservative Vorob'ev quantile
# level with method.param@consVorblLevel

obj_T2 <- EGI(T=T, model=model, method="vorobCons",
 fun=testfun, iter=iter, lower=lower, upper=upper,
 optimcontrol=optimcontrol,
 integcontrol=integcontrol, method.param=method.param)

par(mfrow=c(1,2))
print_uncertainty_2d(model=model, T=T, main="probability of excursion",
 type="pn", new.points=0, cex.points=2, consQuantile = obj_T2$allCE_lvs[1])

print_uncertainty_2d(model=obj_T2$lastmodel, T=T,
 main="probability of excursion, parallel Type II sampling",
 type="pn", new.points=iter, col.points.end="red",
 cex.points=2, consQuantile = obj_T2$allCE_lvs[2])

## Maximize conservative estimate's volume
## Set up method.param
## Here we pass the conservative level computed
## in the previous step for the initial model
method.param = list(typeEx=">", consLevel = 0.95,
 n_discrete_design=500*model@d,
 consVorblLevel=obj_T2$allCE_lvs[1])

obj_consVol <- EGI(T=T, model=model, method="vorobVol",
 fun=testfun, iter=iter, lower=lower, upper=upper,
 optimcontrol=optimcontrol,
Description

Sequential sampling based on the optimization of a kriging-based criterion, with model update after each iteration. The criteria aim at identifying an excursion set or one/many level sets. At each iteration batchsize new locations are evaluated. Different criteria are available for selecting experiments. The pointwise criteria are "bichon", "ranjan", "tmse", "tsee" and are fast to compute. These criteria can be used only with batchsize = 1. In addition, integral criteria require numerical integration and can potentially deliver more than one new location per iteration. Available integral criteria are "imse", "timse", "sur", "jn", "vorob", "vorobCons", "vorobVol".

Usage

\[
\text{EGIparallel}(T, \text{model} = \text{NULL}, \text{method} = \text{NULL}, \text{method.param} = \text{NULL}, \\
\text{fun}, \text{iter}, \text{batchsize} = 1, \\
\text{lower}, \text{upper}, \text{new.noise.var} = 0, \\
\text{optimcontrol} = \text{NULL}, \text{kmcontrol} = \text{NULL}, \text{integcontrol} = \text{NULL}, \ldots)
\]

Arguments

- **T**
  Array containing one or several thresholds. The criteria which can be used with multiple thresholds are "tmse", "timse", "sur", "jn".

- **model**
  A Kriging model of \text{kml} class.

- **method**
  Criterion used for choosing observations.

- **method.param**
  Optional method parameters. For methods
  - "ranjan", "bichon",
  "tmse" and "timse": the tolerance value (scalar). If not provided, default value is used (1 for ranjan and bichon, 0 for tmse and timse).
- "vorob": a list containing penalization (scalar, default=1), type I penalization, and typeEx (character, default=">") either ">" or "<" denoting the type of excursion.
- "vorobCons" and "vorobVol": a list containing penalization (scalar, default=1), typeEx (character, default=">"), consLevel (scalar, default=0.95), n_discrete_design (scalar, default=500*model@d), design (data.frame, default=as.data.frame(sobol (n = method.param$n_discrete_design, dim = model@d))), pred (result of predict.km on model at design) and consVorblevel, the conservative estimate Vorob'ev quantile computed from pred. See also the arguments alpha, pred, design, type from the function conservativeEstimate, package anMC, for more details.

batchsize  
Number of points to sample simultaneously. The sampling criterion will return batchsize points at each iteration. Some criteria can be used only with batchsize = 1 (see description).

ewNnoiseNvar  
Optional scalar value of the noise variance of the new observations.

fun  
Objective function.

iter  
Number of iterations.

lower  
Vector containing the lower bounds of the variables to be optimized over.

upper  
Vector containing the upper bounds of the variables to be optimized over.

optimcontrol  
Optional list of control parameters for the optimization of the sampling criterion. The field method defines which optimization method is used: it can be either "genoud" (default) for an optimisation using the genoud algorithm, or "discrete" for an optimisation over a specified discrete set. If the field method is set to "genoud", one can set some parameters of this algorithm: pop.size (default: 50*d), max.generations (default: 10*d), wait.generations (2), BFGSburnin (2) and the mutations P1, P2, up to P9 (see genoud). Numbers into brackets are the default values. If the field method is set to "discrete", one can set the field optim.points: p * d matrix corresponding to the p points where the criterion will be evaluated. If nothing is specified, 100*d points are chosen randomly. Finally, one can control the field optim.option in order to decide how to optimize the sampling criterion. If optim.option is set to 2 (default), batchsize sequential optimizations in dimension d are performed to find the optimum. If optim.option is set to 1, only one optimization in dimension batchsize*d is performed. This option is only available with "genoud". This option might provide more global and accurate solutions, but is a lot more expensive.

kmcontrol  
Optional list representing the control variables for the re-estimation of the kriging model once new points are sampled. The items are the same as in km.

integcontrol  
Optional list specifying the procedure to build the integration points and weights. Many options are possible. A) If nothing is specified, 100*d points are chosen using the Sobol sequence.
B) One can directly set the field integration.points (a p * d matrix) for prespecified integration points. In this case these integration points and the corresponding vector integration.weights will be used for all the iterations of the algorithm.
C) If the field integration.points is not set then the integration points are renewed at each iteration. In that case one can control the number of integration points n.points (default: 100*d) and a specific distribution
Possible values for \texttt{distrib} are: "sobol", "MC", "timse", "imse", "sur" and "jn" (default: "sobol"). C.1) The choice "sobol" corresponds to integration points chosen with the Sobol sequence in dimension d (uniform weight). C.2) The choice "MC" corresponds to points chosen randomly, uniformly on the domain. C.3) The choices "timse", "imse", "sur" and "jn" correspond to importance sampling distributions (unequal weights). It is strongly recommended to use the importance sampling distribution corresponding to the chosen sampling criterion. When important sampling procedures are chosen, \texttt{n.points} points are chosen using importance sampling among a discrete set of \texttt{n.candidates} points (default: \texttt{n.points*10}) which are distributed according to a distribution \texttt{init.distrib} (default: "sobol"). Possible values for \texttt{init.distrib} are the space filling distributions "sobol" and "MC" or an user defined distribution "spec". The "sobol" and "MC" choices correspond to quasi random and random points in the domain. If the "spec" value is chosen the user must fill in manually the field \texttt{init.distrib.spec} to specify himself a \texttt{n.candidates * d} matrix of points in dimension d.

Other arguments of the target function \texttt{fun}.

**Details**

The function used to build the integration points and weights (based on the options specified in \texttt{integcontrol}) is the function \texttt{integration\_design}.

**Value**

A list with components:

- \texttt{par} \hspace{1cm} The added observations ((iter*batchsize) * d matrix)
- \texttt{value} \hspace{1cm} The value of \texttt{fun} at the added observations (size: iter*batchsize)
- \texttt{nsteps} \hspace{1cm} The number of added observations (=iter*batchsize).
- \texttt{lastmodel} \hspace{1cm} The current (last) kriging model of \texttt{km} class.
- \texttt{lastvalue} \hspace{1cm} The value of the criterion at the last added batch of points.
- \texttt{allvalues} \hspace{1cm} If an optimization on a discrete set of points is chosen, the value of the criterion at all these points, for the last iteration, for the last point of the batch.

If \texttt{method="vorobCons"} or \texttt{method="vorobVol"} the list also has components:

- \texttt{current.CE} \hspace{1cm} Conservative estimate computed on \texttt{lastmodel}.
- \texttt{allCE\_lvs} \hspace{1cm} The conservative estimate levels computed at each iteration.

**Author(s)**

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References


See Also

`EGI`, `max_sur_parallel`

Examples

```r
#EGIparallel

set.seed(9)
N <- 20 #number of observations
T <- c(20,60) #thresholds
testfun <- branin
lower <- c(0,0)
upper <- c(1,1)

#a 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfun(design)

#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=~, design = design,
           response = response,covtype="matern3_2")

optimcontrol <- list(method="genoud",pop.size=50)
integcontrol <- list(distrib="sur",n.points=50)
iter <- 1
batchsize <- 6

## Not run:
obj <- EGIparallel(T=T,model=model,method="sur",batchsize=batchsize,
fun=testfun,iter=iter,lower=lower,upper=upper,
optimcontrol=optimcontrol,integcontrol=integcontrol)

par(mfrow=c(1,2))
print_uncertainty_2d(model=model,T=T,main="probability of excursion",
type="pn",new.points=0,cex.points=2)
print_uncertainty_2d(model=lastmodel,T=T,
```

```r}
```
main="probability of excursion, parallel sur sampling",
type="pn",new.points=iter*batchsize,col.points.end="red",cex.points=2)

## End(Not run)

#################################
#same example with noisy initial observations and noisy new observations
branin.noise <- function(x) return(branin(x)+rnorm(n=1,sd=30))

set.seed(9)
N <- 20; T <- c(20,60)
testfun <- branin.noise
lower <- c(0,0); upper <- c(1,1)
design <- data.frame( matrix(runif(2*N),ncol=2) )
response.noise <- apply(design,1,testfun)
response.noise - response

model.noise <- km(formula=~., design = design, response = response.noise, 
covtype="matern_2",noise.var=rep(30*30,times=N))

optimcontrol <- list(method="genoud",pop.size=50)
integcontrol <- list(distrib="sur",n.points=50)
iter <- 1
batchsize <- 6

## Not run:
obj <- EGIparallel(T=T,model=model.noise,method="sur",batchsize=batchsize, 
fun=testfun,iter=iter,lower=lower,upper=upper, 
optimcontrol=optimcontrol,integcontrol=integcontrol, 
new.noise.var=10*10)

par(mfrow=c(1,2))
print_uncertainty_2d(model=model.noise,T=T, 
main="probability of excursion, noisy obs.", 
type="pn",new.points=0,cex.points=2)

print_uncertainty_2d(model=obj$lastmodel,T=T, 
main="probability of excursion, parallel sur sampling, noisy obs.", 
type="pn",new.points=iter*batchsize,col.points.end="red",cex.points=2)

## End(Not run)

#################################
# Conservative estimates with non-noisy initial observations
## Not run:
testfun <- branin
# The conservative sampling strategies
# only work with 1 threshold
T <- 20
## Minimize Type II error sampling
# The list method.param contains all parameters for the
# conservative estimate and the conservative sequential
# strategy. Below are parameters for a type II strategy
# with conservative estimates at 0.95
method.param = list(penalization=0, # Type II strategy
                  typeEx="">", consLevel = 0.95,
                  n_discrete_design=500*model@d)
# If the CE for the initial model is already computed
# it is possible to pass the conservative Vorob'ev quantile
# level with method.param@consVorLevel

obj_T2 <- EGIparallel(T=T,model=model@model,method="vorobCons",batchsize=batchsize,
                  fun=testfun,iter=iter,lower=lower,upper=upper,
                  optimcontrol=optimcontrol,
                  integcontrol=integcontrol,method.param=method.param)

par(mfrow=c(1,2))
print_uncertainty_2d(model=model,T=T,main="probability of excursion",
                  type="pn",new.points=0,cex.points=2,consQuan= obj_T2$allCE_lvs[1])

print_uncertainty_2d(model=obj_T2$model@lastmodel,T=T,
                  main="probability of excursion, parallel Type II sampling",
                  type="pn",new.points=iter*batchsize,col.points.end="red",
                  cex.points=2,consQuan= obj_T2$allCE_lvs[2])

## Maximize conservative estimate's volume
# Set up method.param
# Here we pass the conservative level computed
# in the previous step for the initial model
method.param = list(typeEx="">", consLevel = 0.95,
                  n_discrete_design=500*model@d,
                  consVorLevel=obj_T2$allCE_lvs[1]
                  )

obj_consVol <- EGIparallel(T=T,model=model@model,method="vorobVol",batchsize=batchsize,
                  fun=testfun,iter=iter,lower=lower,upper=upper,
                  optimcontrol=optimcontrol,
                  integcontrol=integcontrol,method.param=method.param)

par(mfrow=c(1,2))
print_uncertainty_2d(model=model,T=T,main="probability of excursion",
                  type="pn",new.points=0,cex.points=2,consQuan= obj_consVol$allCE_lvs[1])

print_uncertainty_2d(model=obj_consVol@lastmodel,T=T,
                  main="probability of excursion, parallel consVol sampling",
                  type="pn",new.points=iter*batchsize,col.points.end="red",
                  cex.points=2,consQuan= obj_consVol$allCE_lvs[2])

## End(Not run)
Excursion probability

Description
Probability that Gaussian random variables with some mean and variance are over a threshold $T$, or in an union of intervals. If $T$ is a vector of size $p$, $T_1,T_2,...,T_p$ then the considered union of intervals is $(T_1,T_2) \cup ... \cup (T_{p-1}, T_p)$ if $p$ is odd, and $(T_1,T_2) \cup ... \cup (T_p, +\infty)$ if $p$ is even.

Usage
excursion_probability(mn,sn,T)

Arguments
- $mn$ Array of size $k$ containing the expectations of the Gaussian random variables.
- $sn$ Array of size $k$ containing the standard deviations of the Gaussian random variables.
- $T$ Array containing one or several thresholds.

Value
Array of size $k$ containing the $k$ excursion probabilities.

Author(s)
Clement Chevalier (University of Neuchatel, Switzerland)

References

See Also
predict_nobias_km

Examples
#excursion_probability
set.seed(9)
N <- 20 #number of observations
testfun <- branin

#a 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfunHdesignL

#km object with matern3.2 covariance
#params estimated by ML from the observations
model <- km(formula=-.design = design,
            response = response,covtype="matern3.2")

some_points <- matrix(runif(20),ncol=2)
pred <- predict_nobias_km(object = model,newdata = some_points,
        type = "UK",se.compute = TRUE)

T <- c(60,80,100)
excursion_probability(mn = pred$mean,sn = pred$sd,T=T)
# probability to be in the interval [60,80] U [100, infty]

---

integration_design

Construction of a sample of integration points and weights

Description

Generic function to build integration points for some sampling criterion. Available important sampling schemes are "sur", "jn", "timse", "vorob" and "imse". Each of them corresponds to a sampling criterion.

Usage

integration_design(integcontrol = NULL, d = NULL,
lower, upper, model = NULL, T = NULL,min.prob=0.001)

Arguments

integcontrol Optional list specifying the procedure to build the integration points and weights, relevant only for the sampling criteria based on numerical integration: ("imse", "timse", "sur", "vorob" or "jn"). Many options are possible. A) If nothing is specified, 100*d points are chosen using the Sobol sequence. B) One can directly set the field integration.points (a p * d matrix) for prespecified integration points. In this case these integration points and the corresponding vector integration.weights will be used for all the iterations of the algorithm. C) If the field integration.points is not set then the integration points are renewed at each iteration. In that case one can control the number of integration points n.points (default: 100*d) and a specific distribution distrib. Possible values for distrib are: "sobol", "MC", "timse", "imse", "sur", "vorob" and "jn" (default: "sobol"). C.1) The choice "sobol" corresponds to integration points chosen with the Sobol sequence in dimension d (equal weights). C.2) The choice "MC" corresponds to points chosen randomly, uniformly on the domain (equal weights). C.3) The choices "timse", "imse", "sur", "vorob" and "jn" correspond to importance sampling distributions (unequal weights). It is recommended to use the importance sampling distribution corresponding to
the chosen sampling criterion. When important sampling procedures are chosen, \texttt{n.points} points are chosen using importance sampling among a discrete set of \texttt{n.candidates} points (default: \texttt{n.points*10}) which are distributed according to a distribution \texttt{init.distrib} (default: "sobol"). Possible values for \texttt{init.distrib} are "sobol" or "MC" (uniform random points) or an user defined distribution "spec". If the "spec" value is chosen the user must fill manually the field \texttt{init.distrib.spec} with a \texttt{n.candidates*d} matrix of points in dimension \(d\).

\(d\) The dimension of the input set. If not provided \(d\) is set equal to the length of \texttt{lower}.

\texttt{lower} Vector containing the lower bounds of the design space.

\texttt{upper} Vector containing the upper bounds of the design space.

\texttt{model} A Kriging model of \texttt{km} class.

\(T\) Array containing one or several thresholds.

\texttt{min.prob} This argument applies only when importance sampling distributions are chosen. For numerical reasons we give a minimum probability for a point to belong to the importance sample. This avoids potential importance sampling weights equal to infinity. In an importance sample of \(M\) points, the maximum weight becomes \(1/\text{min.prob} \times 1/M\).

\section*{Details}

The important sampling aims at improving the accuracy of the computation of criteria which involve numerical integration, like "time", "sur", etc.

\section*{Value}

A list with components:

\texttt{integration.points} \(p\times d\) matrix of \(p\) points used for the numerical calculation of integrals

\texttt{integration.weights} Vector of size \(p\) corresponding to the weights of each points. If all the points are equally weighted, \texttt{integration.weights} is set to \texttt{NULL}

\texttt{alpha} If the "vorob" important sampling schemes is chosen, the function also returns a scalar, \(\alpha\), being the calculated Vorob’ev threshold

\section*{Author(s)}

Clement Chevalier (University of Neuchatel, Switzerland)

\section*{References}


See Also

max_timse_parallel, max_sur_parallel

Examples

# integration_design

# when nothing is specified: integration points
# are chosen with the sobol sequence
integ.param <- integration_design(lower=c(0,0), upper=c(1,1))
plot(integ.param$integration.points)

# an example with pure random integration points
integcontrol <- list(distrib="MC", n.points=50)
integ.param <- integration_design(integcontrol=integcontrol, lower=c(0,0), upper=c(1,1))
plot(integ.param$integration.points)

# an example with important sampling distributions
# these distributions are used to compute integral criterion like
# "sur", "timse" or "imse"

# for these, we need a kriging model
set.seed(9)
N <- 16; testfun <- branin
lower <- c(0,0); upper <- c(1,1)
design <- data.frame( matrix(runif(2*N), ncol=2) )
response <- testfun(design)
model <- km(formula=., design = design,
response = response, covtype="matern3_2")
integcontrol <- list(distrib="sur", n.points=200, n.candidates=5000,
init.distrib="MC")

T <- c(60,100)
# we are interested in the set of points where the response is in [60,100]

integ.param <- integration_design(integcontrol=integcontrol, lower=c(0,0), upper=c(1,1), model=model, T=T)

print_uncertainty_2d(model=model, T=T, type="sur",
col.points.init="red", cex.points=2, main="sur uncertainty and one sample of integration points")
points(integ.param$integration.points, pch=17, cex=1)
Description

Evaluation of the parallel jn criterion for some candidate points. To be used in optimization routines, like in \texttt{max_sur_parallel}. To avoid numerical instabilities, the new points are evaluated only if they are not too close to an existing observation, or if there is some observation noise. The criterion is the integral of the posterior expected "jn" uncertainty, which is the posterior expected variance of the excursion set's volume.

Usage

\begin{verbatim}
jn_optim_parallel(x, integration.points, integration.weights = NULL,
intpoints.oldmean, intpoints.oldsd,
precalc.data, model, T,
new.noise.var = NULL, batchsize, current.sur, ai_precalc)
\end{verbatim}

Arguments

- \texttt{x} Vector of size batchsize*d at which one wants to evaluate the criterion. This argument is NOT a matrix.
- \texttt{integration.points} Matrix of points for numerical integration. Two cases are handled. If the "jn" importance sampling distribution has been used, this is a (2p)*d matrix containing p couples of integration points in D x D, where D is the integration domain. If instead a p*d matrix is given, then the function will perform the integration by using all p^2 couples.
- \texttt{integration.weights} Vector of size p corresponding to the weights of these integration points.
- \texttt{intpoints.oldmean} Vector of size p, or 2p, corresponding to the kriging mean at the integration points before adding the batchsize points \texttt{x} to the design of experiments.
- \texttt{intpoints.oldsd} Vector of size p, or 2p, corresponding to the kriging standard deviation at the integration points before adding the batchsize points \texttt{x} to the design of experiments.
- \texttt{precalc.data} List containing useful data to compute quickly the updated kriging variance. This list can be generated using the \texttt{precomputeUpdateData} function.
- \texttt{model} Object of class \texttt{km} (Kriging model).
- \texttt{T} Array containing one or several thresholds.
- \texttt{new.noise.var} Optional scalar value of the noise variance for the new observations.
- \texttt{batchsize} Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.
- \texttt{current.sur} Current value of the sur criterion (before adding new observations).
- \texttt{ai_precalc} This is a matrix with ith row equal to \texttt{intpoints.oldmean} - T[i]. The argument DOES ALWAYS need to be filled, even if there is only one threshold T.
Details

The first argument x has been chosen to be a vector of size batchsize*d (and not a matrix with batchsize rows and d columns) so that an optimizer like genoud can optimize it easily. For example if d=2, batchsize=3 and x=c(0,1,0,2,0,3,0,4,0,5,0,6), we will evaluate the parallel criterion at the three points (0.1,0.2),(0.3,0.4) and (0.5,0.6).

Value

Parallel jn value

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

EGIparallel, max_sur_parallel

Examples

#jn_optim_parallel

set.seed(9)
N <- 20 #number of observations
T <- c(0,100) #thresholds
testfun <- branin

design <- data.frame( matrix(rnorm(2*N),nrow=2) )
response <- testfun(design)

#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=-., design = design,
response = response,covtype="matern3_2")

### we need to compute some additional arguments:
### integration points, and current kriging means and variances at these points
n.points <- 200
integcontrol <- list(n.points=n.points,distrib="jn",init.distrib="MC")
obj <- integration_design(integcontrol=integcontrol,
lower=c(0,0),upper=c(1,1),model=model,T=T)
Integration points: `obj$integration.points` (2n.points)*d matrix
Integration weights: `obj$integration.weights` vector of size n.points

Prediction: `predict_nobias_km(object=model, newdata=integration.points, type="UK", se.compute=TRUE)`

In points old mean: `pred$mean`; In points old sd: `pred$sd`

Another precomputation:
PrecomputeData(model, integration.points)

Number of thresholds: `nT <- 2`

AI precalc: `matrix(rep(intpoints.oldmean, times=nT),
  nrow=nT, ncol=length(intpoints.oldmean), byrow=TRUE)`

AI precalc: `ai_precalc - T` # Subtracts T to the ith row of ai_precalc

Batch size: `4`

X: `c(0.1.0.2.0.3.0.4.0.5.0.6.0.7.0.8)`

One evaluation of the sur_optim_parallel criterion
We calculate the expectation of the future "sur" uncertainty
When 4 points are added to the doe
The 4 points are (0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8)

Evaluation of the parallel jn criterion for some candidate points, assuming that some other points
are also going to be evaluated. To be used in optimization routines, like in max_sur_parallel.
To avoid numerical instabilities, the new points are evaluated only if they are not too close to an
existing observation, or if there is some observation noise. The criterion is the integral of the
posterior expected "jn" uncertainty, which is the posterior expected variance of the excursion set's
volume.

### Usage

```
jn_optim_parallel2(x, other.points, 
  integration.points, integration.weights = NULL, 
  intpoints.oldmean, intpoints.oldsd, precalc.data, 
  model, T, new.noise.var = NULL, 
  batchsize, current.sur, ai_precalc)
```

---

**jn_optim_parallel2**  
**Parallel jn criterion**

**Description**

Evaluation of the parallel jn criterion for some candidate points, assuming that some other points
are also going to be evaluated. To be used in optimization routines, like in max_sur_parallel.
To avoid numerical instabilities, the new points are evaluated only if they are not too close to an
existing observation, or if there is some observation noise. The criterion is the integral of the
posterior expected "jn" uncertainty, which is the posterior expected variance of the excursion set's
volume.

**Usage**

```
jn_optim_parallel2(x, other.points, 
  integration.points, integration.weights = NULL, 
  intpoints.oldmean, intpoints.oldsd, precalc.data, 
  model, T, new.noise.var = NULL, 
  batchsize, current.sur, ai_precalc)
```
Arguments

- **x**: Input vector of size d at which one wants to evaluate the criterion. This argument corresponds to only ONE point.
- **other.points**: Vector giving the other batchsize-1 points at which one wants to evaluate the criterion.
- **integration.points**: Matrix of points for numerical integration. Two cases are handled. If the "jn" importance sampling distribution has been used, this is a (2p)*d matrix containing p couples of integration points in D x D, where D is the integration domain. If instead a p*d matrix is given, then the function will perform the integration by using all p^2 couples.
- **integration.weights**: Vector of size p corresponding to the weights of these integration points.
- **intpoints.oldmean**: Vector of size p, or 2p, corresponding to the kriging mean at the integration points before adding x to the design of experiments.
- **intpoints.oldsd**: Vector of size p, or 2p, corresponding to the kriging standard deviation at the integration points before adding x to the design of experiments.
- **precalc.data**: List containing useful data to compute quickly the updated kriging variance. This list can be generated using the `precomputeUpdateData` function.
- **model**: Object of class `km` (Kriging model).
- **t**: Array containing one or several thresholds.
- **new.noise.var**: Optional scalar value of the noise variance of the new observations.
- **batchsize**: Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.
- **current.sur**: Current value of the sur criterion (before adding new observations).
- **ai_precalc**: When multiple thresholds are used (i.e. when T is a vector), this is an nT*p matrix with ith row equal to intpoints.oldmean-T[i]. The argument DOES ALWAYS need to be filled, even if there is only one threshold T.

Details

The first argument x has been chosen to be a vector of size d so that an optimizer like genoud can optimize it easily. The second argument other.points is a vector of size (batchsize-1)*d corresponding to the batchsize-1 other points.

Value

Parallel jn value

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)
References


See Also

EGIparallel, max_sur_parallel

Examples

```r
#jn.optim_parallel2

set.seed(9)
N <- 20 #number of observations
T <- c(0,100) #threshold or thresholds
testfun <- branin

da 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
testfun <- testfun(design)

#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=-., design = design,
response = response,covtype="matern3_2")

#we need to compute some additional arguments:
#integration points, and current kriging means and variances at these points
integcontrol <- list(n.points=200,distrib="jn",init.distrib="MC")
obj <- integration_design(integcontrol=integcontrol,lower=c(0,0),upper=c(1,1),
model=model,T=T)

integration.points <- obj$integration.points
integration.weights <- obj$integration.weights
pred <- predict.nobias_km(object=model,newdata=integration.points,
type="UK",se.compute=TRUE)
intpoints.oldsmean <- pred$mean ; intpoints.oldsds<-pred$sd

#another precomputation
precalc.data <- precomputeUpdateData(model,integration.points)
nT <- 2 # number of thresholds
ai_precalc <- matrix(rep(intpoints.oldsmean,times=nT),
nrow=nT,ncol=length(intpoints.oldsmean),byrow=TRUE)
ai_precalc <- ai_precalc - T # substracts Ti to the ith row of ai_precalc

batchsize <- 4
other.points <- c(0.7,0.5,0.5,0.9,0.9,0.8)
x <- c(0.1,0.2)
```
Maximize parallel volume criterion

Description

Maximizes the criterion vorobVol_optim_parallel.

Usage

max_futureVol_parallel(lower, upper, optimcontrol = NULL, batchsize, integration.param, T, model, new.noise.var = 0, typeEx = "")
Arguments

lower  lower bounds of the domain
upper  upper bounds of the domain
optimcontrol  optional list of control parameters for optimization aspects, see max_vorob_parallel for details
batchsize  size of the batch of new points
integration.param
  Optional list of control parameter for the computation of integrals, containing the fields integration.points: a p*d matrix corresponding to p integrations points and integration.weights: a vector of size p corresponding to the weights of these integration points. If nothing is specified, default values are used (see: function integration_design for more details).

T  threshold
model  a km Model
new.noise.var  Optional scalar with the noise variance at the new observation
typeEx  a character (">" or "<") identifying the type of excursion

Value

A list containing par, the best set of parameters found, value the value of the criterion and alpha, the Vorob'ev quantile corresponding to the conservative estimate.

Author(s)

Dario Azzimonti (IDSIA, Switzerland)

References


See Also

EGIparallel.max_vorob_parallel
Examples

```r
#max_futureVol_parallel

set.seed(9)
N <- 20  # number of observations
t <- 80  # threshold
testfun <- branin
lower <- c(0,0)
upper <- c(1,1)

# a 20 points initial design
design <- data.frame( matrix(runif(2*N),nrow=2) )
response <- testfun(design)

design <- design[order(response),]

# km object with matern3_2 covariance
model <- km(formula=~., design = design,
            response = response, covtype="matern3_2")

optimcontrol <- list(method="genoud", pop.size=200, optim.option=2)
integcontrol <- list(distrib="timse", n.points=400, init.distrib="MC")
integration.param <- integration_design(integcontrol=integcontrol,d=2,
                                         lower=lower, upper=upper, model=model,
                                         T=T)

batchsize <- 5  # number of new points

# Not run:
obj <- max_futureVol_parallel(lower=lower,upper=upper,optimcontrol=optimcontrol,
                               batchsize=batchsize,T=T,model=model,
                               integration.param=integration.param)

# 5 optim in dimension 2 !

obj$par; obj$value  # optimum in 5 new points
new.model <- update(object=model, newX=obj$par, newy=apply(obj$par,1,testfun),
                    cov.reestim=TRUE)

consLevel = 0.95; n_discrete_design=500*new.model@d
CE_design=as.matrix( randtoolbox::sobol( n = n_discrete_design,
                                          dim = new.model@d) )
colnames(CE_design) <- colnames(new.model@X)
current.pred = predict.km(object = new.model,
                          newdata = CE_design,
                          type = "UK", cov.compute = TRUE)
current.pred$cov <- current.pred$cov + 1e-7*diag(nrow = nrow(current.pred$cov),
                                              ncol = ncol(current.pred$cov))
current.CE = anMC::conservativeEstimate(alpha = consLevel,
                                         pred=current.pred,
                                         design=CE_design, threshold=T, pn = NULL,
                                         type = ">", verb = 1,
                                         lightReturn = TRUE, algo = "GANMC")
```
max_infill_criterion

```r
par(mfrow=c(1,2))
print_uncertainty(model=model,T=T,type="pn",lower=lower,upper=upper,
  cex.points=2.5,main="probability of excursion",consQuanquantile=obj$alpha)

print_uncertainty(model=new.model,T=T,type="pn",lower=lower,upper=upper,
  new.points=batchsize,col.points.end="red",cex.points=2.5,
  main="updated probability of excursion",consQuanquantile=current.CE$1vs)
```

```r
## End(Not run)
```

max_infill_criterion  

Optimizer for the infill criteria

Description

Optimization, of the chosen infill criterion (maximization or minimization, depending on the case)

Usage

```r
max_infill_criterion(lower, upper, optimcontrol = NULL,
  method, T, model, method.param = NULL)
```

Arguments

- `lower`: Vector containing the lower bounds of the design space.
- `upper`: Vector containing the upper bounds of the design space.
- `optimcontrol`: Optional list of control parameters for the optimization of the sampling criterion. The field `method` defines which optimization method is used. It can be either "genoud" (default) for an optimization using the genoud algorithm, or "discrete" for an optimization over a specified discrete set. If the field `method` is set to "genoud", one can set some parameters of this algorithm: `pop.size` (default: 50*d), `max.generations` (10*d), `wait.generations` (2), `BFGSBburnin` (2) and the mutations `P1`, `P2`, up to `P9` (see `genoud`). Numbers into brackets are the default values. If the field `method` is set to "discrete", one can set the field `optim.points`: `p * d` matrix corresponding to the `p` points where the criterion will be evaluated. If nothing is specified, 100*d points are chosen randomly.
- `method`: Criterion used for choosing observations: "ranjan" (default), "bichon", "tsee", or "tmse".
- `T`: Array containing one or several thresholds. The "tmse" criterion can be used with multiple thresholds. The "ranjan", "bichon", "tsee" criteria can be used with only one threshold.
- `model`: A Kriging model of `km` class.
- `method.param`: Optional tolerance value (scalar). Default value is 1 for "ranjan" and "bichon", and 0 for "tmse".
max_infill_criterion

Value

A list with components:

- par The best set of parameters found.
- value The value of the chosen criterion at par.
- allvalues If an optimization on a discrete set of points is chosen, the value of the criterion at all these points.

Author(s)

Victor Picheny (INRA, Toulouse, France)
David Ginsbourger (IDIAP Martigny and University of Bern, Switzerland)
Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

EGI, ranjan_optim, tmse_optim, bichon_optim, tsee_optim

Examples

```r
#max_infill_criterion

set.seed(9)
N <- 20 #number of observations
T <- 80 #threshold
testfun <- bramin
lower <- c(0,0)
upper <- c(1,1)

#a 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfun(design)

#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=-., design = design,
```
max_sur_parallel

Minimizer of the parallel "sur" or "jn" criterion

Description

Minimization, based on the package rgenoud (or on exhaustive search on a discrete set), of the "sur" or "jn" criterion for a batch of candidate sampling points.

Usage

```
max_sur_parallel(lower, upper, optimcontrol = NULL,
batchsize, integration.param, T,
model, new.noise.var = 0, real.volume.variance=FALSE)
```

Arguments

- `lower` Vector containing the lower bounds of the design space.
- `upper` Vector containing the upper bounds of the design space.
- `optimcontrol` Optional list of control parameters for the optimization of the sampling criterion. The field method defines which optimization method is used: it can be either "genoud" (default) for an optimisation using the genoud algorithm, or "discrete" for an optimisation over a specified discrete set. If the field method is set to "genoud", one can set some parameters of this algorithm: pop.size (default: 50*d), max.generations (10*d), wait.generations (2), BFGSburnin (2) and the mutations P1, P2, up to P9 (see genoud). Numbers into brackets are the default values. If the field method is set to "discrete", one can set the field optim.points: p * d matrix corresponding to the p points where the criterion will be evaluated. If nothing is specified, 100*d points are chosen.
max_sur_parallel

randomly. Finally, one can control the field optim.option in order to decide how to optimize the sampling criterion. If optim.option is set to 2 (default), batch-size sequential optimizations in dimension d are performed to find the optimum. If optim.option is set to 1, only one optimization in dimension batchsize*d is performed. This option is only available with "genoud". This option might provide more global and accurate solutions, but is a lot more expensive.

batchsize
Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.

integration.param
Optional list of control parameter for the computation of integrals, containing the fields integration.points: a p*d matrix corresponding to p integrations points and integration.weights: a vector of size p corresponding to the weights of these integration points. If nothing is specified, default values are used (see: function integration_design for more details).

T
Target value (scalar).

model
A Kriging model of km class.

new.noise.var
Optional scalar value of the noise variance of the new observations.

real.volume.variance
Optional argument to use the "jn" criterion instead of "sur". Default: FALSE

Value
A list with components:

par
the best set of points found.

value
the value of the sur criterion at par.

allvalues
If an optimization on a discrete set of points is chosen, the value of the criterion at all these points.

Author(s)
Clement Chevalier (University of Neuchatel, Switzerland)

References

See Also
EGIparallel,sur_optim_parallel,jn_optim_parallel
Examples

```r
#max_sur_parallel

set.seed(9)
N <- 20 # number of observations
t <- c(40,80) # thresholds
testfun <- branin
lower <- c(0,0)
upper <- c(1,1)

design <- data.frame(matrix(runif(2*N),ncol=2))
response <- testfun(design)

# km object with matern3_2 covariance
model <- km(formula = ~ , design = design,
            response = response, covtype = "matern3_2")

optimcontrol <- list(method = "genoud", pop.size = 50, optim.option = 1)
integcontrol <- list(distrib = "sur", n.points = 50, init.distrib = "MC")
integration.param <- integration_design(integcontrol = integcontrol, d = 2,
                                        lower = lower, upper = upper, model = model, T = T)

batchsize <- 5 # number of new points

## Not run:
obj <- max_sur_parallel(lower = lower, upper = upper, optimcontrol = optimcontrol,
                         batchsize = batchsize, T = T, model = model,
                         integration.param = integration.param)
# one (hard) optim in dimension 5x2!

obj$par; obj$value # optimum in 5 new points
new.model <- update(object = model, newX = obj$par, newy = apply(obj$par, 1, testfun),
                     cov.reestim = TRUE)

par(mfrow = c(1,2))
print_uncertainty(model = model, T = T, type = "pn", lower = lower, upper = upper,
                  cex.points = 2.5, main = "probability of excursion")

print_uncertainty(model = new.model, T = T, type = "pn", lower = lower, upper = upper,
                  new.points = batchsize, col.points.end = "red", cex.points = 2.5,
                  main = "updated probability of excursion")

## End(Not run)
```
max_timse_parallel

Description

Minimization, based on the package rgenoud (or on exhaustive search on a discrete set), of the timse criterion for a batch of candidate sampling points.

Usage

max_timse_parallel(lower, upper, optimcontrol = NULL,
batchsize, integration.param, T,
model, new.noise.var = 0,
epsilon=0, imse=FALSE)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>lower</td>
<td>Vector containing the lower bounds of the design space.</td>
</tr>
<tr>
<td>upper</td>
<td>Vector containing the upper bounds of the design space.</td>
</tr>
<tr>
<td>optimcontrol</td>
<td>Optional list of control parameters for the optimization of the sampling criterion. The field method defines which optimization method is used: it can be either &quot;genoud&quot; (default) for an optimisation using the genoud algorithm, or &quot;discrete&quot; for an optimisation over a specified discrete set. If the field method is set to &quot;genoud&quot;, one can set some parameters of this algorithm: pop.size (default : 50<em>d), max.generations (10</em>d), wait.generations (2), BFGSburnin (2) and the mutations P1, P2, up to P9 (see genoud). Numbers into brackets are the default values. If the field method is set to &quot;discrete&quot;, one can set the field optim.points: p * d matrix corresponding to the p points where the criterion will be evaluated. If nothing is specified, 100<em>d points are chosen randomly. Finally, one can control the field optim.option in order to decide how to optimize the sampling criterion. If optim.option is set to 2 (default), batch-size sequential optimizations in dimension d are performed to find the optimum. If optim.option is set to 1, only one optimization in dimension batchsize</em>d is performed. This option is only available with &quot;genoud&quot;. This option might provide more global and accurate solutions, but is a lot more expensive.</td>
</tr>
<tr>
<td>batchsize</td>
<td>Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.</td>
</tr>
<tr>
<td>integration.param</td>
<td>Optional list of control parameter for the computation of integrals, containing the fields integration.points: a p*d matrix corresponding to p integrations points and integration.weights: a vector of size p corresponding to the weights of these integration points. If nothing is specified, default values are used (see: function integration_design for more details).</td>
</tr>
<tr>
<td>T</td>
<td>Array containing one or several thresholds.</td>
</tr>
<tr>
<td>model</td>
<td>A Kriging model of km class.</td>
</tr>
<tr>
<td>new.noise.var</td>
<td>Optional scalar value of the noise variance of the new observations.</td>
</tr>
<tr>
<td>epsilon</td>
<td>Optional tolerance value (a real positive number). Default value is 0.</td>
</tr>
<tr>
<td>imse</td>
<td>Optional boolean to decide if the &quot;imse&quot; criterion should be used instead of &quot;timse&quot;. default: FALSE.</td>
</tr>
</tbody>
</table>
Value

A list with components:

- `par` the best set of parameters found.
- `value` the value of the sur criterion at `par`.
- `allvalues` If an optimization on a discrete set of points is chosen, the value of the criterion at all these points.

Author(s)

Victor Picheny (INRA, Toulouse, France)
Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

`EGI_parallel`, `max_sur_parallel`

Examples

```r
# max_timse_parallel

set.seed(9)
N <- 20  # number of observations
T <- c(40,80)  # thresholds
testfun <- branin
lower <- c(0,0)
upper <- c(1,1)

# a 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfun(design)

# km object with matern3_2 covariance
# params estimated by ML from the observations
model <- km(formula=-., design = design,
response = response,covtype="matern3_2")

optimcontrol <- list(method="genoud",pop.size=200,optim.option=2)
```
**max_vorob_parallel**

Minimizer of the parallel vorob criterion

---

**Description**

Minimization, based on the package rgenoud (or on exhaustive search on a discrete set), of the Vorob’ev criterion for a batch of candidate sampling points.

**Usage**

```r
max_vorob_parallel(lower, upper, optimcontrol = NULL,
                    batchsize, integration.param, T,
                    model, new.noise.var = 0,
                    penalisation = NULL, typeEx = ">")
```

**Arguments**

- `lower` Vector containing the lower bounds of the design space.
- `upper` Vector containing the upper bounds of the design space.
- `optimcontrol` Optional list of control parameters for the optimization of the sampling criterion. The field method defines which optimization method is used: it can be either "genoud" (default) for an optimisation using the genoud algorithm,

---

```r
integcontrol <- list(distrib="timse", n.points=400, init.distrib="MC")
integration.param <- integration_design(integcontrol=integcontrol,d=2,
                                        lower=lower,upper=upper,model=model,
                                        T=T)

batchsize <- 5 # number of new points

## Not run:
obj <- max_timse_parallel(lower=lower,upper=upper,optimcontrol=optimcontrol,
                          batchsize=batchsize,T=T,model=model,
                          integration.param=integration.param,epsilon=0,imse=FALSE)
# 5 optim in dimension 2 !

obj$par; obj$value # optimum in 5 new points
new.model <- update(object=model,newX=obj$par,newy=apply(obj$par,1,testfun),
                    cov.reestim=TRUE)

par(mfrow=c(1,2))
print_uncertainty(model=model,T=T,type="pn",lower=lower,upper=upper,
cex.points=2.5,main="probability of excursion")

print_uncertainty(model=new.model,T=T,type="pn",lower=lower,upper=upper,
new.points=batchsize,col.points.end="red",cex.points=2.5,
main="updated probability of excursion")

## End(Not run)
```
or "discrete" for an optimisation over a specified discrete set. If the field method is set to "genoud", one can set some parameters of this algorithm: pop.size (default: 50*d), max.generations (10*d), wait.generations (2), BFS.burnin (2) and the mutations P1, P2, up to P9 (see genoud). Numbers into brackets are the default values. If the field method is set to "discrete", one can set the field optim.points: a * d matrix corresponding to the p points where the criterion will be evaluated. If nothing is specified, 100*d points are chosen randomly. Finally, one can control the field optim.option in order to decide how to optimize the sampling criterion. If optim.option is set to 2 (default), batch-size sequential optimizations in dimension d are performed to find the optimum. If optim.option is set to 1, only one optimization in dimension batchsize*d is performed. This option is only available with "genoud". This option might provide more global and accurate solutions, but is a lot more expensive.

batchsize Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.

integration.param Optional list of control parameter for the computation of integrals, containing the fields integration.points: a p*d matrix corresponding to p integrations points and integration.weights: a vector of size p corresponding to the weights of these integration points. If nothing is specified, default values are used (see: function integration_design for more details).

T Target value (scalar). The criterion CANNOT be used with multiple thresholds.

model A Kriging model of km class.

new.noise.var Optional scalar value of the noise variance of the new observations.

penalisation Optional penalization constant for type I errors. If equal to zero, computes the Type II criterion.

typeEx A character (">" or "<") identifying the type of excursion

Value

A list with components:

par the best set of parameters found.

value the value of the Vorob'ev criterion at par.

allvalues If an optimization on a discrete set of points is chosen, the value of the criterion at all these points.

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)

Dario Azzimonti (IDSIA, Switzerland)

References


### See Also

Egi_parallel, max_sur_parallel

### Examples

```r
# max_vorob_parallel

set.seed(9)
N <- 20 # number of observations
T <- 80 # threshold
testfun <- branin
lower <- c(0,0)
upper <- c(1,1)

# a 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfun(design)

# km object with matern3_2 covariance
# params estimated by ML from the observations
model <- km(formula=~., design = design,
response = response,covtype="matern3_2")

optimcontrol <- list(method="genoud",pop.size=200,optim.option=2)
timecontrol <- list(distrib="time",n.points=400,init.distrib="MC")
integration.param <- integration_design(integcontrol=integcontrol,d=2,
lower=lower,upper=upper,model=model,
T=T)

batchsize <- 5 # number of new points

## Not run:
obj <- max_vorob_parallel(lower=lower,upper=upper,optimcontrol=optimcontrol,
batchsize=batchsize,T=T,model=model,
integration.param=integration.param)
# 5 optim in dimension 2 !

obj$par;obj$value # optimum in 5 new points
new.model <- update(object=model,newX=obj$par,newy=apply(obj$par,1,testfun),
cov.reestim=TRUE)

par(mfrow=c(1,2))
print_uncertainty(model=model,T=T,type="pn",lower=lower,upper=upper,vorobmean=TRUE,
cex.points=2.5,main="probability of excursion")

print_uncertainty(model=new.model,T=T,type="pn",lower=lower,upper=upper,vorobmean=TRUE,
new.points=batchsize,col.points.end="red",cex.points=2.5,
new.points=batchsize,col.points.end="red",cex.points=2.5,
)```
precomputeUpdateData

main="updated probability of excursion"

## End(Not run)

---

**precomputeUpdateData**  
*Useful precomputations to quickly update kriging mean and variance*

**Description**

This function is used in combination with `computeQuickKrigcov` and computes an output list that serves as input in that function.

**Usage**

```r
precomputeUpdateData(model, integration.points)
```

**Arguments**

- `model` A Kriging model of `km` class.
- `integration.points`  
  
  p*d matrix of points for numerical integration in the X space.

**Value**

A list with components:

- `Kinv.c.olddata` Matrix equal to $K^{-1}c$ where $K$ is the non conditional covariance matrix at the design points and $c$ is the non conditional covariances between the design points and the integration points.
- `Kinv.F` Matrix equal to $K^{-1}F$ where $F$ is a matrix with the values of the trend functions at the design points.
- `first.member` Matrix with a complicated expression.

**Author(s)**

Clement Chevalier (University of Neuchatel, Switzerland)

**References**


predict_nobias_km

See Also

computeQuickKrigcov

Examples

# precomputeUpdateData

set.seed(9)
N <- 20 # number of observations
testfun <- branin

# a 20 points initial design
design <- data.frame(matrix(runif(2*N),nrow=2)
response <- testfun(design)

# km object with matern3_2 covariance
# params estimated by ML from the observations
model <- km(formula=., design = design,
response = response,covtype="matern3_2")

# the points where we want to compute prediction (if a point new.x is added to the doe)
n.grid <- 20 # you can run it with 100
x.grid <- y.grid <- seq(0,1,length=n.grid)
integration.points <- expand.grid(x.grid,y.grid)
integration.points <- as.matrix(integration.points)
precalc.data <- precomputeupdatedata(model=model,integration.points=integration.points)

# now we can compute quickly kriging covariances
# between the integration.points and any other points
newdata <- matrix(c(0.6,0.6),ncol=2)
pred <- predict_nobias_km(object=model,newdata=newdata,type="UK",se.compute=TRUE)

kn <- computeQuickKrigcov(model=model,integration.points=integration.points,X.new=newdata,
precalc.data=precalc.data,F.newdata=pred$F.newdata,
c.newdata=pred$c)

z.grid <- matrix(kn, n.grid, n.grid)

# plots: contour of the covariances, DOE points and new point
# these covariances have been computed quickly with computeQuickKrigcov
image(x=x.grid,y=y.grid,z=z.grid,col=grey.colors(10))
contour(x=x.grid,y=y.grid,z=z.grid,15,add=TRUE)
points(design, col="black", pch=17, lwd=4,cex=2)
points(newdata, col="red", pch=17, lwd=4,cex=3)
title("Kriging covariances with the point (0.6,0.6), in red")
predict_nobias_km

Description

This function is similar to the predict.km function from the DiceKriging package. The only change is the additional F.newdata output.

Usage

predict_nobias_km(object, newdata, type = "UK",
se.compute = TRUE, cov.compute = FALSE, low.memory=FALSE,...)

Arguments

- **object**: A Kriging model of km class.
- **newdata**: Vector, matrix or data frame containing the points where to perform predictions.
- **type**: Character string corresponding to the kriging family, to be chosen between simple kriging ("SK"), or universal kriging ("UK").
- **se.compute**: Optional boolean. If false, only the kriging mean is computed. If true, the kriging standard deviation and confidence intervals are computed too.
- **cov.compute**: Optional boolean. If true the conditional covariance matrix is computed.
- **low.memory**: Optional boolean. If set to true the function will only return kriging means and standard deviations.
- **...**: No other arguments.

Value

- **mean**: kriging mean (including the trend) computed at newdata.
- **sd**: kriging standard deviation computed at newdata. Not computed if se.compute=FALSE.
- **cov**: kriging conditional covariance matrix. Not computed if cov.compute=FALSE (default).
- **lower95**, **upper95**: bounds of the 95 % confidence interval computed at newdata (to be interpreted with special care when parameters are estimated, see description above). Not computed if se.compute=FALSE.
- **c**: an auxiliary matrix, containing all the covariances between newdata and the initial design points.
- **Tinv.c**: an auxiliary vector, equal to T^(-1)*c.
- **F.newdata**: value of the trend function at newdata.

Warning

Beware that the only consistency check between newdata and the experimental design is to test whether they have same number of columns. In that case, the columns of newdata are interpreted in the same order as the initial design.
predict_nobias_km

Author(s)
O. Roustant (Ecole des Mines de St-Etienne, France)
David Ginsbourger (IDIAP Martigny and University of Bern, Switzerland)

References

D.G. Krige (1951), A statistical approach to some basic mine valuation problems on the witwatersrand, J. of the Chem., Metal. and Mining Soc. of South Africa, 52 no. 6, 119-139.
J.D. Martin and T.W. Simpson (2005), Use of kriging models to approximate deterministic computer models, AIAA Journal, 43 no. 4, 853-863.
G. Matheron (1963), Principles of geostatistics, Economic Geology, 58, 1246-1266.

See Also
predict.km, km

Examples

#predict_nobias_km
set.seed(9)
N <- 20 #number of observations
testfun <- branin

#a 20 points initial design
design <- data.frame( matrix(runif(2*N),nrow=2) )
response <- testfun(design)

#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=-., design = design,
response = response,covtype="matern3_2")

n.grid <- 100
x.grid <- y.grid <- seq(0,1,length=n.grid)

newdata <- expand.grid(x.grid,y.grid)
predict_update_km_parallel

Quick update of kriging means and variances when one or many new points are added to the DOE.

Description

The functions uses the kriging update formulas to quickly compute kriging mean and variances at points newdata, when \( r \) new points newX are added.

Usage

```r
predict_update_km_parallel(newXmean, newXvar, newXvalue, Sigma.r, newdata.oldmean, newdata.oldsd, kn)
```

Arguments

- `newXmean`: Vector of size \( r \): old kriging mean at points \( x_{(n+1)},...,x_{(n+r)} \).
- `newXvar`: Vector of size \( r \): kriging variance at points \( x_{(n+1)},...,x_{(n+r)} \).
- `newXvalue`: Vector of size \( r \): value of the objective function at \( x_{(n+1)},...,x_{(n+r)} \).
- `Sigma.r`: An \( r \times r \) matrix: kriging covariances between the points \( x_{(n+1)},...,x_{(n+r)} \).
- `newdata.oldmean`: Vector: old kriging mean at the points newdata (before adding \( x_{(n+1)},...,x_{(n+r)} \))
- `newdata.oldsd`: Vector: old kriging standard deviations at the points newdata (before adding \( x_{(n+1)},...,x_{(n+r)} \))
- `kn`: Kriging covariances between the points newdata and the \( r \) points newX. These covariances can be computed using the function `computeQuickKrigcov`
Value

A list with the following fields:

- **mean**: Updated kriging mean at points newdata
- **sd**: Updated kriging standard deviation at points newdata
- **lambda**: New kriging weight of x_(n+1),...,x_(n+r) for the prediction at points newdata

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

computeQuickKrigcov, precomputeUpdateData

Examples

```r
#predict_update_km_parallel

set.seed(9)
N <- 20  # number of observations
testfun <- branin

# a 20 points initial design
design <- data.frame(matrix(runif(2*N),ncol=2))
response <- testfun(design)

# km object with matern3_2 covariance
# params estimated by ML from the observations
model <- km(formula=NULL, design = design,
response = response,covtype="matern3_2")

# points where we want to compute prediction (if a point new.x is added to the doe)
n.grid <- 20  # you can run it with 100
x.grid <- y.grid <- seq(-1,1,length=n.grid)
ewdata <- expand.grid(x.grid,y.grid)
newdata <- as.matrix(newdata)
precalc.data <- precomputeUpdateData(model=model,integration.points=newdata)
pred2 <- predict_nobias_km(object=model,newdata=newdata,type="UK",se.compute=TRUE)
newdata.oldmean <- pred2$mean; newdata.oldsd <- pred2$sd

# the point that we are going to add
new.x <- matrix(c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8),ncol=2,byrow=TRUE)
pred1 <- predict_nobias_km(object=model,newdata=new.x,type="UK",
se.compute=TRUE,cov.compute=TRUE)
newXmean <- pred1$mean; newXVar <- pred1$sd^2; newXvalue <- pred1$mean + 2*pred1$sd
```
print_uncertainty

Prints a measure of uncertainty for a function of any dimension.

Description

This function prints the value of a given measure of uncertainty. The function can be used to print relevant outputs after having used the function EGI or EGIParallel.

Usage

print_uncertainty(model, T, type = "pn", ...)

Arguments

model Kriging model of km class.
T Array containing one or several thresholds.
type Type of uncertainty that the user wants to print. Possible values are "pn" (probability of excursion), or "sur", "imse", "timse", "vorob" if we print a measure of uncertainty corresponding to one criterion.
... Other arguments of the functions print_uncertainty_1d, 2d or nd.
Value
the integrated uncertainty

Author(s)
Clement Chevalier (University of Neuchatel, Switzerland)

References
Bect J., Ginsbourger D., Li L., Picheny V., Vazquez E. (2012), Sequential design of computer
experiments for the estimation of a probability of failure, Statistics and Computing vol. 22(3), pp
773-793

See Also
print_uncertainty_1d, print_uncertainty_2d, print_uncertainty_nd

Examples
# print_uncertainty
set.seed(9)
N <- 20  # number of observations
T <- c(0, 100)  # threshold
testfun <- branin
lower <- c(0, 0)
upper <- c(1, 1)

# a 20 points initial design
design <- data.frame(matrix(runif(2*N), ncol=2))
response <- testfun(design)

# km object with matern3_2 covariance
# params estimated by ML from the observations
model <- km(formula = ~ ., design = design,
            response = response, covtype = "matern3_2")

# you could do many plots, but only one is run here
print_uncertainty(model=model, T=T, main="probability of excursion", type="pn")
print_uncertainty(model=model, T=T, main="vorob'ev uncertainty", type="vorob")
print_uncertainty(model=model, T=T, main="imse uncertainty", type="imse")
print_uncertainty(model=model, T=T, main="timse uncertainty", type="timse")
print_uncertainty(model=model, T=T, main="sur uncertainty", type="sur")
print_uncertainty(model=model, T=T, main="probability of excursion", type="pn",
                 vorobmean=TRUE)
**print_uncertainty_1d**  
*Prints a measure of uncertainty for 1d function.*

**Description**

This function draws the value of a given measure of uncertainty over the whole input domain (1D). The function can be used to print relevant outputs after having used the function `EGI` or `EGIparallel`.

**Usage**

```r
print_uncertainty_1d(model, T, type = "pn",
lower = 0, upper = 1, resolution = 500, new.points = 0,
xscale = c(0, 1), show.points = TRUE, cex.points = 1,
cex.axis = 1, pch.points.init = 17, pch.points.end = 17,
col.points.init = "black", col.points.end = "red", xaxislab = NULL,
yaxislab = NULL, xaxispoint = NULL, yaxispoint = NULL,
vorobmean=FALSE,krigmeanplot=FALSE,Tplot=FALSE,consQuantile=NULL,...)
```

**Arguments**

- **model**  
  Kriging model of `km` class.

- **T**  
  Array containing one or several thresholds.

- **type**  
  Type of uncertainty that the user wants to print. Possible values are "pn" (probability of excursion), or "sur", "imse", "timse", "vorob" if we print a measure of uncertainty corresponding to one criterion.

- **lower**  
  Lower bound for the input domain.

- **upper**  
  Upper bound for the input domain.

- **resolution**  
  Number of points to discretize the interval (lower,upper).

- **new.points**  
  Number of new observations. These observations are the last new.points observations and can be printed in another color and the initial observations (see argument: `col.points.end`).

- **xscale**  
  If one wants to rescale the input domain on another interval it is possible to set this vector of size 2. The new interval will be translated by `xscale[1]` and expanded by a factor `xscale[2] - xscale[1]`.

- **show.points**  
  Boolean: should we show the observations on the graph?

- **cex.points**  
  Multiplicative factor for the size of the points.

- **cex.axis**  
  Multiplicative factor for the size of the axis graduations.

- **pch.points.init**  
  Symbol for the `n-new.points` first observations.

- **pch.points.end**  
  Symbol for the `new.points` last observations.

- **col.points.init**  
  Color for the `n-new.points` first observations.
col.points.end  Color for the new.points last observations.

xaxislab  Optional new labels that will replace the normal levels on x axis.

yaxislab  Optional new labels that will replace the normal levels on y axis.

xaxispoint  Position of these new labels on x axis.

yaxispoint  Position of these new labels on y axis.

vorobmean  Optional boolean. When it is set to TRUE the Vorob’ev expectation is plotted. It corresponds to the averaged excursion set, using the definition of Vorob’ev. Here, the estimated set is the set above the Vorob’ev threshold (plotted in blue).

krigmeanplot  When set to TRUE a kriging mean is plotted on a second y axis.

tplot  When set to TRUE, and if krigmeanplot is also set to TRUE, draws horizontal lines corresponding to the different thresholds T.

consQuantile  Optional value for plotting conservative quantiles. In order to plot
  • Conservative estimates: consQuantile is a list containing at least consLevel (scalar), with the option typeEx (character, default = ">").
  • Generic Vorob’ev quantiles: consQuantile is a scalar corresponding to the Vorob’ev quantile level.

Value

The integrated uncertainty. If the conservative estimate is computed, it also returns the conservative quantile level.

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)

Dario Azzimonti (IDSIA, Switzerland)

References


See Also

print_uncertainty_2d, print_uncertainty_nd

Examples

# print_uncertainty_1d

set.seed(9)
N <- 9  # number of observations
T <- c(-0.2,0.2)  # thresholds

testfun <- sin
lower <- c(0)
print_uncertainty_2d

Prints a measure of uncertainty for 2d function.

Description

This function draws the value of a given measure of uncertainty over the whole input domain (2D). The function can be used to print relevant outputs after having used the function EGI or EGIparallel.

Usage

print_uncertainty_2d(model, T, type = "pn", lower = c(0, 0), upper = c(1, 1), resolution = 200, new.points = 0, xscale = c(0, 1), yscale = c(0, 1), show.points = TRUE, cex.contourlab = 1, cex.points = 1, cex.axis = 1, pch.points.init = 17, pch.points.end = 17, col.points.init = "black", col.points.end = "red", nlevels = 10, levels = NULL, xaxislab = NULL, yaxislab = NULL,
xaxispoint = NULL, yaxispoint = NULL,
krigmeanplot = FALSE, vorobmean = FALSE, consQuantile = NULL,...

Arguments

model  
Kriging model of km class.

T  
Array containing one or several thresholds.

type  
Type of uncertainty that the user wants to print. Possible values are "pn" (probability of excursion), or "sur", "imse", "timse", "vorob" if we print a measure of uncertainty corresponding to one criterion.

lower  
Vector containing the lower bounds of the input domain.

upper  
Vector containing the upper bounds of the input domain.

resolution  
Number of points to discretize the domain. This discretization is used in each dimension, so that the total number of points is resolution^2.

new.points  
Number of new observations. These observations are the last new.points observations and can be printed in another color and the initial observations (see argument: col.points.end).

xscale  
If one wants to rescale the input domain on another interval it is possible to set this vector of size 2. The new interval will be translated by xscale[1] and expanded by a factor xscale[2] - xscale[1].

yscale  
see: xscale.

show.points  
Boolean: should we show the observations on the graph ?

cex.contourlab  
Multiplicative factor for the size of labels of the contour plot.

cex.points  
Multiplicative factor for the size of the points.

cex.axis  
Multiplicative factor for the size of the axis graduations.

pch.points.init  
Symbol for the n-new.points first observations.

pch.points.end  
Symbol for the new.points last observations.

col.points.init  
Color for the n-new.points first observations.

col.points.end  
Color for the new.points last observations.

nlevels  
Integer corresponding to the number of levels of the contour plot.

levels  
Array: one can directly set the levels of the contour plot.

xaxislab  
Optional new labels that will replace the normal levels on x axis.

yaxislab  
Optional new labels that will replace the normal levels on y axis.

xaxispoint  
Position of these new labels on x axis.

yaxispoint  
Position of these new labels on y axis.

krigmeanplot  
Optional boolean. When it is set to FALSE (default) the contour plot corresponds to the uncertainty selected. When it is set to TRUE the contour plot gives the kriging mean.

vorobmean  
Optional boolean. When it is set to TRUE the Vorob’ev expectation is plotted. It corresponds to the averaged excursion set, using the definition of Vorob’ev.
consQuantile  Optional value for plotting conservative quantiles. In order to plot
• Conservative estimates: consQuantile is a list containing at least consLevel (scalar), with the option typeEx (character, default = ">").
• Generic Vorob’ev quantiles: consQuantile is a scalar corresponding to the Vorob’ev quantile level.

Additional arguments to the image function.

Value
The integrated uncertainty. If the conservative estimate is computed, it also returns the conservative quantile level.

Author(s)
Clement Chevalier (University of Neuchatel, Switzerland)
Dario Azzimonti (IDSIA, Switzerland)

References

See Also
print_uncertainty_1d, print_uncertainty_nd

Examples
# print_uncertainty_2d

set.seed(9)
N <- 20  # number of observations
T <- c(20, 40)  # thresholds
testfun <- branin
lower <- c(0, 0)
upper <- c(1, 1)

# a 20 points initial design
design <- data.frame(matrix(runif(2*N), ncol=2))
response <- testfun(design)

# km object with matern3_2 covariance
# params estimated by ML from the observations
model <- km(formula=-., design = design,
response = response, covtype="matern3_2")

## Not run:
print_uncertainty_2d(model=model, T=T, main="probability of excursion",
type="pn", krigmeanplot=TRUE, vorobmean=TRUE)
print_uncertainty_nd

Print a measure of uncertainty for functions with dimension \(d\) strictly larger than 2.

Description

This function draws projections on various plans of a given measure of uncertainty. The function can be used to print relevant outputs after having used the function \texttt{EGI} or \texttt{EGIparallel}.

Usage

\begin{verbatim}
print_uncertainty_nd(model,T,type="pn",lower=NULL,upper=NULL,
                     resolution=20, nintegpoints=400,
                     cex.lab=1, cex.contourlab=1, cex.axis=1,
                     nlevels=10, levels=NULL,
                     xdecal=3, ydecal=3, option="mean", pairs=NULL,...)
\end{verbatim}

Arguments

- \texttt{model} Kriging model of \texttt{km} class.
- \texttt{T} Array containing one or several thresholds.
- \texttt{type} Type of uncertainty that the user wants to print. Possible values are "\texttt{pn}\" (probability of excursion), or "\texttt{sur}\", "\texttt{imse}\", "\texttt{timse}\" if we print a measure of uncertainty corresponding to one criterion. The "\texttt{vorob}\" option is not available due to the difficulty of computing a Vorob'ev threshold.
- \texttt{lower} Vector containing the lower bounds of the input domain. If nothing is set we use a vector of 0.
upper Vector containing the upper bounds of the input domain. If nothing is set we use a vector of 1.

resolution Number of points to discretize a plan included in the domain. For the moment, we cannot use values higher than 40 do to computation time, except when the argument "pairs" is not set to its default value.

nintegpoints to do

cex.lab Multiplicative factor for the size of titles of the axis.

cex.contourlab Multiplicative factor for the size of labels of the contour plot.

cex.axis Multiplicative factor for the size of the axis graduations.

levels Integer corresponding to the number of levels of the contour plot.

xdecal Optional position shifting of the titles of the x axis.

ydecal Optional position shifting of the titles of the y axis.

option Optional argument (a string). The 3 possible values are "mean" (default), "max" and "min".

pairs Optional argument. When set to codeNULL (default) the function performs the projections on plans spanned by each pair (i,j) of dimension. Otherwise, the argument is an array of size 2 corresponding to the dimensions spanning the (only) plan on which the projection is performed.

Value The integrated uncertainty

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

print_uncertainty_1d, print_uncertainty_2d

Examples

# print_uncertainty_nd

set.seed(9)
N <- 30 # number of observations
T <- -1 # threshold
testfun <- hartman3  
#The hartman3 function is defined over the domain [0,1]^3.

lower <- rep(0,times=3)  
upper <- rep(1,times=3)  

#a 30 points initial design  
design <- data.frame( matrix(runif(3*N),ncol=3) )  
response <- apply(design,1,testfun)  

#km object with matern3_2 covariance  
#params estimated by ML from the observations  
model <- km(formula=-~design, response = response,covtype="matern3_2")  

## Not run:  
print_uncertainty.nd(model=model,T=T,main="average probability of excursion",type="pn",  
option="mean")  
print_uncertainty.nd(model=model,T=T,main="maximum probability of excursion",type="pn",  
option="max")  

## End(Not run)

ranjan_optim <- Ranjan et al.'s Expected Improvement criterion

Description

Evaluation of Ranjan's Expected Feasibility criterion. To be used in optimization routines, like in max_infill_criterion.

Usage

ranjan_optim(x, model, T, method.param = 1)

Arguments

x  Input vector at which one wants to evaluate the criterion. This argument can be either a vector of size d (for an evaluation at a single point) or a p x d matrix (for p simultaneous evaluations of the criterion at p different points).

model  An object of class km (Kriging model).

T  Target value (scalar).

method.param  Scalar tolerance around the target T. Default value is 1.
**ranjan_optim**

**Value**

Ranjan EI criterion. When the argument \( x \) is a vector the function returns a scalar. When the argument \( x \) is a \( p \times d \) matrix the function returns a vector of size \( p \).

**Author(s)**

Victor Picheny (INRA, Toulouse, France)

David Ginsbourger (IDIAP Martigny and University of Bern, Switzerland)

Clement Chevalier (University of Neuchatel, Switzerland)

**References**


**See Also**

`EGI.max_infill_criterion`

**Examples**

```r
# a 20 points initial design
design <- data.frame(matrix(runif(2*N), ncol=2))
response <- testfun(design)

# km object with matern3_2 covariance
model <- km(formula=~., design = design,
            response = response, covtype="matern3_2")

x <- c(0.5,0.4)# one evaluation of the ranjan criterion
ranjan_optim(x=x, T=T, model=model)

n.grid <- 20 # you can run it with 100
x.grid <- y.grid <- seq(0,1,length=n.grid)
x <- expand.grid(x.grid, y.grid)
ranjan.grid <- ranjan_optim(x=x, T=T, model=model)
z.grid <- matrix(ranjan.grid, n.grid, n.grid)
```
sur_optim_parallel

## Description

Evaluation of the parallel sur criterion for some candidate points. To be used in optimization routines, like in `max_sur_parallel`. To avoid numerical instabilities, the new points are evaluated only if they are not too close to an existing observation, or if there is some observation noise. The criterion is the integral of the expected future sur uncertainty when the candidate points are added.

## Usage

```r
define sur_optim_parallel(x, integration.points, integration.weights = NULL, intpoints.oldmean, intpoints.oldsd, precalc.data, model, T, new.noise.var = NULL, batchsize, current.sur, ai_precalc = NULL)
```

## Arguments

- `x`: Vector of size `batchsize*d` at which one wants to evaluate the criterion. This argument is **NOT** a matrix.
- `integration.points`: `p*d` matrix of points for numerical integration in the X space.
- `integration.weights`: Vector of size `p` corresponding to the weights of these integration points.
- `intpoints.oldmean`: Vector of size `p` corresponding to the kriging mean at the integration points before adding the batchsize points `x` to the design of experiments.
- `intpoints.oldsd`: Vector of size `p` corresponding to the kriging standard deviation at the integration points before adding the batchsize points `x` to the design of experiments.
- `precalc.data`: List containing useful data to compute quickly the updated kriging variance. This list can be generated using the `precomputeUpdateData` function.
model Object of class \texttt{km} (Kriging model).
\texttt{T} Array containing one or several thresholds.
\texttt{new.noise.var} Optional scalar value of the noise variance for the new observations.
\texttt{batchsize} Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.
\texttt{current.sur} Current value of the sur criterion (before adding new observations)
\texttt{ai_precalc} When multiple thresholds are used (i.e. when \texttt{T} is a vector), this is an \texttt{nT*p} matrix with ith row equal to \texttt{intpoints.oldmean-T[i]}. The argument does not need to be filled if only one threshold is used.

Details
The first argument \texttt{x} has been chosen to be a vector of size batchsize*d (and not a matrix with batchsize rows and d columns) so that an optimizer like genoud can optimize it easily. For example if \texttt{d=2}, \texttt{batchsize=3} and \texttt{x=c(0.1,0.2,0.3,0.4,0.5,0.6)}, we will evaluate the parallel criterion at the three points (0.1,0.2),(0.3,0.4) and (0.5,0.6).

Value
Parallel sur value

Author(s)
Clement Chevalier (University of Neuchatel, Switzerland)

References

See Also
\texttt{EGIparallel}, \texttt{max_sur_parallel}

Examples
```r
#sur_optim_parallel

set.seed(9)
N <- 20 #number of observations
T <- c(0,100) #thresholds
testfun <- branin

#a 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfun(design)
```
#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=~., design = design,
response = response,covtype="matern3_2")

### we need to compute some additional arguments:
#integration points, and current kriging means and variances at these points
integcontrol <- list(n.points=50,distrib="sur",init.distrib="MC")
obj <- integration_design(integcontrol=integcontrol,
lower=c(0,0),upper=c(1,1),model=model,T=T)

integration.points <- obj$integration.points
integration.weights <- obj$integration.weights
pred <- predict_nobias_km(object=model,newdata=integration.points,
type="UK",se.compute=TRUE)
intpoints.oldmean <- pred$mean ; intpoints.oldsd<-pred$sd

# another precomputation
precalc.data <- precomputeUpdateData(model,integration.points)
nt <- 2 # number of thresholds
ai_precalc <- matrix(rep(intpoints.oldmean, times=nT),
nrow=nT,ncol=length(intpoints.oldmean), byrow=TRUE)
ai_precalc <- ai_precalc - T # substracts Ti to the ith row of ai_precalc

batchsize <- 4
x <- c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8)
# one evaluation of the sur_optim_parallel criterion
# we calculate the expectation of the future "sur" uncertainty
# when 4 points are added to the doe
# the 4 points are (0.1,0.2) , (0.3,0.4), (0.5,0.6), (0.7,0.8)
sur_optim_parallel(x=x,integration.points=integration.points,
integration.weights=integration.weights,
intpoints.oldmean=intpoints.oldmean,intpoints.oldsd=intpoints.oldsd,
precalc.data=precalc.data,T=T,model=model,
batchsize=batchsize,current.sur=Inf,ai_precalc=ai_precalc)

# the function max_sur_parallel will help to find the optimum:
# ie: the batch of 4 minimizing the expectation of the future uncertainty

---

**sur_optim_parallel2**  
*Parallel sur criterion*

**Description**

Evaluation of the parallel sur criterion for some candidate points, assuming that some other points are also going to be evaluated. To be used in optimization routines, like in `max_sur_parallel`. To avoid numerical instabilities, the new points are evaluated only if they are not too close to an existing observation, or if there is some observation noise. The criterion is the integral of the expected future sur uncertainty when the candidate points are added.
sur_optim_parallel2

Usage

sur_optim_parallel2(x, other.points,
integration.points, integration.weights = NULL,
intpoints.oldmean, intpoints.oldsd, precalc.data,
model, T, new.noise.var = NULL,
batchsize, current.sur, ai_precalc = NULL)

Arguments

x Input vector of size d at which one wants to evaluate the criterion. This argument
 corresponds to only ONE point.
other.points Vector giving the other batchsize-1 points at which one wants to evaluate the
criterion
integration.points p*d matrix of points for numerical integration in the X space.
integration.weights Vector of size p corresponding to the weights of these integration points.
intpoints.oldmean Vector of size p corresponding to the kriging mean at the integration points be-
fore adding x to the design of experiments.
intpoints.oldsd Vector of size p corresponding to the kriging standard deviation at the integration
points before adding x to the design of experiments.
precalc.data List containing useful data to compute quickly the updated kriging variance.
This list can be generated using the precomputeupdatedata function.
model Object of class km (Kriging model).
T Array containing one or several thresholds.
new.noise.var Optional scalar value of the noise variance of the new observations.
batchsize Number of points to sample simultaneously. The sampling criterion will return
batchsize points at a time for sampling.
current.sur Current value of the sur criterion (before adding new observations)
ai_precalc When multiple thresholds are used (i.e. when T is a vector), this is an nT*p
matrix with ith row equal to intpoints.oldmean-T[i]. The argument does
not need to be filled if only one threshold is used.

Details

The first argument x has been chosen to be a vector of size d so that an optimizer like genoud
can optimize it easily. The second argument other.points is a vector of size (batchsize-1)*d
corresponding to the batchsize-1 other points.

Value

Parallel sur value
Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

EGIparallel, max_sur_parallel

Examples

```r
#sur_optim_parallel2

set.seed(9)
n <- 20 #number of observations
t <- c(0,100) #thresholds
testfun <- branin

design <- data.frame(matrix(runif(2*n),ncol=2))
response <- testfun(design)

#km object with matern3_2 covariance
params estimated by ML from the observations
model <- km(formula=., design = design,
             response = response,covtype="matern3_2")

###we need to compute some additional arguments:
###integration points, and current kriging means and variances at these points
integcontrol <- list(n.points=50,distrib="sur",init.distrib="MC")
obj <- integration_design(integcontrol=integcontrol,lower=c(0,0),upper=c(1,1),model=model,T=T)
integration.points <- obj$integration.points
integration.weights <- obj$integration.weights
pred <- predict_nobias_km(object=model,newdata=integration.points,
                         type="UK",se.compute=TRUE)
intpoints.oldmean <- pred$mean ; intpoints.oldsd<-pred$sd

#another precomputation
precalc.data <- precomputeUpdateData(model,integration.points)
nT <- 2 # number of thresholds
ai_precalc <- matrix(rep(intpoints.oldmean,times=nT),
                      nrow=nT,ncol=length(intpoints.oldmean),byrow=TRUE)
ai_precalc <- ai_precalc - T # substracts Ti to the ith row of ai_precalc
```
timse_optim_parallel

Parallel targeted IMSE criterion

Description

Evaluation of the "timse" criterion for some candidate points. To be used in optimization routines, like in max_timse_parallel. To avoid numerical instabilities, the new points are evaluated only if they are not too close to an existing observation, or if there is some observation noise. The criterion is the integral of the posterior timse uncertainty.
Usage

```r
timse_optim_parallel(x, integration.points, integration.weights = NULL,
intpoints.oldmean = NULL, intpoints.oldsd = NULL,
precalc.data, model, T, new.noise.var = 0, weight = NULL,
batchsize, current.timse)
```

Arguments

- `x`: Input vector of size d at which one wants to evaluate the criterion.
- `integration.points`: p*d matrix of points for numerical integration in the X space.
- `integration.weights`: Vector of size p corresponding to the weights of these integration points.
- `intpoints.oldmean`: Vector of size p corresponding to the kriging mean at the integration points before adding x to the design of experiments.
- `intpoints.oldsd`: Vector of size p corresponding to the kriging standard deviation at the integration points before adding x to the design of experiments.
- `precalc.data`: List containing useful data to compute quickly the updated kriging variance. This list can be generated using the `precomputeUpdateData` function.
- `model`: Object of class `km` (Kriging model).
- `T`: Array containing one or several thresholds.
- `new.noise.var`: Optional scalar value of the noise variance of the new observations.
- `weight`: Vector of weight function (length must be equal to the number of lines of the matrix integration.points). If nothing is set, the imse criterion is used instead of timse. It corresponds to equal weights.
- `batchsize`: Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.
- `current.timse`: Current value of the timse criterion (before adding new observations).

Value

Targeted imse value

Author(s)

Victor Picheny (INRA, Toulouse, France)
Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

`EGIparallel, max_timse_parallel`

Examples

```r
#timse_optim_parallel

set.seed(9)
N <- 20 #number of observations
T <- c(80,100) #thresholds
testfun <- branin

#a 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfun(design)

#km object with matern3.2 covariance
#params estimated by ML from the observations
model <- km(formula=-., design = design, 
response = response,covtype="matern3_2")

### we need to compute some additional arguments: 
#integration points, and current kriging means and variances at these points
integcontrol <- list(n.points=1000,distrib="timse",init.distrib="MC")
obj <- integration_design(integcontrol=integcontrol,lower=c(0,0), 
upper=c(1,1),model=model,T=T)

integration.points <- obj$integration.points
integration.weights <- obj$integration.weights
pred <- predict_nobias_km(object=model,newdata=integration.points, 
type="UK",se.compute=TRUE)
intpoints.oldmean <- pred$mean ; intpoints.oldsd<-pred$sd

#another precomputation
precalc.data <- precomputeupdatedata(model,integration.points)

#we also need to compute weights. Otherwise the (more simple) 
imse criterion will be evaluated
weight0 <- 1/sqrt( 2*pi*(intpoints.oldsd^2) )
weight <- 0
for(i in 1:length(T)){
  Ti <- T[i]
  weight <- weight + weight0 * exp(-0.5*((intpoints.oldmean-Ti)/sqrt(intpoints.oldsd^2))^2)
}

batchsize <- 4
x <- c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8)
```
# one evaluation of the timse_optim_parallel criterion
# we calculate the expectation of the future "timse"
# uncertainty when 4 points are added to the doe
# the 4 points are (0.1,0.2), (0.3,0.4), (0.5,0.6), (0.7,0.8)
timse_optim_parallel(x=x, integration.points=integration.points,
                   integration.weights=integration.weights,
                   intpoints.oldmean=intpoints.oldmean, intpoints.oldsd=intpoints.oldsd,
                   precalc.data=precalc.data, T=T, model=model, weight=weight,
                   batchsize=batchsize, current.timse=Inf)

# the function max_timse_parallel will help to find the optimum:
# ie: the batch of 4 minimizing the expectation of the future uncertainty

timse_optim_parallel2  Parallel timse criterion

Description

Evaluation of the parallel timse criterion for some candidate points, assuming that some other points are also going to be evaluated. To be used in optimization routines, like in max_timse_parallel. To avoid numerical instabilities, the new points are evaluated only if they are not too close to an existing observation, or if there is some observation noise. The criterion is the integral of the posterior timse uncertainty.

Usage

timse_optim_parallel2(x, other.points,
                    integration.points, integration.weights = NULL,
                    intpoints.oldmean, intpoints.oldsd, precalc.data,
                    model, T, new.noise.var = NULL, weight = NULL,
                    batchsize, current.timse)

Arguments

x  Input vector of size d at which one wants to evaluate the criterion. This argument corresponds to only ONE point.
other.points  Vector giving the other batchsize-1 points at which one wants to evaluate the criterion
integration.points  p*d matrix of points for numerical integration in the X space.
inTEGRATION.weights  Vector of size p corresponding to the weights of these integration points.
inpoints.oldmean  Vector of size p corresponding to the kriging mean at the integration points before adding x to the design of experiments.
inpoints.oldsd  Vector of size p corresponding to the kriging standard deviation at the integration points before adding x to the design of experiments.
precalc.data List containing useful data to compute quickly the updated kriging variance. This list can be generated using the precomputeUpdateData function.

model Object of class km (Kriging model).

T Array containing one or several thresholds.

ew.noise.var Optional scalar value of the noise variance for the new observations.

weight Vector of weight function (length must be equal to the number of lines of the matrix integration.points). If nothing is set, the imse criterion is used instead of timse. It corresponds to equal weights.

batchsize Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.

current.timse Current value of the timse criterion (before adding new observations)

Details

The first argument x has been chosen to be a vector of size d so that an optimizer like genoud can optimize it easily. The second argument other.points is a vector of size (batchsize-1)*d corresponding to the batchsize-1 other points.

Value

Parallel timse value

Author(s)

Victor Picheny (INRA, Toulouse, France)
Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

EGIparallel, max_timse_parallel

Examples

#timse_optim_parallel2

set.seed(9)
N <- 20 #number of observations
T <- c(80, 100)  # thresholds
testfun <- branin

# a 20 points initial design
design <- data.frame( matrix(runif(2*N), ncol=2) )
response <- testfun(design)

# km object with matern3.2 covariance
# params estimated by ML from the observations
model <- km(formula=-, design = design, response = response, covtype="matern3_2")

### we need to compute some additional arguments:
### integration points, and current kriging means and variances at these points
integcontrol <- list(n.points=1000, distrib="timse", init.distrib="MC")
obj <- integration.design(integcontrol=integcontrol, lower=c(0, 0), upper=c(1, 1), model=model, T=T)

integration.points <- obj$integration.points
integration.weights <- obj$integration.weights
pred <- predict.nobias_km(object=model, newdata=integration.points, type="UK", se.compute=TRUE)
intpoints.oldmean <- pred$mean; intpoints.oldsd <- pred$sd

# another precomputation
precalc.data <- precomputeUpdateData(model, integration.points)

# we also need to compute weights. Otherwise the (more simple)
# imse criterion will be evaluated
weight0 <- 1/sqrt(2*pi*intpoints.oldsd^2)
weight <- 0
for(i in 1:length(T)){
    Ti <- T[i]
    weight <- weight + weight0 * exp(-0.5*((intpoints.oldmean-Ti)/sqrt(intpoints.oldsd^2))^2)
}

batchsize <- 4
other.points <- c(0.7, 0.5, 0.5, 0.9, 0.9, 0.8)
x <- c(0.1, 0.2)
# one evaluation of the timse_optim_parallel criterion2
# we calculate the expectation of the future "timse" uncertainty
# when 1+3 points are added to the doe
# the 1+3 points are (0.1, 0.2) and (0.7, 0.5), (0.5, 0.9), (0.9, 0.8)
timse_optim_parallel2(x=x, other.points, integration.points=integration.points, integration.weights=integration.weights, intpoints.oldmean=intpoints.oldmean, intpoints.oldsd=intpoints.oldsd, precalc.data=precalc.data, T=T, model=model, weight=weight, batchsize=batchsize, current.timse=Inf)

n.grid <- 20  # you can run it with 100
x.grid <- y.grid <- seq(0, 1, length=n.grid)
x <- expand.grid(x.grid, y.grid)
timse_parallel.grid <= apply(x=x, FUN=timse_optim_parallel2, MARGIN=1, other.points,
tmse_optim

Targeted MSE criterion

Description

Evaluation of the Targeted MSE criterion. To be used in optimization routines, like in max_infill_criterion

Usage

tmse_optim(x, model, T, method.param = NULL)

Arguments

x Input vector at which one wants to evaluate the criterion. This argument can be either a vector of size d (for an evaluation at a single point) or a p*d matrix (for p simultaneous evaluations of the criterion at p different points).

model An object of class km (Kriging model).

T Array containing one or several thresholds.

method.param Scalar tolerance around the targets T.

Value

targeted MSE value. When the argument x is a vector the function returns a scalar. When the argument x is a p*d matrix the function returns a vector of size p.

```r
integration.points=integration.points,
integration.weights=integration.weights,
intpoints.oldmean=intpoints.oldmean,intpoints.oldsd=intpoints.oldsd,
precalc.data=precalc.data,T=T,model=model,weight=weight,
batchsize=batchsize,current.timse=Inf)
z.grid <- matrix(tmse_parallel.grid, n.grid, n.grid)

# plots: contour of the criterion, doe points and new point
image(x=x.grid,y=y.grid,z=z.grid,col=grey.colors(10))
contour(x=x.grid,y=y.grid,z=z.grid,15,add=TRUE)
points design, col="black", pch=17, lwd=4, cex=2)
points(matrix(other.points, ncol=2, byrow=TRUE), col="red", pch=17, lwd=4, cex=2)

i.best <- which.min(tmse_parallel.grid)
points(x[i.best,], col="blue", pch=17, lwd=4, cex=3)

# plots the real (unknown in practice) curve f(x)=T
testfun.grid <- apply(x,1,testfun)
z.grid.2 <- matrix(testfun.grid, n.grid, n.grid)
contour(x.grid,y.grid,z.grid.2,levels=T,col="blue",add=TRUE,lwd=5)
title("Contour lines of tmse_parallel criterion (black) and of f(x)=T (blue)")
```
Author(s)

Victor Picheny (INRA, Toulouse, France)
David Ginsbourger (IDIAP Martigny and University of Bern, Switzerland)
Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

EGI, max_infill_criterion

Examples

#tmse_optim

set.seed(9)
N <- 20 #number of observations
T <- c(0,80) #thresholds
testfun <- branin

da 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfun(design)

#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=..., design = design,
            response = response,covtype="matern3_2")

x <- c(0.5,0.4)#one evaluation of the tmse criterion

tmse_optim(x=x,T=T,model=model)

n.grid <- 20 #you can run it with 100
x.grid <- y.grid <- seq(0,1,length=n.grid)
x <- expand.grid(x.grid, y.grid)
tmse.grid <- tmse_optim(x=x,T=T,model=model)
z.grid <- matrix(tmse.grid, n.grid, n.grid)

#plots: contour of the criterion, doe points and new point
image(x=x.grid,y=y.grid,z=z.grid,col=grey.colors(10))
contour(x=x.grid,y=y.grid,z=z.grid,25,add=TRUE)
points(design, col="black", pch=17, lwd=4,cex=2)
i.best <- which.max(tmse.grid)
points(x[i.best,], col="blue", pch=17, lwd=4,cex=3)
#plots the real (unknown in practice) curve f(x)=T
testfun.grid <- apply(x,1,testfun)
z.grid.2 <- matrix(testfun.grid, n.grid, n.grid)
contour(x.grid,y.grid,z.grid.2,levels=T,col="blue",add=TRUE,lwd=5)
title("Contour lines of tmse criterion (black) and of f(x)=T (blue")

---

**tsee_optim**

*Two Sided Expected Exceedance criterion*

**Description**

Evaluation of the Two-Sided Expected Exceedance criterion. To be used in optimization routines, like in `max_infill_criterion`.

**Usage**

```r
tsee_optim(x, model, T)
```

**Arguments**

- `x` Input vector at which one wants to evaluate the criterion. This argument can be either a vector of size `d` (for an evaluation at a single point) or a `p*d` matrix (for `p` simultaneous evaluations of the criterion at `p` different points).
- `model` An object of class `km` (Kriging model).
- `T` Target value (scalar).

**Value**

tsee criterion. When the argument `x` is a vector the function returns a scalar. When the argument `x` is a `p*d` matrix the function returns a vector of size `p`.

**Author(s)**

Clement Chevalier (University of Neuchatel, Switzerland)

Yann Richet (IRSN, France)

**See Also**

`EGI`, `max_infill_criterion`
Examples

```r
#tsee_optim

set.seed(9)
N <- 20 #number of observations
T <- 80 #threshold
testfun <- branin

#a 20 points initial design
design <- data.frame( matrix(runif(2*N),nrow=2) )
response <- testfun(design)

#km object with matern3_2 covariance
#params estimated by ML from the observations
model <- km(formula=-., design = design,
             response = response,covtype="matern3_2")

x <- c(0.5,0.4)#one evaluation of the tsee criterion
tsee_optim(x=x,T=T,model=model)

n.grid <- 20 #you can run it with 100
x.grid <- seq(0,1,length=n.grid)

x <- expand.grid(x.grid, y.grid)
tsee.grid <- tsee_optim(x=x,T=T,model=model)
z.grid <- matrix(tsee.grid, n.grid, n.grid)

#plots: contour of the criterion, doe points and new point
image(x=x.grid,y=y.grid,z=z.grid,col=grey.colors(10))
contour(x=x.grid,y=y.grid,z=z.grid,25,add=TRUE)
points(design, col="black", pch=17,lwd=4,cex=2)

i.best <- which.max(tsee.grid)
points(x[i.best,], col="blue", pch=17,lwd=4,cex=3)

#plots the real (unknown in practice) curve f(x)=T
testfun.grid <- apply(x,1,testfun)
z.grid.2 <- matrix(testfun.grid, n.grid, n.grid)
contour(x.grid,y.grid,z.grid.2,levels=T,col="blue",add=TRUE,lwd=5)
title("Contour lines of tsee criterion (black) and of f(x)=T (blue)"
```

---

**vorobVol_optim_parallel**

*Compute volume criterion*

---

**Description**

Compute the volume criterion
Usage

vorobVol_optim_parallel(x, integration.points, integration.weights = NULL, intpoints.oldmean, intpoints.oldsd, precalc.data, model, T, new.noise.var = NULL, batchsize, alpha, current_crit, typeEx = ">")

Arguments

x vector of size batchsize*d describing the point(s) where to evaluate the criterion
integration.points
  $ p \times d $ matrix with the integration points for evaluating numerically the integral of the criterion
integration.weights
  vector of size $ p $ containing the integration weights for the integral numerical evaluation
intpoints.oldmean
  Vector of size $ p $ corresponding to the kriging mean at the integration points before adding the batchsize points x to the design of experiments.
intpoints.oldsd
  Vector of size $ p $ corresponding to the kriging standard deviation at the integration points before adding the batchsize points x to the design of experiments.
precalc.data
  List containing useful data to compute quickly the updated kriging variance. This list can be generated using the precomputeUpdatedata function.
model
  a km Model
T threshold
new.noise.var
  Optional scalar with the noise variance at the new observation
batchsize
  size of the batch of new points
alpha
  threshold on pn obtained with conservative estimates
current_crit
  starting value for criterion
typeEx a character (">" or "<") identifying the type of excursion

Value

The value of the criterion at x.

Author(s)

Dario Azzimonti (IDSIA, Switzerland)

References


**See Also**

`EGI_parallel, max_futureVol_parallel`

**Examples**

```r
#vorobVol_optim_parallel

set.seed(9)
N <- 20 # number of observations
T <- 80 # threshold
testfun <- branin

# a 20 points initial design
design <- data.frame(matrix(runif(2*N),ncol=2))
response <- testfun(design)

# km object with matern3_2 covariance
# params estimated by ML from the observations
model <- km(formula=-., design = design,
            response = response, covtype="matern3_2")

### we need to compute some additional arguments:
### integration points, and current kriging means and variances at these points
integcontrol <- list(n.points=50,distrib="vorob",init.distrib="MC")
obj <- integration_design(integcontrol=integcontrol,
                          lower=c(0,0),upper=c(1,1),model=model,T=T)

integration.points <- obj$integration.points
integration.weights <- obj$integration.weights

# alpha, the pn threshold should be computed with conservativeEstimate
# Here it is fixed at 0.992364
alpha <- 0.992364

### Not run:
# You can compute it with the following code
CE_design=as.matrix(randtoolbox::sobol(n = 500*model@d,
                                        dim = model@d))
colnames(CE_design) <- colnames(model@X)

CE_pred = predict.km(object = model, newdata = CE_design,
                      type = "UK", cov.compute = TRUE)
CE_pred$cov <- CE_pred$cov + 1e-7*diag(nrow = nrow(CE_pred$cov), ncol = ncol(CE_pred$cov))
```

vorobVol_optim_parallel2

\[\text{Cestimate} \leftarrow \text{anMC}::\text{conservativeEstimate}(\text{alpha} = 0.95, \text{pred}=\text{CE}\_\text{pred}, \right.
\]
\[\text{design}=\text{CE}\_\text{design}, \text{threshold}=T, \text{pn}=\text{NULL}, \right.
\]
\[\text{type} = "\text{MC}"; \text{verb} = 1, \right.
\]
\[\text{lightReturn} = \text{TRUE}, \text{algo} = "\text{GANMC}"
\]
\[\text{alpha} \leftarrow \text{Cestimate}$.lvs$
\]

## End(Not run)

\[\text{pred} \leftarrow \text{predict_nobias_km}(\text{object}=\text{model}, \text{newdata}=\text{integration}.\text{points}, \right.
\]
\[\text{type}="\text{UK}"; \text{se}.\text{compute}=$\text{TRUE}$
\]
\[\text{intpoints}.\text{oldmean} \leftarrow \text{pred}$mean\ ; \text{intpoints}.\text{oldsd}<\text{pred}$sd
\]

# another precomputation

\[\text{precalc}.\text{data} \leftarrow \text{precomputeUpdateData}(\text{model}, \text{integration}.\text{points})
\]

\[\text{batchsize} \leftarrow 4\]
\[x \leftarrow c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8)
\]

# one evaluation of the vorob_optim_parallel criterion

# we calculate the expectation of the future "vorob" uncertainty

# when 4 points are added to the doe

# the 4 points are (0.1,0.2), (0.3,0.4), (0.5,0.6), (0.7,0.8)

\[\text{vorobVol_optim_parallel}(x=x, \text{integration}.\text{points}=\text{integration}.\text{points}, \right.
\]
\[\text{integration}.\text{weights}=\text{integration}.\text{weights}, \right.
\]
\[\text{intpoints}.\text{oldmean}=\text{intpoints}.\text{oldmean}, \text{intpoints}.\text{oldsd}=\text{intpoints}.\text{oldsd}, \right.
\]
\[\text{precalc}.\text{data}=\text{precalc}.\text{data}, T=T, \text{model}=\text{model}, \right.
\]
\[\text{batchsize}=\text{batchsize}, \text{alpha}=\alpha
\]

# the function max_futureVol_parallel will help to find the optimum:

# i.e: the batch of 4 maximizing the expectation of the future

# uncertainty (future volume of the Vorob'ev quantile)

---

### vorobVol_optim_parallel2

**Compute volume criterion**

---

### Description

Compute the volume criterion. Useful for optimization routines.

### Usage

\[\text{vorobVol_optim_parallel2}(x, \text{other}.\text{points}, \text{integration}.\text{points}, \right.
\]
\[\text{integration}.\text{weights} = \text{NULL}, \text{intpoints}.\text{oldmean}, \text{intpoints}.\text{oldsd}, \right.
\]
\[\text{precalc}.\text{data}, \text{model}, T, \text{new}.\text{noise}.\text{var} = \text{NULL}, \text{batchsize}, \text{alpha}, \right.
\]
\[\text{current}.\text{crit}, \text{typeEx} = "$\text{MC}$"
\]
Arguments

- **x** One point where to evaluate the criterion
- **other.points** remaining points of the batch
- **integration.points** \(p \times d\) matrix with the integration points for evaluating numerically the integral of the criterion
- **integration.weights** vector of size \(p\) containing the integration weights for the integral numerical evaluation
- **intpoints.oldmean** Vector of size \(p\) corresponding to the kriging mean at the integration points before adding the batchsize points \(x\) to the design of experiments.
- **intpoints.oldsd** Vector of size \(p\) corresponding to the kriging standard deviation at the integration points before adding the batchsize points \(x\) to the design of experiments.
- **precalc.data** List containing useful data to compute quickly the updated kriging variance. This list can be generated using the `precomputeUpdateData` function.
- **model** a km Model
- **T** threshold
- **new.noise.var** Optional scalar with the noise variance at the new observation
- **batchsize** size of the batch of new points
- **alpha** threshold on \(pn\) obtained with conservative estimates
- **current.crit** starting value for criterion
- **typeEx** a character (“>” or “<”) identifying the type of excursion

Value

The value of the criterion at \(x\).

Author(s)

Dario Azzimonti (IDSIA, Switzerland)

References


See Also

`EGIparallel, max_futureVol_parallel`

Examples

```r
#vorobVol_optim_parallel2

set.seed(9)
N <- 20  # number of observations
T <- 80  # threshold
testfun <- branin

# a 20 points initial design
design <- data.frame(matrix(runif(2*N),nrow=2))
response <- testfun(design)

# km object with matern3.2 covariance
design $ points initial design
model <- km(formula = ~ ., design = design,
response = response, covtype = "matern3.2")

### we need to compute some additional arguments:
### integration points, and current kriging means and variances at these points
integcontrol <- list(n.points = 50, distrib = "vorob", init.distrib = "MC")
obj <- integration_design(integcontrol = integcontrol,
  lower = c(0, 0), upper = c(1, 1), model = model, T = T)

integration.points <- obj$integration.points
integration.weights <- obj$integration.weights

# alpha, the pn threshold should be computed with conservativeEstimate
# Here it is fixed at 0.992364
alpha <- 0.992364

## Not run:
# You can compute it with the following code
CE_design <- as.matrix(randtoolbox::sobol(n = 500 * model@d,
  dim = model@d))
colnames(CE_design) <- colnames(model@x)
CE_pred <- predict.km(object = model, newdata = CE_design,
  type = "UK", cov.compute = TRUE)
CE_pred$cov <- CE_pred$cov + 1e-7 * diag(nrow = nrow(CE_pred$cov), ncol = ncol(CE_pred$cov))

Cestimate <- anMC::conservativeEstimate(alpha = 0.95, pred = CE_pred,
  design = CE_design, threshold = T, pn = NULL,
  type = ">", verb = 1,
  lightReturn = TRUE, algo = "GAMMC")
alpha <- Cestimate$lv

## End(Not run)
```
```r
pred <- predict_nobias_km(object=model,newdata=integration.points, type="UK",se.compute=TRUE)
intpoints.oldmean <- pred$mean; intpoints弛sd<-pred$sd

# another precomputation
precalc.data <- precomputeUpdateData(model,integration.points)

batchsize <- 4
other.points <- c(0.7,0.5,0.5,0.9,0.9,0.8)
x <- c(0.1,0.2)

# one evaluation of the vorobVol_optim_parallel criterion
# we calculate the expectation of the future volume vorobev uncertainty when
# the 1+3 points are added to the doe
vorobVol_optim_parallel2(x=x,other.points=other.points,integration.points=integration.points,
integration.weights=integration.weights,
intpoints.oldmean=intpoints.oldmean,intpoints.oldsd=intpoints.oldsd,
precalc.data=precalc.data,T=T,model=model,
batchsize=batchsize,alpha=alpha)

n.grid <- 20 # you can run it with 100
x.grid <- y.grid <- seq(0,1,length=n.grid)
x <- expand.grid(x.grid, y.grid)
vorobVol_parallel.grid <- apply(x=x,FUN=vorobVol_optim_parallel2,MARGIN=1,other.points=other.points,
integration.points=integration.points,
integration.weights=integration.weights,
intpoints.oldmean=intpoints.oldmean,intpoints.oldsd=intpoints.oldsd,
precalc.data=precalc.data,T=T,model=model,
batchsize=batchsize,alpha=alpha)

z.grid <- matrix(vorobVol_parallel.grid, n.grid, n.grid)

# plots: contour of the criterion, doe points and new point
image(x=x.grid,y=y.grid,z=z.grid,col=grey.colors(10))
contour(x=x.grid,y=y.grid,z=z.grid,15,add=TRUE)
points.design$, col="black", pch=17, lwd=4,cex=2)
points(matrix(other.points,ncol=2,byrow=TRUE), col="red", pch=17, lwd=4,cex=2)

# Note that we want to maximize this criterion.
i.best <- which.max(vorobVol_parallel.grid)
points(x[i.best,], col="blue", pch=17, lwd=4,cex=3)

# plots the real (unknown in practice) curve f(x)=T
testfun.grid <- apply(x,1,testfun)
z.grid.2 <- matrix(testfun.grid, n.grid, n.grid)
contour(x.grid,y.grid,z.grid.2,levels=T,col="blue",add=TRUE,lwd=5)
title("Contour lines of vorobVol_parallel criterion (black) and of f(x)=T (blue)")
```
**vorob_optim_parallel**  
*Parallel Vorob’ev criterion*

**Description**

Evaluation of the parallel Vorob’ev criterion for some candidate points. To be used in optimization routines, like in `max_vorob_parallel`. To avoid numerical instabilities, the new points are evaluated only if they are not too close to an existing observation, or if there is some observation noise. The criterion is the integral of the posterior Vorob’ev uncertainty.

**Usage**

```r
vorob_optim_parallel(x, integration.points, integration.weights = NULL,  
                      intpoints.oldmean, intpoints.oldsd,  
                      precalc.data, model, T,  
                      new.noise.var = NULL, batchsize, alpha, current.vorob,  
                      penalisation=NULL, typeEx="\"\")
```

**Arguments**

- `x`  
  Input vector of size batchsize*d at which one wants to evaluate the criterion. This argument is NOT a matrix.

- `integration.points`  
  p*d matrix of points for numerical integration in the X space.

- `integration.weights`  
  Vector of size p corresponding to the weights of these integration points.

- `intpoints.oldmean`  
  Vector of size p corresponding to the kriging mean at the integration points before adding the batchsize points x to the design of experiments.

- `intpoints.oldsd`  
  Vector of size p corresponding to the kriging standard deviation at the integration points before adding the batchsize points x to the design of experiments.

- `precalc.data`  
  List containing useful data to compute quickly the updated kriging variance. This list can be generated using the `precomputeupdatedata` function.

- `model`  
  Object of class `km` (Kriging model).

- `T`  
  Target value (scalar). The criterion CANNOT be used with multiple thresholds.

- `new.noise.var`  
  Optional scalar value of the noise variance for the new observations.

- `batchsize`  
  Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.

- `alpha`  
  The Vorob’ev threshold.

- `current.vorob`  
  Current value of the vorob criterion (before adding new observations)

- `penalisation`  
  Optional penalization constant for type I errors. If equal to zero, computes the Type II criterion.

- `typeEx`  
  A character ("\"" or "\"\") identifying the type of excursion
Details

The first argument x has been chosen to be a vector of size batchsize\(d\) (and not a matrix with batchsize rows and d columns) so that an optimizer like genoud can optimize it easily. For example if \(d=2\), batchsize=3 and \(x=[0.1,0.2,0.3,0.4,0.5,0.6]\), we will evaluate the parallel criterion at the three points \((0.1,0.2),(0.3,0.4)\) and \((0.5,0.6)\).

Value

Parallel vorob value

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)
Dario Azzimonti (IDSIA, Switzerland)

References


See Also

EGIparallel, max_vorob_parallel

Examples

```r
#vorob_optim_parallel
set.seed(9)
N <- 20 #number of observations
T <- 80 #threshold
testfun <- bramin

# a 20 points initial design
design <- data.frame( matrix(runif(2*N),ncol=2) )
response <- testfun(design)

# km object with matern3_2 covariance
# params estimated by ML from the observations
model <- km(formula=-., design = design,
response = response,covtype="matern3_2")

###we need to compute some additional arguments:
# integration points, and current kriging means and variances at these points
integcontrol <- list(n.points=50,distrib="vorob",init.distrib="MC")
```

vorob_optim_parallel2

```r
obj <- integration_design(integcontrol=integcontrol, lower=c(0,0), upper=c(1,1), model=model, T=T)

integration.points <- obj$integration.points
integration.weights <- obj$integration.weights
alpha <- obj$alpha
pred <- predict_nobias_km(object=model, newdata=integration.points, type="UK", se.compute=TRUE)
intpoints.oldmean <- pred$mean ; intpoints.oldsd <- pred$sd

# another precomputation
precalc.data <- precomputeUpdateData(model, integration.points)

batchsize <- 4
x <- c(0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8)
# one evaluation of the vorob_optim_parallel criterion
# we calculate the expectation of the future "vorob" uncertainty
# when 4 points are added to the doe
# the 4 points are (0.1, 0.2), (0.3, 0.4), (0.5, 0.6), (0.7, 0.8)
vorob_optim_parallel(x=x, integration.points=integration.points, integration.weights=integration.weights, intpoints.oldmean=intpoints.oldmean, intpoints.oldsd=intpoints.oldsd, precalc.data=precalc.data, T=T, model=model, batchsize=batchsize, alpha=alpha, current.vorob=Inf)

# the function max_vorob_parallel will help to find the optimum:
# ie: the batch of 4 minimizing the expectation of the future uncertainty
```

---

**vorob_optim_parallel2  Parallel Vorob’ev criterion**

**Description**

Evaluation of the Vorob’ev criterion for some candidate points, assuming that some other points are also going to be evaluated. To be used in optimization routines, like in `max_vorob_parallel`. To avoid numerical instabilities, the new points are evaluated only if they are not too close to an existing observation, or if there is some observation noise. The criterion is the integral of the posterior Vorob’ev uncertainty.

**Usage**

```r
vorob_optim_parallel2(x, other.points, integration.points, integration.weights = NULL, intpoints.oldmean, intpoints.oldsd, precalc.data, model, T, new.noise.var = NULL, batchsize, alpha, current.vorob, penalisation = NULL, typeEx = ">")
```
Arguments

- **x**: Input vector of size d at which one wants to evaluate the criterion. This argument corresponds to only ONE point.

- **other.points**: Vector giving the other batchsize-1 points at which one wants to evaluate the criterion.

- **integration.points**: p*d matrix of points for numerical integration in the X space.

- **integration.weights**: Vector of size p corresponding to the weights of these integration points.

- **intpoints.oldmean**: Vector of size p corresponding to the kriging mean at the integration points before adding x to the design of experiments.

- **intpoints.oldsd**: Vector of size p corresponding to the kriging standard deviation at the integration points before adding x to the design of experiments.

- **precalc.data**: List containing useful data to compute quickly the updated kriging variance. This list can be generated using the `precomputeUpdateData` function.

- **model**: Object of class `km` (Kriging model).

- **T**: Target value (scalar). The criterion CANNOT be used with multiple thresholds.

- **new.noise.var**: Optional scalar value of the noise variance of the new observations.

- **batchsize**: Number of points to sample simultaneously. The sampling criterion will return batchsize points at a time for sampling.

- **alpha**: The Vorob’ev threshold.

- **current.vorob**: Current value of the vorob criterion (before adding new observations)

- **penalisation**: Optional penalization constant for type I errors. If equal to zero, computes the Type II criterion.

- **typeEx**: A character ("" or ") identifying the type of excursion

Details

The first argument x has been chosen to be a vector of size d so that an optimizer like genoud can optimize it easily. The second argument other.points is a vector of size (batchsize-1)*d corresponding to the batchsize-1 other points.

Value

Parallel Vorob’ev value

Author(s)

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References


See Also

EGIparallel, max_vorob_parallel

Examples

```r
#vorob_optim_parallel2

set.seed(9)
N <- 20 #number of observations
T <- 80 #threshold
testfun <- branin

#a 20 points initial design
design <- data.frame(matrix(runif(2*N),ncol=2))
response <- testfun(design)

#km object with matern3.2 covariance
#params estimated by ML from the observations
model <- km(formula=-., design = design,
response = response,covtype="matern3_2")

###we need to compute some additional arguments:
#integration points, and current kriging means and variances at these points
integcontrol <- list(n.points=50,distrib="vorob",init.distrib="MC")
obj <- integration_design(integcontrol=integcontrol,
lower=c(0,0),upper=c(1,1),model=model,T=T)

integration.points <- obj$integration.points
integration.weights <- obj$integration.weights
alpha <- obj$alpha
pred <- predict_nobias_km(object=model,newdata=integration.points,
type="UK",se.compute=TRUE)
intpoints.oldmean <- pred$mean ; intpoints.oldsd<-pred$sd

#another precomputation
precalc.data <- precomputeupdatedata(model,integration.points)

batchsize <- 4
other.points <- c(0.7,0.5,0.5,0.9,0.9,0.8)
x <- c(0.1,0.2)
#one evaluation of the vorob_optim_parallel criterion2
#we calculate the expectation of the future "vorob" uncertainty when
#1+3 points are added to the doe
```

# Calculation of the Vorob'ev threshold

**Description**

Evaluation of the Vorob'ev threshold given an excursion probability vector. This threshold is such that the volume of the set \( x : p_n(x) > \text{threshold} \) is equal to the integral of \( p_n \).

**Usage**

\[
\text{vorob_threshold}(p_n)
\]

**Arguments**

\[
\begin{align*}
\text{pn} & \quad \text{Input vector of arbitrary size containing the excursion probabilities } p_n(x).
\end{align*}
\]
Details

In this function, all the points x are supposed to be equally weighted.

Value

a scalar: the Vorob’ev threshold

Author(s)

Clement Chevalier (University of Neuchatel, Switzerland)

References


See Also

max_vorob_parallel, vorob_optim_parallel

Examples

# vorob_threshold

set.seed(9)
N <- 20 # number of observations
T <- 80 # threshold
testfun <- branin

# a 20 points initial design
design <- data.frame( matrix(runif(2*N), ncol=2) )
response <- testfun(design)

# km object with matern3_2 covariance
# params estimated by ML from the observations
model <- km(formula=-., design = design,
response = response, covtype="matern3_2")

## Not run:
#### we need to compute some additional arguments:
# integration points, and current kriging means and variances at these points
integcontrol <- list(n.points=50, distrib="sobol")
obj <- integration_design(integcontrol=integcontrol,
lower=c(0,0), upper=c(1,1), model=model, T=T)

integration.points <- obj$integration.points

pred <- predict_nobias_km(object=model, newdata=integration.points,
type="UK", se.compute=TRUE
pn <- pnorm((pred$mean - T)/pred$sd)

vorob_threshold(pn)

## End(Not run)
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