

# Package ‘EntropyMCMC’

October 12, 2022

**Type** Package

**Title** MCMC Simulation and Convergence Evaluation using Entropy and  
Kullback-Leibler Divergence Estimation

**Version** 1.0.4

**Date** 2019-03-08

**Description**

Tools for Markov Chain Monte Carlo (MCMC) simulation and performance analysis. Simulate MCMC algorithms including adaptive MCMC, evaluate their convergence rate, and compare candidate MCMC algorithms for a same target density, based on entropy and Kullback-Leibler divergence criteria. MCMC algorithms can be simulated using provided functions, or imported from external codes. This package is based upon work starting with Chauveau, D. and Vandekerkhove, P. (2013) <[doi:10.1051/ps/2012004](https://doi.org/10.1051/ps/2012004)> and next articles.

**Depends** R (>= 3.0)

**Imports** RANN, parallel, mixtools

**Suggests** Rmpi, snow

**License** GPL (>= 3)

**LazyLoad** yes

**Author** Didier Chauveau [aut, cre],  
Houssam Alrachid [ctb]

**Maintainer** Didier Chauveau <[didier.chauveau@univ-orleans.fr](mailto:didier.chauveau@univ-orleans.fr)>

**NeedsCompilation** yes

**Repository** CRAN

**Date/Publication** 2019-03-08 17:22:51 UTC

## R topics documented:

EntropyMCMC-package . . . . .	2
accept_ratio . . . . .	4
CollectChains . . . . .	5
DrawInit . . . . .	6
EntropyMCMC . . . . .	7

EntropyParallel . . . . .	9
gaussian_pdf . . . . .	14
MCMCcopies . . . . .	15
MCMCcopies.cl . . . . .	17
MCMCcopies.mc . . . . .	19
normEntropy . . . . .	21
plot.KbMCMC . . . . .	22
plot.plMCMC . . . . .	23
plottarget3d . . . . .	25
plot_Kblist . . . . .	25
RWHM_chain . . . . .	27
summary.plMCMC . . . . .	29

<b>Index</b>	<b>31</b>
--------------	-----------

---

EntropyMCMC-package	<i>(A)MCMC Simulation and Convergence Evaluation using Entropy and Kullback-Leibler Divergence Estimation</i>
---------------------	---

---

## Description

Contains functions to analyse (Adaptive) Markov Chain Monte Carlo (MCMC) algorithms, evaluate their convergence rate, and compare candidate MCMC algorithms for a same target density, based on entropy and Kullback-Leibler divergence criteria. MCMC algorithms can be simulated using provided functions, or imported from external codes. The diagnostics are based on consistent estimates of entropy and Kulback distance between the density at iteration  $t$  and the target density  $f$ , based on iid (parallel) chains.

## Details

Package:	EntropyMCMC
Type:	Package
Version:	1.0.4
Date:	2019-03-08
License:	GPL (>= 3)
LazyLoad:	yes

## Statistical background:

This package allows for simulation of standard or adaptive MCMC samplers for a user-defined target density, and provides statistical tools to evaluate convergence of MCMC's and compare performance of algorithms for the same target density (typically against benchmark samplers).

The criteria are graphical and based on plots against iterations (time)  $t$ , of the *Kullback divergence*  $K(p^t, f)$  between the density  $p^t$  of the MCMC algorithm at time  $t$ , and the target density  $f$ , for  $t = 1$  up to the number of iterations that have been simulated. This requires estimation of the

entropy of  $p^t$ ,

$$E_{p^t}[\log(p^t)],$$

and of the external entropy

$$E_{p^t}[\log(f)].$$

Consistent estimates are computed based on  $N$  iid (parallel) chains, since the  $N$  positions of the chains at iterations  $t$  forms a  $N$ -iid sample from the density  $p^t$ .

### Computational considerations:

The simulation of iid chains can be performed in this package, which provides a mechanism for defining (A)MCMC algorithms and building the iid chains required for convergence evaluation. Each MCMC algorithm is defined by a list with five elements. Each user can define its own MCMC, starting from the standard MCMC algorithms that are already defined:

- **RWHM**: a standard Random-Walk Hastings-Metropolis (HM) algorithm.
- **HMIS\_norm**: an Independence Sampler HM with gaussian proposal
- **AMHaario**: the Haario (2001) Adaptive Hastings-Metropolis algorithm, provided as an example of a standard AMCMC.
- **IID\_norm**: a “fake” MCMC that is just a gaussian IID sampler, used mostly for testing purpose. Simulation of  $N$  iid chains for  $n$  iterations using this algorithm just returns  $N \times n$  gaussian  $d$ -dimensional vectors.

Functions for doing the simulations and the convergence evaluation automatically using these algorithms in their first argument are provided. Two strategies are available:

- *Simulation and Kullback estimation separately*: A “cube” of  $N$  chains for  $n$  iterations in a space of dimension  $d$  is first simulated and stored using `MCMCcopies` or its multicore or cluster versions, then the entropy and Kullback divergence are estimated from that object using `EntropyMCMC` or its multicore version.
- *Simulation and Kullback estimation simultaneously*: For each iteration  $t$ , the next step of all the  $N$  chains are generated, then the Entropy and Kullback divergence  $K(p^t, f)$  are estimated, and the past of the parallel chains is discarded so that the amount of memory requirement is kept small, and only entropy-related estimates are stored and returned. Functions for this strategy are `EntropyParallel` and its multicore and cluster version.

See the Examples section of `plot_Kblist` for an illustration of these two methods.

### Doing the simulations outside from this package

A third hybrid strategy is also available: the simulation of iid chains can be done using an external code (in R, C or any language) and imported in the **EntropyMCMC** package (defining an object of the appropriate class “p1MCMC” and structure, see `MCMCcopies`).

Then the Kullback divergence criterion can be computed using `EntropyMCMC` or its multicore version, and convergence/comparison diagnostics can be displayed using the associated plot method.

### About High Performance Computing

The required simulations can be done using singlecore or HCP (multicore computers, snow or clusters using the `parallel` or `Rmpi` packages). Note that the `parallel` package using socket cluster is not available on Windows machines.

**Author(s)**

Didier Chauveau, Institut Denis Poisson, University of Orleans, CNRS, Orleans France. <https://www.idpoisson.fr/chauveau/>

Maintainer: Didier Chauveau <didier.chauveau@univ-orleans.fr>

Contributor: Houssam Alrachid

**References**

- Chauveau, D. and Vandekerkhove, P. (2013), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.
- Chauveau D. and Vandekerkhove, P. (2014), The Nearest Neighbor entropy estimate: an adequate tool for adaptive MCMC evaluation. *Preprint HAL* <http://hal.archives-ouvertes.fr/hal-01068081>.

---

accept\_ratio

*Acceptance ratio for Hastings-Metropolis simulated MCMC chains*

---

**Description**

Internal function for the package EntropyMCMC, computes the acceptance ratio required in the definition of any Hastings-Metropolis algorithm.

**Usage**

```
accept_ratio(x, y, target, q_pdf, f_param, q_param, symmetric = FALSE)
```

**Arguments**

x	The current position.
y	The next (proposal) position.
target	The target density for which the MCMC algorithm is defined; may be given only up to a multiplicative constant for most MCMC. Target must be a function such as the multidimensional gaussian <code>target_norm(x, param)</code> .
q_pdf	The density of the proposal.
f_param	A list holding all the necessary target parameters, consistent with the target definition.
q_param	A list holding all the necessary parameters for the proposal density of the MCMC algorithm <code>mcmc_algo</code> .
symmetric	If TRUE, the proposal <code>q_pdf</code> is symmetric which simplifies the acceptance ratio computation

**Details**

The `accept_ratio` is used to decide whether to accept or reject a candidate  $y$ . The acceptance ratio indicates how probable the new proposed candidate is with respect to the current candidate  $x$ , according to the distribution target.

**Value**

`accept_ratio` returns a real value `alpha`, which indicates the computed value of the current `accept_ratio`.

**Author(s)**

Didier Chauveau, Houssam Alrachid.

---

CollectChains

*Collect MCMC chains in a single object*

---

**Description**

Utility function for the package **EntropyMCMC**.

**Usage**

```
CollectChains(s)
```

**Arguments**

`s` An object of class `pLMCMC`, such as the one returned by `MCMCcopies`, containing in particular an array of dimension  $(n, d, nmc)$  holding the simulation of  $n$  steps of  $nmc$  parallel chains in dimension  $d$ .

**Details**

Concatenates all simulated copies together in one matrix of dimension  $(n*nmc, d)$ .

**Value**

Returns a matrix of dimension  $(n*nmc, d)$ .

**Author(s)**

Didier Chauveau.

---

`DrawInit`*Random draws for initialization*

---

**Description**

Utility function for the package **EntropyMCMC**, for generating random starting positions for the parallel Markov chains, used by, e.g., [MCMCcopies](#) or [EntropyParallel](#).

**Usage**

```
DrawInit(nmc, d, initpdf="rnorm", ...)
```

**Arguments**

<code>nmc</code>	Number of parallel chains = initial points.
<code>d</code>	Space dimension.
<code>initpdf</code>	Random generator. Generators currently implemented are: "rnorm" as the Normal distribution and "runif" as the uniform distribution.
<code>...</code>	Parameters passed to <code>initpdf</code>

**Value**

`DrawInit` returns a matrix of dimension  $(nmc, d)$  where each row is a  $d$ -dimensional point.

**Note**

It is better for mixing properties to use diffuse initial distributions, such as the one proposed here. However Dirac initial points can also be used, precisely to evaluate the efficiency of a MCMC to escape from a wrong initial position (e.g., in the tails of the target density).

**Author(s)**

Didier Chauveau.

**See Also**

[MCMCcopies](#) and [MCMCcopies.mc](#) for iid MCMC simulations, [EntropyParallel](#) and [EntropyParallel.cl](#) for simultaneous simulation and entropy estimation.

**Examples**

```
Ptheta0 <- DrawInit(10, 5, initpdf="rnorm", mean=0, sd=5)
```

EntropyMCMC

*Kullback and entropy estimation from MCMC simulation output - single and multicore versions***Description**

These functions return estimates of the entropy of the density  $p^t$  of a MCMC algorithm at time  $t$ ,  $E_{p^t}[\log(p^t)]$ , and of the Kullback divergence between  $p^t$  and the target density, for  $t = 1$  up to the number of iterations that have been simulated. The MCMC simulations must be computed before or externally, and passed as a "pLMCMC" object in the first argument (see details). The target may be known only up to a multiplicative constant (see details).

`EntropyMCMC.mc` is a parallel computing version that uses the [parallel](#) package to split the task between the available (virtual) cores on the computer. This version using socket cluster is not available for Windows computers.

**Usage**

```
EntropyMCMC(plmc1, method = "A.Nearest.Neighbor", k=1, trim = 0.02, eps=0,
  all.f = TRUE, verb = FALSE, EntVect = FALSE,
  uselogtarget = FALSE, logtarget = NULL)
```

```
EntropyMCMC.mc(plmc1, method = "A.Nearest.Neighbor", k = 1, trim = 0.02, eps=0,
  all.f = TRUE, verb = FALSE, EntVect = FALSE, nbcores=detectCores(),
  uselogtarget = FALSE, logtarget = NULL)
```

**Arguments**

<code>plmc1</code>	an objects of class <code>pLMCMC</code> (for parallel MCMC), like the output of <code>MCMCcopies</code> , which contains all the simulations plus target $f$ definition and parameters.
<code>method</code>	The method for estimating the entropy $E_{p^t}[\log(p^t)]$ . Methods currently implemented are : "NearestNeighbor" as in Kozachenko and Leonenko (1987), "k.NearestNeighbor" as in Leonenko et al. (2005), "A.Nearest.Neighbor" (the default) which is as "k.NearestNeighbor" but uses the <b>RANN</b> package for (Approximate) fast computation of nearest neighbors, "Gyorfi.trim" subsampling method as defined in Gyorfi and Vander Mulen (1989), plus a tuning parameter <code>trim</code> for trimming the data (see Chauveau and Vandekerkhove (2011)).
<code>k</code>	The k-nearest neighbor index, the default is $k = 1$ .
<code>trim</code>	Parameter controlling the percentage of smallest data from one subsample that is removed, only for <code>method = "Gyorfi.trim"</code> .
<code>eps</code>	A parameter controlling precision in the "A.Nearest.Neighbor" method, the default means no approximation, see the <b>RANN</b> package.
<code>all.f</code>	If TRUE (the default) relative entropy is computed over the whole sample. Should be removed in next version.

verb	Verbose mode
EntVect	If FALSE (the default), the entropy is computed only on the kth-nearest neighbor. If TRUE, the entropy is computed for all j-NN's for $j = 1$ to $k$ (the latter being mostly for testing purposes).
nbcores	Number of required (virtual) cores, defaults to all as returned by <code>detectCores()</code> .
uselogtarget	Set to FALSE by default; useful in some cases where $\log(f(\theta))$ returns <code>-Inf</code> values in Kullback computations because $f(\theta)$ itself returns too small values for some $\theta$ far from modal regions. In these case using a function computing the logarithm of the target can remove the infinity values.
logtarget	The function defining $\log(f(\theta))$ , NULL by default, required if <code>uselogtarget</code> equals TRUE. This option and <code>uselogtarget</code> are currently implemented only for the "A.Nearest.Neighbor" method, and for the default <code>EntVect = FALSE</code> option.

### Details

Methods based on Nearest Neighbors (NN) should be preferred since these require less tuning parameters. Some options, as `uselogtarget` are in testing phase and are not implemented in all the available methods (see Arguments).

### Value

An object of class `KbMCMC` (for Kullback MCMC), containing:

Kullback	A vector of estimated divergences $K(p^t, f)$ , for $t = 1$ up to the number of iterations that have been simulated. This is the convergence/comparison criterion.
Entp	A vector of estimated entropies $E_{p^t}[\log(p^t)]$ , for $t = 1$ up to the number of iterations that have been simulated.
nmc	The number of iid copies of each single chain.
dim	The state space dimension of the MCMC algorithm.
algo	The name of the MCMC algorithm that have been used to simulate the copies of chains, see <a href="#">MCMCcopies</a> .
target	The target density for which the MCMC algorithm is defined; ususally given only up to a multiplicative constant for MCMC in Bayesian models. <code>target</code> must be a function such as the multidimensional gaussian <code>target_norm(x,param)</code> with argument and parameters passed like in the example below.
method	The method input parameter (see above).
f_param	A list holding all the necessary target parameters, consistent with the target definition.
q_param	A list holding all the necessary parameters for the proposal density of the MCMC algorithm that have been used.

### Note

The method "Resubst" is implemented for testing, without theoretical guarantee of convergence.



**Author(s)**

Didier Chauveau, Houssam Alrachid.

**References**

- Chauveau, D. and Vandekerkhove, P. (2013), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.
- Chauveau D. and Vandekerkhove, P. (2014), The Nearest Neighbor entropy estimate: an adequate tool for adaptive MCMC evaluation. *Preprint HAL* <http://hal.archives-ouvertes.fr/hal-01068081>.

**See Also**

[MCMCcopies](#) and [MCMCcopies.mc](#) for iid MCMC simulations (single core and multicore), [EntropyParallel](#) and [EntropyParallel.cl](#) for simultaneous simulation and entropy estimation (single core and multicore).

**Examples**

```
## Toy example using the bivariate gaussian target
## with default parameters value, see target_norm_param
n = 150; nmc = 50; d=2 # bivariate example
varq=0.1 # variance of the proposal (chosen too small)
q_param=list(mean=rep(0,d),v=varq*diag(d))
## initial distribution, located in (2,2), "far" from target center (0,0)
Ptheta0 <- DrawInit(nmc, d, initpdf = "rnorm", mean = 2, sd = 1)
# simulation of the nmc iid chains, singlecore
s1 <- MCMCcopies(RWHM, n, nmc, Ptheta0, target_norm,
                target_norm_param, q_param, verb = FALSE)
summary(s1) # method for "plMCMC" object
e1 <- EntropyMCMC(s1) # computes Entropy and Kullback divergence estimates
par(mfrow=c(1,2))
plot(e1) # default plot.plMCMC method, convergence after about 80 iterations
plot(e1, Kullback = FALSE) # Plot Entropy estimates over time
abline(normEntropy(target_norm_param), 0, col=8, lty=2) # true E_f[log(f)]
```

## Description

This function simulates “parallel chains” (iid copies) of a MCMC algorithm, i.e. for each “time” iteration  $t$  the next step of all the nmc chains are generated, then the Entropy of the density  $p^t$  of the algorithm at iteration  $t$ ,  $E_{p^t}[\log(p^t)]$ , and the Kullback divergence between  $p^t$  and the target density are estimated, based on these nmc steps iid from  $p^t$ . By default `keep.all = FALSE` i.e. the past of the parallel chains is discarded so that the amount of memory requirement is kept small, and only entropy-related estimates are returned. If `keep.all = TRUE`, the entire set of chains trajectories is saved in an array of dimensions  $(n, d, nmc)$ , such as the one returned by [MCMCcopies](#) or [MCMCcopies.cl](#).

A version of this function implementing several HPC (parallel) computing strategies is available (see details).

## Usage

```
EntropyParallel(mcmc_algo, n = 100, nmc = 10, Ptheta0, target, f_param, q_param,
  method = "A.Nearest.Neighbor", k=1, trim = 0.02, keep.all = FALSE,
  verb = TRUE, EntVect = FALSE)
```

```
EntropyParallel.cl(mcmc_algo, n = 100, nmc = 10, Ptheta0, target, f_param, q_param,
  method = "A.Nearest.Neighbor", k=1, eps = 0, trim=0.02,
  verb=TRUE, EntVect = FALSE, cltype="PAR_SOCKET", nbnodes = 4,
  par.logf = FALSE, uselogtarget = FALSE, logtarget = NULL)
```

## Arguments

<code>mcmc_algo</code>	a list defining an MCMC algorithm in terms of the functions it uses, such as RWHM, see details below.
<code>n</code>	The number of (time) iterations of each single chain to run.
<code>nmc</code>	The number of iid copies of each single chain.
<code>Ptheta0</code>	A $(nmc, d)$ matrix, with the $i$ th row giving a $d$ -dimensional initial theta values for the $i$ th chain.
<code>target</code>	The target density for which the MCMC algorithm is defined; may be given only up to a multiplicative constant for most MCMC. <code>target</code> must be a function such as the multidimensional gaussian <code>target_norm(x, param)</code> with argument and parameters passed like in the example below.
<code>f_param</code>	A list holding all the necessary target parameters, including the data in an actual Bayesian model, and consistent with the target definition.
<code>q_param</code>	A list holding all the necessary parameters for the proposal density of the MCMC algorithm <code>mcmc_algo</code> .
<code>method</code>	The method for estimating the entropy $E_{p^t}[\log(p^t)]$ . The methods currently implemented for this function are "Nearest.Neighbor" as in Kozachenko and Leonenko (1987), "k.Nearest.Neighbor" as in Leonenko et al. (2005) (the default in the single core version), and "A.Nearest.Neighbor" which is "k.NearestNeighbor" using the <b>RANN</b> package for (Approximate) fast computation of nearest neighbors, instead of R code (the default for the cluster version). Other methods such as "Gyorfi.trim" subsampling method as defined

	in Gyorfi and Vander Mulen (1989) are available as well (see Chauveau and Vandekerkhove (2012)).
k	The k-nearest neighbor index, the default is $k = 1$ .
eps	Error bound: default of 0.0 implies exact nearest neighbour search, see the <b>RANN</b> package.
trim	not used in this implementation, only for method="Gyorfi.trim"
keep.all	If TRUE, all the simulated chains are stored in a 3-dimensional array of dimensions (n, d, nmc), such as the one returned by <code>MCMCcopies</code>
verb	Verbose mode for summarizing output during the simulation.
EntVect	If FALSE (the default), the entropy is computed only on the kth-nearest neighbor. If TRUE, the entropy is computed for all j-NN's for $j = 1$ to $k$ (the latter being mostly for testing purposes).
cltype	Character string specifying the type of cluster; currently implemented types are: "PAR_SOCKET" for socket cluster with <code>parallel</code> library, the default; "SNOW_SOCKET" for socket cluster with <code>snow</code> library, and "SNOW_RMPI" for snow MPI cluster with <code>Rmpi</code> library.
nbnodes	The number of nodes or virtual cores requested to run the nmc simulations in parallel. For the snow version, defaults to all; for the cluster version, defaults to 4.
par.logf	if TRUE, then the computation of the log of the target density at each of the nmc chain locations, needed for the NN procedure is also executed in parallel using <code>parRapply()</code> . This may speed up the process if the target is complicated i.e. takes some time to evaluate. If the target is simple enough (like <code>target_norm</code> ), then communications between nodes are slower than computations, in which case <code>par.logf = FALSE</code> (the default) should be preferred.
uselogtarget	Set to FALSE by default; useful in some cases where $\log(f(\theta))$ returns <code>-Inf</code> values in Kullback computations because $f(\theta)$ itself returns too small values for some $\theta$ far from modal regions. In these case using a function computing the logarithm of the target can remove the infinity values.
logtarget	The function defining $\log(f(\theta))$ , NULL by default, required if <code>uselogtarget</code> equals TRUE. This option and <code>uselogtarget</code> are currently implemented only for the "A.Nearest.Neighbor" method, and for the default <code>EntVect = FALSE</code> option.

## Details

### About parallel computing:

For the HPC (parallel) version, the computation of the nmc chains next step are done by the cluster nodes: `EntropyParallel.cl` is a generic *cluster* version implementing several types of cluster for running on a single, multicore computer or on a true cluster using MPI communications. It is under development and may not work on all platform/OS. For instance the parallel socket cluster version does not work on Windows machines (see the **parallel** package documentation). Currently tested under LINUX, Mac OSX, and a cluster using OpenMPI and Sun Grid Engine.

Note that the parallel computing for this approach is less efficient than the two-steps procedure consisting in (i) parallel simulation of the iid chains using `MCMCcopies.cl` to generate the "cube" of simulated values, and then (ii) entropy and Kullback estimation using `EntropyMCMC.mc`. This

is because each node computes only one iteration at a time for the `nmc` chains here, whereas it computes all the  $n$  iterations once for the `nmc` chains when the entire cube is saved first. This is a trade-off between memory and speed.

Note also that the `Rmpi` option is less efficient than the default option using **parallel** if you are running on a single computer. MPI communication are required only for running on a true cluster/grid.

#### About passing your MCMC algorithm:

The list `mcmc_algo` must contain the named elements:

- `name`, the name of the MCMC, such as "RWHM"
- `chain`, the function for simulation of  $n$  steps of a single chain
- `step`, the function for simulation of 1 step of that algorithm
- `q_pdf`, the density of the proposal
- `q_proposal`, the function that simulates a proposal

For examples, see the algorithms currently implemented: RWHM, the Random Walk Hasting-Metropolis with gaussian proposal; HMISS\_norm, an Independence Sampler HM with gaussian proposal; IID\_norm, a gaussian iid sampler which is merely a "fake" MCMC for testing purposes.

Currently only non-adaptive Markov chains or adaptive chains for which the past can be summarized by some sufficient statistics are eligible for this computation forgetting the past of the `nmc` chains. Adaptive chains such as AMHaario, the Adaptive-Metropolis (AM) from Haario (2001) are not yet tested for this function.

#### Value

An object of class "KbMCMC", containing

<code>Kullback</code>	A vector of estimated $K(p^t, f)$ , for $t = 1$ up to the number of iterations $n$ . This is the convergence/comparison criterion.
<code>Entp</code>	A vector of estimated $E_{p^t}[\log(p^t)]$ , for $t = 1$ up to the number of iterations that have been simulated.
<code>nmc</code>	The number of iid copies of each single chain.
<code>dim</code>	The state space dimension of the MCMC algorithm.
<code>algo</code>	The name of the MCMC algorithm that have been used to simulate the copies of chains, see <a href="#">MCMCcopies</a> .
<code>target</code>	The target density for which the MCMC algorithm is defined; may be given only up to a multiplicative constant for most MCMC. <code>target</code> must be a function such as the multidimensional gaussian <code>target_norm(x,param)</code> with argument and parameters passed like in this example.
<code>method</code>	The method input parameter (see above).
<code>f_param</code>	A list holding all the necessary target parameters, consistent with the target definition.
<code>q_param</code>	A list holding all the necessary parameters for the proposal density of the MCMC algorithm that have been used.
<code>prob. accept</code>	Estimated rate of acceptance (meaningful for accept/reject-type algorithms).
<code>Ptheta</code>	The <code>nmc</code> copies of chains in an array( $n,d,nmc$ ) of simulated values, where 1st value ( $1,d,nmc$ ) is <code>Ptheta0</code> .

**Author(s)**

Didier Chauveau, Houssam Alrachid.

**References**

- Chauveau, D. and Vandekerkhove, P. (2013), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.
- Chauveau D. and Vandekerkhove, P. (2014), The Nearest Neighbor entropy estimate: an adequate tool for adaptive MCMC evaluation. *Preprint HAL* <http://hal.archives-ouvertes.fr/hal-01068081>.

**See Also**

[MCMCcopies](#), [MCMCcopies.mc](#) and [MCMCcopies.cl](#) for just simulating the iid chains, and [EntropyMCMC](#) or [EntropyMCMC.mc](#) for computing entropy and Kullback estimates from an already simulated set of iid chains (internally or from external code).

**Examples**

```
## Toy example using the bivariate gaussian target
## same as for MCMCcopies
n = 150; nmc = 50; d=2 # bivariate example
varq=0.1 # variance of the proposal (chosen too small)
q_param=list(mean=rep(0,d),v=varq*diag(d))
## initial distribution, located in (2,2), "far" from target center (0,0)
Ptheta0 <- DrawInit(nmc, d, initpdf = "rnorm", mean = 2, sd = 1)
# simulations and entropy + Kullback using the singlecore version
e1 <- EntropyParallel(RWHM, n, nmc, Ptheta0, target_norm,
                    target_norm_param, q_param, verb = FALSE)
par(mfrow=c(1,2))
plot(e1) # default plot.plMCMC method, convergence after about 80 iterations
plot(e1, Kullback = FALSE) # Plot Entropy estimates over time
abline(normEntropy(target_norm_param), 0, col=8, lty=2) # true E_f[log(f)]

# Another example using multicore version, (not available on Windows)
varq=0.05 # variance of the proposal, even smaller
q_param=list(mean=rep(0,d),v=varq*diag(d))
n=300 # requires more iterations to show convergence
e1 <- EntropyParallel.cl(RWHM, n, nmc, Ptheta0, target_norm,
                       target_norm_param, q_param, cltype="PAR_SOCKET",
                       verb = FALSE, nbnodes = 2)
plot(e1) # convergence after about 150 iterations
```

---

`gaussian_pdf`*Proposal density evaluation and simulation*

---

**Description**

Functions for proposal density evaluation and random generation in MCMC algorithms, in the case where these are Gaussian.

**Usage**

```
gaussian_pdf(y, x, param)
```

```
gaussian_proposal(x, param)
```

**Arguments**

<code>y</code>	Candidate for next move, a vector of dimension $d$
<code>x</code>	Current position of a chain, a vector of dimension $d$
<code>param</code>	The proposal parameters, that must contains the $d \times d$ variance matrix in <code>param\$V</code> .

**Details**

The Gaussian proposal density  $q(y|x)$  used in, e.g., random walk Hastings-Metropolis algorithm RWHM is the multivariate Gaussian  $N(x, v)$  density evaluated at point  $y$ . Similarly, the Gaussian proposal (next move) is a random draw  $y \sim N(x, v)$  when the chain is at position  $x$ .

**Value**

The value of the density, or the random draw, both in dimension  $d$

**Note**

These functions are calling multivariate Gaussian density and random generation functions imported from the **mixtools** package (chosen for efficiency) and wrapped in the format required by the **EntropyMCMC** package.

**Author(s)**

Didier Chauveau.

MCMCcopies

*Simulates iid copies of a MCMC algorithm***Description**

Simulates `nmc` iid copies of a MCMC algorithm `mcmc_algo` for `n` (time) iterations and returns an object of class `pLMCMC` (for parallel MCMC) holding an array of the trajectories and running information.

**Usage**

```
MCMCcopies(mcmc_algo, n = 100, nmc = 10, Ptheta0, target, f_param, q_param, verb = TRUE)
```

**Arguments**

<code>mcmc_algo</code>	a list defining an MCMC algorithm in terms of the functions it uses, such as RWHM, see details below.
<code>n</code>	The number of (time) iterations of each single chain to run.
<code>nmc</code>	The number of iid copies of each single chain.
<code>Ptheta0</code>	A ( <code>nmc</code> x <code>d</code> ) matrix, with the <code>ith</code> row giving a <code>d</code> -dimensional initial theta values for the <code>ith</code> chain.
<code>target</code>	The target density for which the MCMC algorithm is defined; may be given only up to a multiplicative constant for most MCMC. Target must be a function such as the multidimensional gaussian <code>target_norm(x, param)</code> with argument and parameters passed like in this example.
<code>f_param</code>	A list holding all the necessary target parameters, consistent with the target definition.
<code>q_param</code>	A list holding all the necessary parameters for the proposal density of the MCMC algorithm <code>mcmc_algo</code> .
<code>verb</code>	Verbose mode for summarizing output during the simulation.

**Details**

`MCMCcopies` sequentially simulates `nmc` iid copies of the MCMC algorithm passed in the list `mcmc_algo`, for `n` (time) iterations, and returns an object of class `pLMCMC` holding an array of the trajectories and running information. The list `mcmc_algo` must contain the named elements:

- `name`, the name of the MCMC, such as "RWHM"
- `chain`, the function for simulation of `n` steps of a single chain
- `step`, the function for simulation of 1 step of that algorithm
- `q_pdf`, the density of the proposal
- `q_proposal`, the function that simulates a proposal

For examples, see the algorithms currently implemented: `RWHM`, the Random Walk Hasting-Metropolis with gaussian proposal; `HMIS_norm`, an Independence Sampler HM with gaussian proposal; `AMHaario`, the Adaptive-Metropolis (AM) from Haario (2001); `IID_norm`, a gaussian iid sampler which is merely a "fake" MCMC for testing purposes.

**Value**

MCMCcopies returns a list of class pLMCMC with items:

Ptheta	The nmc copies of chains in an array(n,d,nmc) of simulated values, where 1st value (1,d,nmc) is Ptheta0.
prob.accept	The estimated rate of acceptance over all simulations.
algo	The MCMC algorithm name i.e. mcmc_algo\$name.
target	The target density.
f_param	The list holding all the target parameters.
q_param	The list holding all the proposal density parameters.

**Author(s)**

Didier Chauveau.

**References**

- Chauveau, D. and Vandekerkhove, P. (2013), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.

**See Also**

Two multicore and cluster version [MCMCcopies.mc](#) and [MCMCcopies.cl](#), and functions doing simulation and entropy and Kullback estimation simultaneously: [EntropyParallel](#) and [EntropyParallel.cl](#)

**Examples**

```
## Toy example using the bivariate gaussian target
## with default parameters value, see target_norm_param
n = 150; nmc = 20; d=2 # bivariate example
varq=0.1 # variance of the proposal (chosen too small)
q_param=list(mean=rep(0,d),v=varq*diag(d))
## initial distribution, located in (2,2), "far" from target center (0,0)
Ptheta0 <- DrawInit(nmc, d, initpdf = "rnorm", mean = 2, sd = 1)
# simulation
s1 <- MCMCcopies(RWHM, n, nmc, Ptheta0, target_norm,
                target_norm_param, q_param, verb = FALSE)
summary(s1) # method for "pLMCMC" object
par(mfrow=c(1,2))
plot(s1) # just a path of the iid chains, method for "pLMCMC" object
hist(s1$Ptheta[,1,], col=8) # marginal 1
```



---

MCMCcopies.cl	<i>Parallel simulation of iid copies of a MCMC algorithm - cluster versions</i>
---------------	---

---

## Description

This function simulates “parallel chains” (iid copies) of a MCMC algorithm for  $n$  (time) iterations, i.e. for each chain  $k$ , the whole trajectory of the chain is generated. It returns an object of class `p1MCMC` (for parallel MCMC) holding an array of the trajectories and running information. This functions is similar to `MCMCcopies` and `MCMCcopies.mc` except that it uses HPC in a more generic way, implementing several types of HPC for running on a single, multicore computer or on a true cluster using MPI communications.

## Usage

```
MCMCcopies.cl(mcmc_algo, n=100, nmc=10, Ptheta0, target, f_param, q_param,
              cltype="PAR_SOCKET", nbnodes=4)
```

## Arguments

<code>mcmc_algo</code>	a list defining an MCMC algorithm in terms of the functions it uses, such as RWHM, see details below.
<code>n</code>	The number of (time) iterations of each single chain to run.
<code>nmc</code>	The number of iid copies of each single chain.
<code>Ptheta0</code>	A ( $nmc \times d$ ) matrix, with the $i$ th row giving a $d$ -dimensional initial theta values for the $i$ th chain.
<code>target</code>	The target density for which the MCMC algorithm is defined; may be given only up to a multiplicative constant for most MCMC. <code>target</code> must be a function such as the multidimensional gaussian <code>target_norm(x, param)</code> with argument and parameters passed like in this example.
<code>f_param</code>	A list holding all the necessary target parameters, consistent with the target definition.
<code>q_param</code>	A list holding all the necessary parameters for the proposal density of the MCMC algorithm <code>mcmc_algo</code> .
<code>cltype</code>	Character string specifying the type of cluster; currently implemented types are: "PAR_SOCKET" for socket cluster with <code>parallel</code> library, the default; "SNOW_SOCKET" for socket cluster with <code>snow</code> library, and "SNOW_RMPI" for <code>snow</code> MPI cluster with <code>Rmpi</code> library.
<code>nbnodes</code>	The number of nodes or virtual cores requested to run the <code>nmc</code> simulations in parallel. For the <code>snow</code> version, defaults to all; for the cluster version, defaults to 4.

## Details

MCMCcopies.cl simulates in parallel `nmc` iid copies of the MCMC algorithm passed in the list `mcmc_algo`, for `n` (time) iterations, and returns an object of class `p1MCMC` holding an array of the trajectories and running information.

### About parallel computing:

The `Rmpi` option is less efficient than the default option using **parallel** if you are running on a single computer. MPI communication are required only for running on a true cluster/grid.

This generic *cluster* version implementing several types of cluster for running on a single, multicore computer or on a true cluster using MPI communications may not work on all platform/OS. For instance the parallel socket cluster version does not work on Windows machines (see the **parallel** package documentation).

### About passing your MCMC algorithm:

The list `mcmc_algo` must contain the named elements:

- `name`, the name of the MCMC, such as "RWHM"
- `chain`, the function for simulation of `n` steps of a single chain
- `step`, the function for simulation of 1 step of that algorithm
- `q_pdf`, the density of the proposal
- `q_proposal`, the function that simulates a proposal

For examples, see the algorithms currently implemented: RWHM, the Random Walk Hasting-Metropolis with gaussian proposal; HMIS\_norm, an Independence Sampler HM with gaussian proposal; AMHaario, the Adaptive-Metropolis (AM) from Haario (2001); IID\_norm, a gaussian iid sampler which is merely a "fake" MCMC for testing purposes.

## Value

MCMCcopies.cl returns a list of class `p1MCMC` with items:

<code>Ptheta</code>	The <code>nmc</code> copies of chains in an array( <code>n,d,nmc</code> ) of simulated values, where 1st value ( <code>1,d,nmc</code> ) is <code>Ptheta0</code> .
<code>prob.accept</code>	The estimated rate of acceptance over all simulations.
<code>algo</code>	The MCMC algorithm name i.e. <code>mcmc_algo\$name</code> .
<code>target</code>	The target density.
<code>f_param</code>	The list holding all the target parameters.
<code>q_param</code>	The list holding all the proposal density parameters.

## Author(s)

Houssam Alrachid and Didier Chauveau.

## References

- Chauveau, D. and Vandekerkhove, P. (2013), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.
- Chauveau D. and Vandekerkhove, P. (2014), The Nearest Neighbor entropy estimate: an adequate tool for adaptive MCMC evaluation. *Preprint HAL* <http://hal.archives-ouvertes.fr/hal-01068081>.

## See Also

A simpler cluster version [MCMCcopies.mc](#), a single core version [MCMCcopies](#), and functions doing simulation and entropy and Kullback estimation simultaneously: [EntropyParallel](#) and [EntropyParallel.cl](#)

## Examples

```
## Toy example using the bivariate gaussian target

n = 150; nmc = 20; d=2 # bivariate example
varq=0.1 # variance of the proposal (chosen too small)
q_param=list(mean=rep(0,d),v=varq*diag(d))
## initial distribution, located in (2,2), "far" from target center (0,0)
Ptheta0 <- DrawInit(nmc, d, initpdf = "rnorm", mean = 2, sd = 1)
# simulations (may be compared with the singlecore version using system.time)
s1 <- MCMCcopies.cl(RWHM, n, nmc, Ptheta0, target_norm,
                  target_norm_param, q_param, nbnodes = 2)
summary(s1) # method for "pLMCMC" object

## see MCMCcopies example for plots
```

---

MCMCcopies.mc

*Simulates iid copies of a MCMC algorithm - multicore version*


---

## Description

Simulates *nmc* iid copies of a MCMC algorithm *mcmc\_algo* for *n* (time) iterations and returns an object of class *pLMCMC* (for parallel MCMC) holding an array of the trajectories and running information. This functions is similar to [MCMCcopies](#) except that it uses the **parallel** package (available in the main distribution, but not for Windows machines) to split the task between the available virtual cores on the computer.

## Usage

```
MCMCcopies.mc(mcmc_algo, n = 100, nmc = 10, Ptheta0, target, f_param, q_param,
              verb = TRUE, nbcores=detectCores())
```

**Arguments**

mcmc_algo	a list defining an MCMC algorithm in terms of the functions it uses, such as RWHM, see details below.
n	The number of (time) iterations of each single chain to run.
nmc	The number of iid copies of each single chain.
Ptheta0	A ( $nmc \times d$ ) matrix, with the $i$ th row giving a $d$ -dimensional initial theta values for the $i$ th chain.
target	The target density for which the MCMC algorithm is defined; may be given only up to a multiplicative constant for most MCMC. target must be a function such as the multidimensional gaussian <code>target_norm(x,param)</code> with argument and parameters passed like in this example.
f_param	A list holding all the necessary target parameters, consistent with the target definition.
q_param	A list holding all the necessary parameters for the proposal density of the MCMC algorithm <code>mcmc_algo</code> .
verb	Verbose mode for summarizing output during the simulation.
nbccores	Number of required (virtual) cores, defaults to all as returned by <code>detectCores()</code> .

**Details**

MCMCcopies.mc, like [MCMCcopies](#), sequentially simulates `nmc` iid copies of the MCMC algorithm passed in the list `mcmc_algo`, for `n` (time) iterations, and returns an object of class `p1MCMC` holding an array of the trajectories and running information. The list `mcmc_algo` must contain the named elements:

- `name`, the name of the MCMC, such as "RWHM"
- `chain`, the function for simulation of `n` steps of a single chain
- `step`, the function for simulation of 1 step of that algorithm
- `q_pdf`, the density of the proposal
- `q_proposal`, the function that simulates a proposal

For examples, see the algorithms currently implemented: RWHM, the Random Walk Hasting-Metropolis with gaussian proposal; HMIS\_norm, an Independence Sampler HM with gaussian proposal; AMHaario, the Adaptive-Metropolis (AM) from Haario (2001); IID\_norm, a gaussian iid sampler which is merely a "fake" MCMC for testing purposes.

**Value**

MCMCcopies returns a list of class `p1MCMC` with items:

Ptheta	The <code>nmc</code> copies of chains in an array( $n,d,nmc$ ) of simulated values, where 1st value ( $1,d,nmc$ ) is <code>Ptheta0</code> .
prob.accept	The estimated rate of acceptance over all simulations.
algo	The MCMC algorithm name i.e. <code>mcmc_algo\$name</code> .
target	The target density.
f_param	The list holding all the target parameters.
q_param	The list holding all the proposal density parameters.

**Author(s)**

Didier Chauveau.

**References**

- Chauveau, D. and Vandekerkhove, P. (2013), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.
- Chauveau D. and Vandekerkhove, P. (2014), The Nearest Neighbor entropy estimate: an adequate tool for adaptive MCMC evaluation. *Preprint HAL* <http://hal.archives-ouvertes.fr/hal-01068081>.

**See Also**

A more general cluster version [MCMCcopies.cl](#), a single core version [MCMCcopies](#), and functions doing simulation and entropy and Kullback estimation simultaneously: [EntropyParallel](#) and [EntropyParallel.cl](#)

**Examples**

```
## Toy example using the bivariate gaussian target

## not working on Windows since socket cluster not implemented
n = 150; nmc = 20; d=2 # bivariate example
varq=0.1 # variance of the proposal (chosen too small)
q_param=list(mean=rep(0,d),v=varq*diag(d))
## initial distribution, located in (2,2), "far" from target center (0,0)
Ptheta0 <- DrawInit(nmc, d, initpdf = "rnorm", mean = 2, sd = 1)
# simulations (may be compared with the singlecore version using system.time)
s1 <- MCMCcopies.mc(RWHM, n, nmc, Ptheta0, target_norm,
                  target_norm_param, q_param, nbcores = 2)
summary(s1) # method for "pLMCMC" object

## see MCMCcopies example for plots
```

---

normEntropy

*Theoretical value of the entropy for the multivariate gaussian*

---

**Description**

This function computes the entropy  $E_f[\log(f)]$  of the density of the multivariate gaussian, with parameters in a list, as it is the case for MCMC target density parameters. This function is used mostly for benchmarking entropy estimation performed by the package (using, e.g., the iid algorithm IID\_norm).

**Usage**

```
normEntropy(target_param)
```

**Arguments**

target\_param    A list of two elements: the mean target\_param\$mean and the covariance matrix target\_param\$v.

**Value**

The entropy of the Gaussian with these parameters.

**Author(s)**

Didier Chauveau.

**Examples**

```
d=2 # model dimension
mu=rep(0,d); v = diag(d) # mean and variance
target_param = list(mean=mu, v=v) # parameters
normEntropy(target_param) # the entropy
```

---

plot.KbMCMC

*Plot sequences of estimates of Kullback distance or Entropy against iterations*

---

**Description**

This S3 method for plot plots by default sequences of estimates of the Kullback distance  $K(p^t, f)$  between the (estimated) pdf of the MCMC algorithm at time  $t$ ,  $p^t$ , and the target density  $f$ , for  $t = 1$  up to the number of iterations that have been provided/computed. It can also plot the first term in the Kullback distance, i.e. the Entropy  $E_{p^t}[\log(p^t)]$ . Its argument is an object of class KbMCMC such as the one returned by, e.g., [EntropyMCMC](#).

**Usage**

```
## S3 method for class 'KbMCMC'
plot(x, Kullback = TRUE, lim = NULL, ylim = NULL,
      new.plot = TRUE, title = NULL, ...)
```

**Arguments**

x                    An object of class KbMCMC, such as the one returned by [EntropyMCMC](#).

Kullback            TRUE to plot the Kullback distance, FALSE to plot the Entropy.

lim                  for zooming over 1:lim iterations only.

ylim                y limits, passed to plot.

new.plot            set to FALSE to add the plot to an existing plot.  
 title                The title; if NULL, then a default title is displayed.  
 ...                  Further parameters passed to plot or lines.

**Value**

The graphic to plot.

**Author(s)**

Didier Chauveau.

**References**

- Chauveau, D. and Vandekerkhove, P. (2012), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, (2013) 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.
- Chauveau D. and Vandekerkhove, P. (2014), The Nearest Neighbor entropy estimate: an adequate tool for adaptive MCMC evaluation. *Preprint HAL* <http://hal.archives-ouvertes.fr/hal-01068081>.

**See Also**

[EntropyMCMC](#), [EntropyMCMC.mc](#)

**Examples**

```
## See the EntropyMCMC Examples.
```

---

plot.pIMCMC                      *Plot paths of copies of Markov chains*

---

**Description**

This function plots 2d-projections of the paths of i.i.d. copies of Markov chains output by an MCMC algorithm and stored in an object of class pIMCMC (for parallel MCMC) such as the one returned by, e.g., [MCMCcopies](#) or the multicore version [MCMCcopies.mc](#).

**Usage**

```
## S3 method for class 'pIMCMC'  
plot(x, xax = 1, yax = 2, title = NULL, cname = NULL, ...)
```

### Arguments

x	An object of class plMCMC, such as output from <a href="#">MCMCcopies</a> .
xax	Coordinate for the horizontal axis.
yax	Coordinate for the vertical axis.
title	The title; if NULL, then a default title is displayed.
cname	Coordinate base name; "var" is the default, so that coordinates are named "var1", "var2", and so on.
...	Further parameters except pch which is already used, passed to plot.

### Details

This function is currently limited to a 2D projection path of all the i.i.d. chains for the two selected coordinates. The copies of the Markov chain must be in the 3-dimensional array `s$Ptheta`.

### Value

The graphic to plot.

### Author(s)

Didier Chauveau.

### References

- Chauveau, D. and Vandekerkhove, P. (2012), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, (2013) 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.
- Chauveau D. and Vandekerkhove, P. (2014), The Nearest Neighbor entropy estimate: an adequate tool for adaptive MCMC evaluation. *Preprint HAL* <http://hal.archives-ouvertes.fr/hal-01068081>.

### See Also

[MCMCcopies](#), [MCMCcopies.mc](#), [MCMCcopies.cl](#)

### Examples

```
## See MCMCcopie Example
```



---

plottarget3d	<i>3D plot of a two-dimensional MCMC target, or any function</i>
--------------	--

---

**Description**

Utility function for the package **EntropyMCMC**, to visualize a 2-dimensional target of a MCMC algorithm, mostly for testing purpose. This uses the function `persp` from package **graphics**.

**Usage**

```
plottarget3d(zft, l, r, ms, theta, phi, ...)
```

**Arguments**

<code>zft</code>	a function, typically a 2-dimensional target of a MCMC.
<code>l, r, ms</code>	mesh boundaries and size.
<code>theta, phi</code>	angles defining the viewing direction. <i>theta</i> gives the azimuthal direction and <i>phi</i> the colatitude.
<code>...</code>	additional graphical parameters.

**Value**

Returns a 3D plot on a mesh of size  $(l, r, ms)$ .

**Author(s)**

Didier Chauveau.

---

<code>plot_Kblist</code>	<i>Plot sequences of Kullback distance estimates for comparison of several MCMC algorithms for a same target density</i>
--------------------------	--

---

**Description**

This function draws on a same plot several sequences of estimates of Kullback distances  $K(p^t, f)$ , i.e. the convergence criterion vs. time (iteration  $t$ ), for each MCMC algorithm for which the convergence criterion has been computed.

**Usage**

```
plot_Kblist(Kb, which = 1, lim = NULL, ylim = NULL)
```

**Arguments**

Kb	A list of objects of class "KbMCMC", such as the ones returned by <a href="#">EntropyMCMC</a> or <a href="#">EntropyParallel</a> , or their HPC versions.
which	Controls the level of details in the legend added to the plot (see details)
lim	for zooming over 1:lim iterations only.
ylim	limits on the $y$ axis for zooming, passed to plot.

**Details**

The purpose of this plot is to compare  $K$  MCMC algorithms (typically based on  $K$  different simulation strategies or kernels) for convergence or efficiency in estimating a same target density  $f$ . For the  $k$ th algorithm, the user has to generate the convergence criterion, i.e. the sequence  $K(p^t(k), f)$  for  $t = 1$  up to the number of iterations that has been chosen, and where  $p^t(k)$  is the estimated pdf of the algorithm at time  $t$ .

For the legend, `which=1` displays the MCMC's names together with some technical information depending on the algorithms definition (e.g. the proposal variance for the [RWHM](#) algorithm) and the method used for entropy estimation. The legend for `which=2` is shorter, only displaying the MCMC's names together with the number of parallel chains used for each, typically to compare the effect of that number for a single MCMC algorithm.

**Value**

The graphic to plot.

**Author(s)**

Didier Chauveau.

**References**

- Chauveau, D. and Vandekerkhove, P. (2012), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, (2013) 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.
- Chauveau D. and Vandekerkhove, P. (2014), The Nearest Neighbor entropy estimate: an adequate tool for adaptive MCMC evaluation. *Preprint HAL* <http://hal.archives-ouvertes.fr/hal-01068081>.

**See Also**

[EntropyMCMC](#), [EntropyMCMC.mc](#)

## Examples

```
## Toy example using the bivariate centered gaussian target
## with default parameters value, see target_norm_param
d = 2          # state space dimension
n=300; nmc=100 # number of iterations and iid Markov chains
## initial distribution, located in (2,2), "far" from target center (0,0)
Ptheta0 <- DrawInit(nmc, d, initpdf = "rnorm", mean = 2, sd = 1)

## MCMC 1: Random-Walk Hasting-Metropolis
varq=0.05 # variance of the proposal (chosen too small)
q_param=list(mean=rep(0,d),v=varq*diag(d))

## using Method 1: simulation with storage, and *then* entropy estimation
# simulation of the nmc iid chains, single core here
s1 <- MCMCcopies(RWHM, n, nmc, Ptheta0, target_norm,
                target_norm_param, q_param)
summary(s1) # method for "pLMCMC" object
e1 <- EntropyMCMC(s1) # computes Entropy and Kullback divergence

## MCMC 2: Independence Sampler with large enough gaussian proposal
varq=1; q_param <- list(mean=rep(0,d),v=varq*diag(d))

## using Method 2: simulation & estimation for each t, forgetting the past
## HPC with 2 cores here (using parallel socket cluster, not available on Windows machines)
e2 <- EntropyParallel.cl(HMIS_norm, n, nmc, Ptheta0, target_norm,
                        target_norm_param, q_param,
                        cltype="PAR SOCK", nbnodes=2)

## Compare these two MCMC algorithms
plot_Kblist(list(e1,e2)) # MCMC 2 (HMIS, red plot) converges faster.
```

---

RWHM\_chain

*Simulating MCMC single chains using MCMC algorithms*


---

## Description

These functions are used to define the elements \$chain of the MCMC algorithms that are (and must be) implemented as lists in **EntropyMCMC**. These functions are usually only called by higher-level functions, see details below.

## Usage

```
RWHM_chain(theta0, it = 100, target, f_param, q_param, q_pdf = gaussian_pdf,
            q_proposal = gaussian_proposal)
HMIS_norm_chain(theta0, it = 100, target, f_param, q_param, q_pdf = q_pdf_ISnorm,
                q_proposal = q_proposal_ISnorm)
AMHaario_chain(theta0, it = 100, target, f_param, q_param, q_pdf = gaussian_pdf,
```

```

        q_proposal = gaussian_proposal)
IID_chain(theta0 = NULL, it = 100, target, f_param, q_param = NULL, q_pdf = NULL,
          q_proposal = NULL)

```

### Arguments

<code>it</code>	the number of iterations to simulate
<code>theta0</code>	the initial position of the chain, a $d$ -dim vector
<code>target</code>	the user-defined target density
<code>f_param</code>	the parameters (hyperparameters, data) of the user-defined target density
<code>q_param</code>	the parameters of the proposal density, which structure depends on the algorithm and the proposal density chosen by the user. Defaults are for RWHM: a list with the mean and covariance matrix of the proposal. For AMHaario: a list that must contain three elements: $v$ the initial covariance matrix, $t_0$ the iteration of the end of initial stage with that matrix, and $\epsilon$ the epsilon parameter (for the nondegenerate matrix part), see Haario et. al.(2001).
<code>q_pdf</code>	the proposal density
<code>q_proposal</code>	the function simulating the proposal for the next move

### Details

Each MCMC algorithm is defined as a list with five elements, see the object RWHM for an example. The element `$chain` must provide the name of the function performing simulation of a single chain and returning that chain, with arguments that must follow the definition above. Each user can define its own MCMC starting with the algorithms provided (see also section below). These functions are thus usually called by higher-level functions like `MCMCcopies`, `EntropyParallel`, or their multicore versions, for simulating copies of MCMC chains in an automatic manner.

- `RWHM_chain` is used in `RWHM`, a standard Random-Walk Hastings-Metropolis algorithm.
- `HMIS_norm_chain` is used in `HMIS_norm`, an Independence Sampler HM with gaussian proposal
- `AMHaario_chain` is used in `AMHaario`, the Haario Adaptive Hastings-Metropolis algorithm (Haario 2001), and is provided as an example of a benchmark AMCMC.
- `IID_chain` is used in `IID_norm`, a “fake” MCMC that is just a gaussian IID sampler.

### Value

A list with elements:

<code>theta</code>	the simulated chain in an array of $it$ rows and $d$ columns (the dimension)
<code>paccept</code>	the empirical acceptance rate
<code>finalcov</code>	the last covariance matrix
<code>algo</code>	the name of the algorithm (for plot methods)

### Author(s)

Didier Chauveau.

**References**

H. Haario, E. Saksman, and J. Tamminen (2001), An adaptive Metropolis algorithm. *Bernoulli* 7, 223–242.

**See Also**

The algorithm already implemented, listed in [EntropyMCMC-package](#).

The higher level functions that use these functions for simulation: [MCMCcopies](#), [EntropyParallel](#) and their multicore versions.

---

summary.pLMCMC

*Summarizes content of a pLMCMC object holding iid copies of MCMC's*


---

**Description**

This S3 method for `summary` summarizes the content of an object of class `pLMCMC` (for parallel MCMC) as returned by, e.g., `MCMCcopies`, containing the trajectories of iid copies of trajectories from a MCMC algorithm, and its associated kernel, target and proposal densities.

**Usage**

```
## S3 method for class 'pLMCMC'
summary(object, stats = FALSE, ...)
```

**Arguments**

<code>object</code>	An object of class <code>pLMCMC</code> as returned by, e.g., <code>MCMCcopies</code> .
<code>stats</code>	print additional summary statistics for the variables over all chains.
<code>...</code>	additional arguments passed to other methods

**Value**

Returns the object associated dimensions, the overall rate of acceptance, and descriptive statistics over the variable coordinates if `stats = TRUE`.

**Author(s)**

Didier Chauveau.

**References**

- Chauveau, D. and Vandekerkhove, P. (2012), Smoothness of Metropolis-Hastings algorithm and application to entropy estimation. *ESAIM: Probability and Statistics*, **17**, (2013) 419–431. DOI: <http://dx.doi.org/10.1051/ps/2012004>
- Chauveau D. and Vandekerkhove, P. (2014), Simulation Based Nearest Neighbor Entropy Estimation for (Adaptive) MCMC Evaluation, In *JSM Proceedings, Statistical Computing Section*. Alexandria, VA: American Statistical Association. 2816–2827.

- Chauveau D. and Vandekerkhove, P. (2014), The Nearest Neighbor entropy estimate: an adequate tool for adaptive MCMC evaluation. *Preprint HAL* <http://hal.archives-ouvertes.fr/hal-01068081>.

**See Also**

[MCMCcopies](#), [MCMCcopies.mc](#)

**Examples**

```
## See Example for MCMCcopies
```

# Index

- \* **file**
    - accept\_ratio, 4
    - CollectChains, 5
    - DrawInit, 6
    - EntropyMCMC, 7
    - EntropyParallel, 9
    - MCMCcopies, 15
    - MCMCcopies.cl, 17
    - MCMCcopies.mc, 19
    - normEntropy, 21
    - plot.KbMCMC, 22
    - plot.plMCMC, 23
    - plot\_Kblist, 25
    - plottarget3d, 25
    - RWHM\_chain, 27
    - summary.plMCMC, 29
  - \* **gaussian**
    - gaussian\_pdf, 14
  - \* **package**
    - EntropyMCMC-package, 2
- accept\_ratio, 4
- AMHaario\_chain (RWHM\_chain), 27
- CollectChains, 5
- DrawInit, 6
- EntropyMCMC, 3, 7, 13, 22, 23, 26
- EntropyMCMC-package, 2
- EntropyMCMC.mc, 7, 11, 13, 23, 26
- EntropyParallel, 3, 6, 9, 9, 16, 19, 21, 26, 29
- EntropyParallel.cl, 6, 9, 16, 19, 21
- gaussian\_pdf, 14
- gaussian\_proposal (gaussian\_pdf), 14
- HMIS\_norm\_chain (RWHM\_chain), 27
- IID\_chain (RWHM\_chain), 27
- MCMCcopies, 3, 5, 6, 8–13, 15, 17, 19–21, 23, 24, 29, 30
- MCMCcopies.cl, 10, 11, 13, 16, 17, 21, 24
- MCMCcopies.mc, 6, 9, 13, 16, 19, 19, 23, 24, 30
- normEntropy, 21
- parallel, 3, 7
- plot.KbMCMC, 22
- plot.plMCMC, 23
- plot\_Kblist, 3, 25
- plottarget3d, 25
- RWHM, 26
- RWHM\_chain, 27
- summary.plMCMC, 29