Package 'elhmc'

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Type Package

Title Sampling from a Empirical Likelihood Bayesian Posterior of
Parameters Using Hamiltonian Monte Carlo

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Description A tool to draw samples from a Empirical Likelihood Bayesian posterior
of parameters using Hamiltonian Monte Carlo.

Imports emplik, plyr, stats, MASS, utils

License GPL-2

LazyData TRUE

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NeedsCompilation no

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R topics documented:

ELHMC   *Empirical Likelihood Hamiltonian Monte Carlo Sampling*

Description

This function draws samples from a Empirical Likelihood Bayesian posterior distribution of parameters using Hamiltonian Monte Carlo.

Usage

```
ELHMC(initial, data, fun, dfun, prior, dprior, n.samples = 100,
  lf.steps = 10, epsilon = 0.05, p.variance = 1, tol = 10^-5,
  detailed = FALSE, FUN, DFUN)
```

Arguments

initial	a vector containing the initial values of the parameters
data	a matrix containing the data
fun	the estimating function g. It takes in a parameter vector params as the first argument and a data point vector x as the second parameter. This function returns a vector.
dfun	a function that calculates the gradient of the estimating function g. It takes in a parameter vector params as the first argument and a data point vector x as the second argument. This function returns a matrix.
prior	a function with one argument x that returns the prior densities of the parameters of interest
dprior	a function with one argument x that returns the gradients of the log densities of the parameters of interest
n.samples	number of samples to draw
lf.steps	number of leap frog steps in each Hamiltonian Monte Carlo update
epsilon	the leap frog step size(s). This has to be a single numeric value or a vector of the same length as initial.
p.variance	the covariance matrix of a multivariate normal distribution used to generate the initial values of momentum p in Hamiltonian Monte Carlo. This can also be a single numeric value or a vector. See Details.
tol	EL tolerance
detailed	If this is set to TRUE, the function will return a list with extra information.
FUN	the same as fun but takes in a matrix X instead of a vector x and returns a matrix so that FUN(params, X)[i,] is the same as fun(params, X[i,]). Only one of FUN and fun should be provided. If both are then fun is ignored.
DFUN	the same as dfun but takes in a matrix X instead of a vector x and returns an array so that DFUN(params, X)[, , i] is the same as dfun(params, X[i,]). Only one of DFUN and dfun should be provided. If both are then dfun is ignored.

Details

Suppose there are data $x = (x_1, x_2, ..., x_n)$ where x_i takes values in R^p and follow probability distribution F. Also, F comes from a family of distributions that depends on a parameter $\theta = (\theta_1, ..., \theta_d)$ and there is a smooth function $g(x_i, \theta) = (g_1(x_i, \theta), ..., g_q(x_i, \theta))^T$ that satisfies $E_F[g(x_i, \theta)] = 0$ for $i = 1, ..., n$.

ELHMC draws samples from a Empirical Likelihood Bayesian posterior distribution of the parameter θ, given the data x as data, the smoothing function g as fun, and the gradient of g as dfun or $G(X) = (g(x_1), g(x_2), ..., g(x_n))^T$ as FUN and the gradient of G as DFUN.

Value

The function returns a list with the following elements:

samples   A matrix containing the parameter samples

acceptance.rate

       The acceptance rate

call   The matched call

If detailed = TRUE, the list contains these extra elements:

proposed   A matrix containing the proposed values at n.samaples - 1 Hamiltonian Monte Carlo updates

acceptance   A vector of TRUE/FALSE values indicates whether each proposed value is accepted

trajectory   A list with 2 elements trajectory.q and trajectory.p. These are lists of matrices contraining position and momentum values along trajectory in each Hamiltonian Monte Carlo update.

References

Chaudhuri, S., Mondal, D. and Yin, T. (2015) Hamiltonian Monte Carlo sampling in Bayesian empirical likelihood computation. *Journal of the Royal Statistical Society: Series B*.

Neal, R. (2011) MCMC for using Hamiltonian dynamics. *Handbook of Markov Chain Monte Carlo* (eds S. Brooks, A.Gelman, G. L.Jones and X.-L. Meng), pp. 113-162. New York: Taylor and Francis.

Examples

```
## Not run:
## Suppose there are four data points (1, 1), (1, -1), (-1, -1), (-1, 1)
x = rbind(c(1, 1), c(1, -1), c(-1, -1), c(-1, 1))
## If the parameter of interest is the mean, the smoothing function and
## its gradient would be
f <- function(params, x) {
 x - params
}
df <- function(params, x) {
 rbind(c(-1, 0), c(0, -1))
}
```

```
## Draw 50 samples from the Empirical Likelihood Bayesian posterior distribution
## of the mean, using initial values (0.96, 0.97) and standard normal distributions
## as priors:
normal_prior <- function(x) {
   exp(-0.5 * x[1] ^ 2) / sqrt(2 * pi) * exp(-0.5 * x[2] ^ 2) / sqrt(2 * pi)
}
normal_prior_log_gradient <- function(x) {
   -x
}
set.seed(1234)
mean.samples <- ELHMC(initial = c(0.96, 0.97), data = x, fun = f, dfun = df,
                      n.samples = 50, prior = normal_prior,
                      dprior = normal_prior_log_gradient)
plot(mean.samples$samples, type = "l", xlab = "", ylab = "")

## End(Not run)
```

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