Package: iterLap (via r-universe)

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Type Package

Title Approximate Probability Densities by Iterated Laplace
Approximations

Version 1.1-4

Depends quadprog, randtoolbox, parallel, R (>= 2.15)

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Description The iterLap (iterated Laplace approximation) algorithm
approximates a general (possibly non-normalized) probability
density on R^p, by repeated Laplace approximations to the
difference between current approximation and true density (on
log scale). The final approximation is a mixture of
multivariate normal distributions and might be used for example
as a proposal distribution for importance sampling (eg in
Bayesian applications). The algorithm can be seen as a
computational generalization of the Laplace approximation
suitable for skew or multimodal densities.

License GPL

LazyLoad yes

NeedsCompilation yes

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Repository https://bbnkmp.r-universe.dev

RemoteUrl https://github.com/cran/iterLap

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  iterLap-package   *iterLap package information*

Description

Implementation of iterLap

Details

This package implements the multiple mode Laplace approximation by Gelman and Rubin (via
function GRApprox) and the iterated Laplace approximation (via the function iterLap). Both func-
tions return objects of class mixDist, which contain the fitted mode vectors and covariance matrices.
Print and summary methods exist to display the contents of a mixDist object in human-readable
form. Function IS performs importance sampling, using a mixDist object as input parameter.

Author(s)

Bjoern Bornkamp

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References

Bornkamp, B. (2011). Approximating Probability Densities by Iterated Laplace Approximations,
Journal of Computational and Graphical Statistics, **20**(3), 656–669.

Examples

```
## banana example
banana <- function(pars, b, sigma12){
  dim <- 10
  y <- c(pars[1], pars[2]+b*(pars[1]^2-sigma12), pars[3:dim])
  cc <- c(1/sqrt(sigma12), rep(1, dim-1))
  return(-0.5*sum((y*cc)^2))
}

start <- rbind(rep(0,10),rep(-1.5,10),rep(1.5,10))
## multiple mode Laplace approximation
gr <- GRApprox(banana, start, b = 0.03, sigma12 = 100)
## print mixDist object
gr
## summary method
summary(gr)
## importance sampling using the obtained mixDist object
## using a mixture of t distributions with 10 degrees of freedom
```

```
issamp <- IS(gr, nSim=1000, df = 10, post=banana, b = 0.03,
             sigma12 = 100)
## effective sample size
issamp$ESS

## now use iterated Laplace approximation (using gr mixDist object
## from above as starting approximation)
iL <- iterLap(banana, GRobj = gr, b = 0.03, sigma12 = 100)
ISObj <- IS(iL, nSim=10000, df = 100, post=banana, b = 0.03,
            sigma12 = 100)
## residual resampling to obtain unweighted sample
sims <- resample(1000, ISObj)
plot(sims[,1], sims[,2], xlim=c(-40,40), ylim = c(-40,20))
```

GRApprox   *Gelman-Rubin mode approximation*

Description

Performs the multiple mode approximation of Gelman-Rubin (applies a Laplace approximation to each mode). The weights are determined corresponding to the height of each mode.

Usage

```
GRApprox(post, start, grad, method = c("nlminb", "nlm", "Nelder-Mead", "BFGS"),
         control = list(), ...)
```

Arguments

post	log-posterior density.
start	vector of starting values if dimension=1 otherwise matrix of starting values with the starting values in the rows
grad	gradient of log-posterior
method	Which optimizer to use
control	Control list for the chosen optimizer
...	Additional arguments for log-posterior density specified in post

Value

Produces an object of class mixDist. That a list mit entries
weights Vector of weights for individual components
means Matrix of component medians of components
sigmas List containing scaling matrices
eigenHess List containing eigen decompositions of scaling matrices
dets Vector of determinants of scaling matrix
sigmainv List containing inverse scaling matrices

Author(s)

Bjoern Bornkamp

References

Gelman, A., Carlin, J. B., Stern, H. S. & Rubin, D. B. (2003) Bayesian Data Analysis, 2nd edition, Chapman and Hall. (Chapter 12)

Bornkamp, B. (2011). Approximating Probability Densities by Iterated Laplace Approximations, *Journal of Computational and Graphical Statistics*, **20**(3), 656–669.

See Also

iterLap

Examples

```
## log-density for banana example
banana <- function(pars, b, sigma12){
  dim <- 10
  y <- c(pars[1], pars[2]+b*(pars[1]^2-sigma12), pars[3:dim])
  cc <- c(1/sqrt(sigma12), rep(1, dim-1))
  return(-0.5*sum((y*cc)^2))
}

start <- rbind(rep(0,10),rep(-1.5,10),rep(1.5,10))
## multiple mode Laplace approximation
aa <- GRApprox(banana, start, b = 0.03, sigma12 = 100)
## print mixDist object
aa
## summary method
summary(aa)
## importance sampling using the obtained mixDist object
## using a mixture of t distributions with 10 degrees of freedom
dd <- IS(aa, nSim=1000, df = 10, post=banana, b = 0.03,
         sigma12 = 100)
## effective sample size
dd$ESS
```

Importance Sampling and independence Metropolis Hastings sampling
Monte Carlo sampling using the iterated Laplace approximation.

Description

Use iterated Laplace approximation as a proposal for importance sampling or the independence Metropolis Hastings algorithm.

Usage

```
IS(obj, nSim, df = 4, post, vectorized = FALSE, cores = 1, ...)

IMH(obj, nSim, df = 4, post, vectorized = FALSE, cores = 1, ...)
```

Arguments

`obj`	an object of class "mixDist"
`nSim`	number of simulations
`df`	degrees of freedom of the mixture of t distributions proposal
`post`	log-posterior density
`vectorized`	Logical determining, whether `post` is vectorized
`cores`	number of cores you want to use to evaluate the target density (uses the mclapply function from the parallel package). For Windows machines, a value > 1 will have no effect, see mclapply help for details.
`...`	additional arguments passed to `post`.

Value

A list with entries:
`samp`: Matrix containing sampled values
`w`: Vector of weights for values in samp
`normconst`: normalization constant estimated based on importance sampling
`ESS`: Effective sample size (for IS)
`accept`: Acceptance rate (for IMH)

Author(s)

Bjoern Bornkamp

Examples

```
## see function iterLap for an example on how to use IS and IMH
```

---

iterLap   *Iterated Laplace Approximation*

Description

Iterated Laplace Approximation

Usage

```
iterLap(post, ..., GRobj = NULL, vectorized = FALSE, startVals = NULL,
        method = c("nlminb", "nlm", "Nelder-Mead", "BFGS"), control = NULL,
        nlcontrol = list())
```

Arguments

post	log-posterior density
...	additional arguments to log-posterior density
GRobj	object of class mixDist, for example resulting from a call to GRApprox
vectorized	Logical determining, whether post is vectorized
startVals	Starting values for GRApprox, when GRobj is not specified. Vector of starting values if dimension=1 otherwise matrix of starting values with the starting values in the rows
method	Type of optimizer to be used.
control	List with entries: gridSize Determines the size of the grid for each component delta Stopping criterion based on the maximum error on the grid maxDim Maximum number of components allowed (default 20) eps Stopping criterion based on normalization constant of approximation info How much information should be displayed during iterations: 0 - none, 1 - minimum information, 2 - maximum information
nlcontrol	Control list for the used optimizer.

Value

Produces an object of class mixDist: A list with entries
weights Vector of weights for individual components
means Matrix of component medians of components
sigmas List containing scaling matrices
eigenHess List containing eigen decompositions of scaling matrices
dets Vector of determinants of scaling matrix
sigmainv List containing inverse scaling matrices

Author(s)

Bjoern Bornkamp

References

Bornkamp, B. (2011). Approximating Probability Densities by Iterated Laplace Approximations, *Journal of Computational and Graphical Statistics*, **20**(3), 656–669.

Examples

```
#### banana example
banana <- function(pars, b, sigma12){
  dim <- 10
  y <- c(pars[1], pars[2]+b*(pars[1]^2-sigma12), pars[3:dim])
  cc <- c(1/sqrt(sigma12), rep(1, dim-1))
  return(-0.5*sum((y*cc)^2))
```

```
    }

    ################################################################
    ## first perform multi mode Laplace approximation
    start <- rbind(rep(0,10),rep(-1.5,10),rep(1.5,10))
    grObj <- GRApprox(banana, start, b = 0.03, sigma12 = 100)
    ## print mixDist object
    grObj
    ## summary method
    summary(grObj)
    ## importance sampling using the obtained mixDist object
    ## using a mixture of t distributions with 10 degrees of freedom
    isObj <- IS(grObj, nSim=1000, df = 10, post=banana, b = 0.03,
                sigma12 = 100)
    ## effective sample size
    isObj$ESS
    ## independence Metropolis Hastings algorithm
    imObj <- IMH(grObj, nSim=1000, df = 10, post=banana, b = 0.03,
                 sigma12 = 100)
    ## acceptance rate
    imObj$accept

    ################################################################
    ## now use iterated Laplace approximation
    ## and use Laplace approximation above as starting point
    iL <- iterLap(banana, GRobj = grObj, b = 0.03, sigma12 = 100)
    isObj2 <- IS(iL, nSim=10000, df = 100, post=banana, b = 0.03,
                 sigma12 = 100)
    ## residual resampling to obtain unweighted sample
    samples <- resample(1000, isObj2)
    ## plot samples in the first two dimensions
    plot(samples[,1], samples[,2], xlim=c(-40,40), ylim = c(-40,20))
    ## independence Metropolis algorithm
    imObj2 <- IMH(iL, nSim=1000, df = 10, post=banana, b = 0.03,
                  sigma12 = 100)
    imObj2$accept
    plot(imObj2$samp[,1], imObj2$samp[,2], xlim=c(-40,40), ylim = c(-40,20))

    ## IMH and IS can exploit multiple cores, example for two cores
    ## Not run:
    isObj3 <- IS(iL, nSim=10000, df = 100, post=banana, b = 0.03,
                 sigma12 = 100, cores = 2)

## End(Not run)
```

---

resample	*Residual resampling*

Description

Perform residual resampling to the result of importance sampling

Usage

```
resample(n, obj)
```

Arguments

n	Number of resamples to draw
obj	An object of class IS, as produced by the IS function

Value

Matrix with resampled values

Author(s)

Bjoern Bornkamp

Examples

```
## see function iterLap for an example on how to use resample
```

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