

# Package ‘Bhat’

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**Title** General Likelihood Exploration

**Version** 0.9-12

**Description** Provides functions for Maximum Likelihood Estimation, Markov Chain Monte Carlo, finding confidence intervals. The implementation is heavily based on the original Fortran source code translated to R.

**License** GPL (>= 2)

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`btrf`*Generalized inverse-logit transform*

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**Description**

maps real line onto open interval (x1, xu) using the transform  $y = (\exp(xt) * xu + x1)/(1+\exp(xt))$  where xt is a numeric vector with  $-\text{Inf} < xt < \text{Inf}$

**Usage**

```
btrf(xt, x1, xu)
```

**Arguments**

<code>xt</code>	a numeric vector
<code>x1</code>	a numeric vector of same length as x
<code>xu</code>	a numeric vector of same length as x, and $xu > x1$

**Value**

returns the inverse-logit transform (numeric) of xt

**Author(s)**

E. Georg Luebeck (FHCRC)

**See Also**

[ftrf](#)

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`dfp`*Function minimization with box-constraints*

---

**Description**

This Davidon-Fletcher-Powell optimization algorithm has been ‘hand-tuned’ for minimal setup configuration and for efficiency. It uses an internal logit-type transformation based on the pre-specified box-constraints. Therefore, it usually does not require rescaling (see help for the R `optim` function). `dfp` automatically computes step sizes for each parameter to operate with sufficient sensitivity in the functional output. Performance is comparable to the BFGS algorithm in the R function `optim`. `dfp` interfaces with `newton` to ascertain convergence, compute the eigenvalues of the Hessian, and provide 95% confidence intervals when the function to be minimized is a negative log-likelihood.

**Usage**

```
dfp(x, f, tol = 1e-05, nfcn = 0, ...)
```

**Arguments**

x	a list with components 'label' (of mode character), 'est' (the parameter vector with the initial guess), 'low' (vector with lower bounds), and 'upp' (vector with upper bounds)
f	the function that is to be minimized over the parameter vector defined by the list x
tol	a tolerance used to determine when convergence should be indicated
nfcn	number of function calls
...	other parameters to be passed to 'f'

**Details**

The dfp function minimizes a function f over the parameters specified in the input list x. The algorithm is based on Fletcher's "Switching Method" (Comp.J. 13,317 (1970))

the code has been 'transcribed' from Fortran source code into R

**Value**

list with the following components:

fmin	the function value f at the minimum
label	the labels taken from list x
est	a vector of the estimates at the minimum. dfp does not overwrite x
status	0 indicates convergence, 1 indicates non-convergence
nfcn	no. of function calls

**Note**

This function is part of the Bhat exploration tool

**Author(s)**

E. Georg Luebeck (FHCRG)

**References**

Fletcher's Switching Method (Comp.J. 13,317, 1970)

**See Also**

optim, [newton](#), [ftrf](#), [btrf](#), [logit.hessian](#)

**Examples**

```
# generate some Poisson counts on the fly
dose <- c(rep(0,50),rep(1,50),rep(5,50),rep(10,50))
data <- cbind(dose,rpois(200,20*(1+dose*.5*(1-dose*.05))))

# neg. log-likelihood of Poisson model with 'linear-quadratic' mean:
lkh <- function (x) {
  ds <- data[, 1]
  y <- data[, 2]
  g <- x[1] * (1 + ds * x[2] * (1 - x[3] * ds))
  return(sum(g - y * log(g)))
}

# for example define
x <- list(label=c("a","b","c"),est=c(10.,10.,.01),low=c(0,0,0),upp=c(100,20,.1))

# call:
results <- dfp(x,f=lkh)
```

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dqstep                      *step size generator*

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**Description**

dqstep determines the smallest steps  $ds$  from  $s$  so that  $\text{abs}(f(s+ds)-f(s))$  equals a pre-specified sensitivity

**Usage**

```
dqstep(x, f, sens)
```

**Arguments**

x	a list with components 'label' (of mode character), 'est' (the parameter vector with the initial guess), 'low' (vector with lower bounds), and 'upp' (vector with upper bounds)
f	the function that is to be minimized over the parameter vector defined by the list x
sens	target sensitivity (i.e. the value of $f(s+ds)-f(s)$ )

**Details**

uses simple quadratic interpolation

**Value**

returns a vector with the desired step sizes

**Note**

This function is part of the Bhat exploration tool

**Author(s)**

E. Georg Luebeck (FHCRC)

**See Also**

[dfp](#), [newton](#), [logit.hessian](#)

**Examples**

```
## Rosenbrock Banana function
fr <- function(x) {
  x1 <- x[1]
  x2 <- x[2]
  100 * (x2 - x1 * x1)^2 + (1 - x1)^2
}
## define
x <- list(label=c("a", "b"), est=c(1,1), low=c(0,0), upp=c(100,100))
dqstep(x, fr, sens=1)
```

---

ftrf

*Generalized logit transform*


---

**Description**

maps a bounded parameter  $x$  onto the real line according to  $y=\log((x-x_l)/(x_u-x))$ , with  $x_l < x < x_u$ . If this constraint is violated, an error occurs.  $x$  may be vector

**Usage**

```
ftrf(x, x1, xu)
```

**Arguments**

$x$	a numeric vector
$x_l$	a numeric vector of same length as $x$ with $x > x_l$
$x_u$	a numeric vector of same length as $x$ with $x < x_u$

**Value**

returns numerical vector of transforms

**Author(s)**

E. Georg Luebeck (FHCRC)

**See Also**[btrf](#)

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`global`*Random search for a global function minimum*

---

**Description**

This function generates MCMC samples from a (posterior) density function  $f$  (not necessarily normalized) in search of a global minimum of  $f$ . It uses a simple Metropolis algorithm to generate the samples. `Global` monitors the mcmc samples and returns the minimum value of  $f$ , as well as a sample covariance (`covm`) that can be used as input for the Bhat function `mymcmc`.

**Usage**

```
global(
  x,
  nlogf,
  beta = 1,
  mc = 1000,
  scl = 2,
  skip = 1,
  nfcn = 0,
  plot = FALSE
)
```

**Arguments**

<code>x</code>	a list with components 'label' (of mode character), 'est' (the parameter vector with the initial guess), 'low' (vector with lower bounds), and 'upp' (vector with upper bounds)
<code>nlogf</code>	negative log of the density function (not necessarily normalized)
<code>beta</code>	'inverse temperature' parameter
<code>mc</code>	length of MCMC search run
<code>scl</code>	not used
<code>skip</code>	number of cycles skipped for graphical output
<code>nfcn</code>	number of function calls
<code>plot</code>	logical variable. If TRUE the chain and the negative log density ( <code>nlogf</code> ) is plotted

**Details**

standard output reports a summary of the acceptance fraction, the current values of `nlogf` and the parameters for every  $(100 \cdot \text{skip})$  th cycle. Plotted chains show values only for every  $(\text{skip})$  th cycle.

**Value**

list with the following components:

fmin	minimum value of nlogf for the samples obtained
xmin	parameter values at fmin
covm	covariance matrix of differences between consecutive samples in chain

**Note**

This function is part of the Bhat package

**Author(s)**

E. Georg Luebeck (FHCRC)

**References**

too numerous to be listed here

**See Also**

[dfp](#), [newton](#), [logit.hessian](#) [mymcmc](#)

**Examples**

```
# generate some Poisson counts on the fly
dose <- c(rep(0,50),rep(1,50),rep(5,50),rep(10,50))
data <- cbind(dose,rpois(200,20*(1+dose*.5*(1-dose*0.05))))

# neg. log-likelihood of Poisson model with 'linear-quadratic' mean:
nlogf <- function (x) {
  ds <- data[, 1]
  y <- data[, 2]
  g <- x[1] * (1 + ds * x[2] * (1 - x[3] * ds))
  return(sum(g - y * log(g)))
}

# initialize global search
x <- list(label=c("a","b","c"), est=c(10, 0.25, 0.05), low=c(0,0,0), upp=c(100,10,.1))
# samples from posterior density (~exp(-nlogf)) with non-informative
# (random uniform) priors for "a", "b" and "c".
out <- global(x, nlogf, beta = 1., mc=1000, scl=2, skip=1, nfcn = 0, plot=TRUE)
# start MCMC from some other point: e.g. try x$est <- c(16,.2,.02)
```

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logit.hessian	<i>Hessian (curvature matrix)</i>
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**Description**

Numerical evaluation of the Hessian of a real function  $f: R^n \rightarrow R$  on a generalized logit scale, i.e. using transformed parameters according to  $x' = \log((x-x_l)/(x_u-x))$ , with  $x_l < x < x_u$ .

**Usage**

```
logit.hessian(
  x = x,
  f = f,
  del = rep(0.002, length(x$est)),
  dapprox = FALSE,
  nfcn = 0
)
```

**Arguments**

x	a list with components 'label' (of mode character), 'est' (the parameter vector with the initial guess), 'low' (vector with lower bounds), and 'upp' (vector with upper bounds)
f	the function for which the Hessian is to be computed at point x
del	step size on logit scale (numeric)
dapprox	logical variable. If TRUE the off-diagonal elements are set to zero. If FALSE (default) the full Hessian is computed
nfcn	number of function calls

**Details**

This version uses a symmetric grid for the numerical evaluation computation of first and second derivatives.

**Value**

returns list with	
df	first derivatives (logit scale)
ddf	Hessian (logit scale)
nfcn	number of function calls
eigen	eigen values (logit scale)

**Note**

This function is part of the Bhat exploration tool

**Author(s)**

E. Georg Luebeck (FHCRC)

**See Also**[dfp](#), [newton](#), [ftrf](#), [btrf](#), [dqstep](#)**Examples**

```
## Rosenbrock Banana function
fr <- function(x) {
  x1 <- x[1]
  x2 <- x[2]
  100 * (x2 - x1 * x1)^2 + (1 - x1)^2
}
## define
x <- list(label=c("a", "b"), est=c(1,1), low=c(-100,-100), upp=c(100,100))
logit.hessian(x, f=fr, del=dqstep(x, f=fr, sens=0.01))
## shows the differences in curvature at the minimum of the Banana
## function along principal axis (in a logit-transformed coordinate system)
```

mymcmc

*Adaptive Multivariate MCMC sampler***Description**

This function generates MCMC-based samples from a (posterior) density  $f$  (not necessarily normalized). It uses a Metropolis algorithm in conjunction with a multivariate normal proposal distribution which is updated adaptively by monitoring the correlations of successive increments of at least 2 pilot chains. The method is described in De Gunst, Dewanji and Luebeck (submitted). The adaptive method is similar to the one proposed in Gelfand and Sahu (JCGS 3:261–276, 1994).

**Usage**

```
mymcmc(
  x,
  nlogf,
  m1,
  m2 = m1,
  m3,
  scl1 = 0.5,
  scl2 = 2,
  skip = 1,
  covm = 0,
  nfcn = 0,
  plot = FALSE,
  plot.range = 0
)
```

**Arguments**

x	a list with components 'label' (of mode character), 'est' (the parameter vector with the initial guess), 'low' (vector with lower bounds), and 'upp' (vector with upper bounds)
nlogf	negative log of the density function (not necessarily normalized) for which samples are to be obtained
m1	length of first pilot run (not used when covm supplied)
m2	length of second pilot run (not used when covm supplied)
m3	length of final run
scl1	scale for covariance of mv normal proposal (second pilot run)
scl2	scale for covariance of mv normal proposal (final run)
skip	number of cycles skipped for graphical output
covm	covariance matrix for multivariate normal proposal distribution. If supplied, all pilot runs will be skipped and a run of length m3 will be produced. Useful to continue a simulation from a given point with specified covm
nfcn	number of function calls
plot	logical variable. If TRUE the chain and the negative log density (nlogf) is plotted. The first m1+m2 cycles are shown in green, other cycles in red
plot.range	[Not documented. Leave as default]

**Details**

standard output reports a summary of the acceptance fraction, the current values of nlogf and the parameters for every (100\*skip) th cycle. Plotted chains show values only for every (skip) th cycle.

**Value**

list with the following components:

f	values of nlogf for the samples obtained
mcmc	the chain (samples obtained)
covm	current covariance matrix for mv normal proposal distribution

**Note**

This function is part of the Bhat exploration tool

**Author(s)**

E. Georg Luebeck (FHCRC)

**References**

too numerous to be listed here

**See Also**

[dfp](#), [newton](#), [logit.hessian](#)

**Examples**

```
# generate some Poisson counts on the fly
dose <- c(rep(0,50),rep(1,50),rep(5,50),rep(10,50))
data <- cbind(dose,rpois(200,20*(1+dose*.5*(1-dose*0.05))))

# neg. log-likelihood of Poisson model with 'linear-quadratic' mean:
nlogf <- function (x) {
  ds <- data[, 1]
  y <- data[, 2]
  g <- x[1] * (1 + ds * x[2] * (1 - x[3] * ds))
  return(sum(g - y * log(g)))
}

# start MCMC near mle
x <- list(label=c("a","b","c"), est=c(20, 0.5, 0.05), low=c(0,0,0), upp=c(100,10,.1))
# samples from posterior density (~exp(-nlogf)) with non-informative
# (random uniform) priors for "a", "b" and "c".
out <- mymcmc(x, nlogf, m1=2000, m2=2000, m3=10000, scl1=0.5, scl2=2, skip=10, plot=TRUE)
# start MCMC from some other point: e.g. try x$est <- c(16,.2,.02)
```

---

 newton

---

*Function minimization with box-constraints*


---

**Description**

Newton-Raphson algorithm for minimizing a function  $f$  over the parameters specified in the input list  $x$ . Note, a Newton-Raphson search is very efficient in the 'quadratic region' near the optimum. In higher dimensions it tends to be rather unstable and may behave chaotically. Therefore, a (local or global) minimum should be available to begin with. Use the `optim` or `dfp` functions to search for optima.

**Usage**

```
newton(x, f, eps = 0.1, itmax = 10, relax = 0, nfcn = 0)
```

**Arguments**

<code>x</code>	a list with components 'label' (of mode character), 'est' (the parameter vector with the initial guess), 'low' (vector with lower bounds), and 'upp' (vector with upper bounds)
<code>f</code>	the function that is to be minimized over the parameter vector defined by the list <code>x</code>
<code>eps</code>	converges when all (logit-transformed) derivatives are smaller <code>eps</code>

itmax	maximum number of Newton-Raphson iterations
relax	numeric. If 0, take full Newton step, otherwise 'relax' step incrementally until a better value is found
nfcn	number of function calls

**Value**

list with the following components:

fmin	the function value $f$ at the minimum
label	the labels
est	a vector of the parameter estimates at the minimum. newton does not overwrite $x$
low	lower 95% (Wald) confidence bound
upp	upper 95% (Wald) confidence bound

The confidence bounds assume that the function  $f$  is a negative log-likelihood

**Note**

newton computes the (logit-transformed) Hessian of  $f$  (using `logit.hessian`). This function is part of the Bhat exploration tool

**Author(s)**

E. Georg Luebeck (FHCRC)

**See Also**

[dfp](#), [ftrf](#), [btrf](#), [logit.hessian](#), [plkhci](#)

**Examples**

```
# generate some Poisson counts on the fly
dose <- c(rep(0,100),rep(1,100),rep(5,100),rep(10,100))
data <- cbind(dose,rpois(400,20*(1+dose*.5*(1-dose*0.05))))

# neg. log-likelihood of Poisson model with 'linear-quadratic' mean:
lkh <- function (x) {
  ds <- data[, 1]
  y <- data[, 2]
  g <- x[1] * (1 + ds * x[2] * (1 - x[3] * ds))
  return(sum(g - y * log(g)))
}

# for example define
x <- list(label=c("a","b","c"),est=c(10.,10.,.01),low=c(0,0,0),upp=c(100,20,.1))

# calls:
r <- dfp(x, f=lkh)
```

```
x$est <- r$est
results <- newton(x,lkh)
```

---

 plkhci

*Profile-likelihood based confidence intervals*


---

### Description

function to find prob\*100% confidence intervals using profile-likelihood. Numerical solutions are obtained via a modified Newton-Raphson algorithm. The method is described in Venzon and Moolgavkar, Journal of the Royal Statistical Society, Series C vol 37, no.1, 1988, pp. 87-94.

### Usage

```
plkhci(x, nlogf, label, prob = 0.95, eps = 0.001, nmax = 10, nfcn = 0)
```

### Arguments

x	a list with components 'label' (of mode character), 'est' (the parameter vector with the initial guess), 'low' (vector with lower bounds), and 'upp' (vector with upper bounds)
nlogf	the negative log of the density function (not necessarily normalized) for which samples are to be obtained
label	parameter for which confidence bounds are computed
prob	probability associated with the confidence interval
eps	a numerical value. Convergence results when all (logit-transformed) derivatives are smaller eps
nmax	maximum number of Newton-Raphson iterations in each direction
nfcn	number of function calls

### Value

2 component vector giving lower and upper p% confidence bounds

### Note

At this point, only a single parameter label can be passed to plkhci. This function is part of the Bhat exploration tool

### Author(s)

E. Georg Luebeck (FHCR)

### See Also

[dfp](#), [newton](#), [logit.hessian](#)

**Examples**

```
# generate some Poisson counts on the fly
dose <- c(rep(0,50),rep(1,50),rep(5,50),rep(10,50))
data <- cbind(dose,rpois(200,20*(1+dose*.5*(1-dose*0.05))))

# neg. log-likelihood of Poisson model with 'linear-quadratic' mean:
nlogf <- function (x) {
  ds <- data[, 1]
  y <- data[, 2]
  g <- x[1] * (1 + ds * x[2] * (1 - x[3] * ds))
  return(sum(g - y * log(g)))
}

# for example define
x <- list(label=c("a","b","c"),est=c(10.,10.,.01),low=c(0,0,0),upp=c(100,20,.1))

# get MLEs using dfp:
r <- dfp(x,f=nlogf)
x$est <- r$est
plkhci(x,nlogf,"a")
plkhci(x,nlogf,"b")
plkhci(x,nlogf,"c")
# e.g. 90% confidence bounds for "c"
plkhci(x,nlogf,"c",prob=0.9)
```

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