

# Numerical optimization II

Woojoo Lee

## Some optimization functions in R

nlm, optim, optimize, nlminb, constrOptim etc



nlm : non-linear minimization

`nlm {stats}`

Non-Linear Minimization

### Description

This function carries out a minimization of the function `f` using a Newton-type algorithm. See the references for detail

### Usage

```
nlm(f, p, ..., hessian = FALSE, typsize = rep(1, length(p)),  
     fscale = 1, print.level = 0, ndigit = 12, gradtol = 1e-6,  
     stepmax = max(1000 * sqrt(sum((p/typsize)^2)), 1000),  
     steptol = 1e-6, iterlim = 100, check.analyticals = TRUE)
```

### Arguments

- `f` the function to be minimized, returning a single numeric value. This should be a function with first argument.
- If the function value has an attribute called `gradient` or both `gradient` and `hessian` attributes, these will be used. [deriv](#) returns a function with suitable `gradient` attribute and optionally a `hessian` attribute.
- `p` starting parameter values for the minimization.
- `...` additional arguments to be passed to `f`.

## R-example

nlm uses finite differences in its default mode.  
If you provide the derivatives, nlm works better !

```
f <- function(x, a) sum((x-a)^2)
nlm(f, c(10,10), a = c(3,5))
f <- function(x, a)
{
  res <- sum((x-a)^2)
  attr(res, "gradient") <- 2*(x-a)
  res
}
nlm(f, c(10,10), a = c(3,5))
```

Given  $x$ , find  $\mu$  and  $\sigma$  maximizing

$$\ell(\mu, \sigma) = n \log(\sigma) - \sum_{i=1}^n \log(\sigma^2 + (x_i - \mu)^2)$$

```
ell <- function(theta,x) {  
  mu<-theta[1]  
  sigma<-theta[2]  
  n<-length(x)  
  res<--n*log(sigma)+sum(log(sigma^2+(x-mu)^2))
```

```
  denom<-(sigma^2+(x-mu)^2)  
  deriv1<-sum(-2*(x-mu)/denom)  
  deriv2<--n/sigma+ sum(2*sigma/denom)
```

```
  attr(res,"gradient")<-c(deriv1,deriv2)  
  return(res)  
}
```

```
x<-rcauchy(100)  
out<-nlm(ell, c(-0.5,1), x=x)  
out
```

# optim

General-purpose optimization based on Nelder–Mead, quasi-Newton and conjugate-gradient algorithms.

## Usage

```
optim(par, fn, gr = NULL, ...,  
      method = c("Nelder-Mead", "BFGS", "CG", "L-BFGS-B", "SANN",  
                 "Brent"),  
      lower = -Inf, upper = Inf,  
      control = list(), hessian = FALSE)
```

```
optimHess(par, fn, gr = NULL, ..., control = list())
```

## Arguments

<code>par</code>	Initial values for the parameters to be optimized over.
<code>fn</code>	A function to be minimized (or maximized), with first argument the vector of parameters over which minimization is to take place. It should return a scalar result.
<code>gr</code>	A function to return the gradient for the "BFGS", "CG" and "L-BFGS-B" methods. If it is <code>NULL</code> , a finite-difference approximation will be used.  For the "SANN" method it specifies a function to generate a new candidate point. If it is <code>NULL</code> a default Gaussian Markov kernel is used.
<code>...</code>	Further arguments to be passed to <code>fn</code> and <code>gr</code> .
<code>method</code>	The method to be used. See 'Details'. Can be abbreviated.
<code>lower, upper</code>	Bounds on the variables for the "L-BFGS-B" method, or bounds in which to <i>search</i> for method "Brent".
<code>control</code>	A list of control parameters. See 'Details'.

## An example from "?optim"

```
fr <- function(x) { ## Rosenbrock Banana function
  x1 <- x[1]
  x2 <- x[2]
  100 * (x2 - x1 * x1)^2 + (1 - x1)^2
}
grr <- function(x) { ## Gradient of 'fr'
  x1 <- x[1]
  x2 <- x[2]
  c(-400 * x1 * (x2 - x1 * x1) - 2 * (1 - x1),
    200 * (x2 - x1 * x1))
}
optim(c(-1.2,1), fr)
(res <- optim(c(-1.2,1), fr, grr, method = "BFGS"))
optimHess(res$par, fr, grr)
optim(c(-1.2,1), fr, NULL, method = "BFGS", hessian = TRUE)
## These do not converge in the default number of steps
optim(c(-1.2,1), fr, grr, method = "CG")
optim(c(-1.2,1), fr, grr, method = "CG", control = list(type =
2))
```

## Useful reference

Boyd, S. and Vandenberghe, L. (2004)  
Convex Optimization, Cambridge University Press