

Jacobian Calculations for nls()

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Contents

ISSUES	1
TODOS (mostly from nlsrc vignette nlsrc-devdoc.Rmd)	1
Jacobians in nls()	2
An example problem	2
Tools for Jacobians	2
numericDeriv() original version from base R	2
numericDeriv() alternative pure-R version	5
Symbolic methods from nlsrc	8
numDeriv package	10
Comparisons	10
Performance results for different computing environments	12
Discussion of derivative computation for nonlinear least squares	12
Nomenclature	12
Numerical approximation near constraints	13
A case where the initial Jacobian is singular	13
Appendix 1: Base R numericDeriv code	19
From nlsrc.R	19
From nlsrc.c	20
Appendix 2: numericDeriv() from nlsrc package (all in R)	22

ISSUES

- ExDerivs.R file causes a number of failures in the ORIGINAL numericDeriv.
- Need to verify nlsrc:: version of numericDeriv() matches all cases of nlspkg:: version
- Do we need to get a model frame? How? and How to use it?

TODOS (mostly from nlsrc vignette nlsrc-devdoc.Rmd)

- how to insert numerical derivatives when Deriv unable to get result (nlsrc)

- approximations for `jacfn` beyond fwd approximation. How to specify??
- how to force numerical approximations in `nlfb()` in a manner consistent with that used in `optimx::optimr()`, that is, to surround the name of `jacfn` with quotes if it is a numerical approximation, or to provide a logical control to `nlxb()` for this purpose.

Jacobians in `nls()`

This document source is in file **DerivsNLS.Rmd**.

`nls()` and other nonlinear least squares programs in R need a Jacobian matrix calculated at the current set of trial nonlinear model parameters to set up the Gauss-Newton equations or their stabilized modifications in methods such as that of Marquardt (Marquardt (1963)). Unfortunately, `nls()` calls the Jacobian the “gradient,” and uses function `numericDeriv()` to compute them. This document is an attempt to describe different ways to compute the Jacobian for use in `nls()` and related software, and to evaluate these approaches from several perspectives.

In evaluating performance, we need to know the conditions under which the evaluation was conducted. Thus the computations included in this document, which is built using **Rmarkdown**, are specific to the computer in which the document is processed. We will add tables that give the results for different computing environments at the bottom.

An example problem

We will use the Hobbs weed infestation problem (Nash (1979), page 120).

```
# Data for Hobbs problem
ydat <- c(5.308, 7.24, 9.638, 12.866, 17.069, 23.192, 31.443,
          38.558, 50.156, 62.948, 75.995, 91.972) # for testing
tdat <- seq_along(ydat) # for testing

# A simple starting vector -- must have named parameters for nlxb, nls, wrapnlsr.
start1 <- c(b1=1, b2=1, b3=1)
eunsc <- y ~ b1/(1+b2*exp(-b3*tt)) # formula -- display structure with str(eunsc)
# Can we convert a string form of this "model" to a formula
ceunsc <- " y ~ b1/(1+b2*exp(-b3*tt))" # This will give character form: str(ceunsc)
# Next line will be TRUE if we have made the conversion OK
print(as.formula(ceunsc)==eunsc)

## [1] TRUE

weeddata1 <- data.frame(y=ydat, tt=tdat) ## LOCAL DATA IN DATA FRAMES
weedenv <- list2env(weeddata1) ## Put data in an Environment
# Add the parameter data as "variables"
weedenv$b1 <- start1[[1]]; weedenv$b2 <- start1[[2]]; weedenv$b3 <- start1[[3]]
# Display content of the Environment with ## ls.str(weedenv)
# We are now set up for computations
```

Tools for Jacobians

There are a number of ways to get the Jacobian in R.

`numericDeriv()` original version from base R

`numericDeriv` is the R function used by `nls()` to evaluate Jacobians for its Gauss-Newton equations. The R source code is in the file `nls.R`. It calls a C function `numeric_deriv` in `nls.c`. These have been extracted

in an R package form as `nlspkg` by Duncan Murdoch as described in our document **PkgFromRbase.Rmd: Making a package from base R files**, and we will use that version.

In the following we will test and time `numericDeriv()` along with various of its options.

```
rexpr<-call("-",eunsc[[3]], eunsc[[2]]) # Generate the residual "call"
res0<-eval(rexpr, weedenv) # Get the residuals
print(res0) # the base residuals

## [1] -4.576941 -6.359203 -8.685426 -11.883986 -16.075693 -22.194473
## [7] -30.443911 -37.558335 -49.156123 -61.948045 -74.995017 -90.972006
cat("Sumsquares at 1,1,1 is ",sum(res0^2),"\n")

## Sumsquares at 1,1,1 is 23520.58

rexpr<-call("-",eunsc[[3]], eunsc[[2]]) # This is the "call" that computes the residual
## Try the numericDeriv option
theta<-names(start1)
## suppressMessages(library(nlspkg))
suppressMessages(ndnls<-nlspkg::numericDeriv(rexpr, theta, rho=weedenv))
print(ndnls)

## [1] -4.576941 -6.359203 -8.685426 -11.883986 -16.075693 -22.194473
## [7] -30.443911 -37.558335 -49.156123 -61.948045 -74.995017 -90.972006
## attr("gradient")
##          [,1]          [,2]          [,3]
## [1,] 0.7310585 -1.966119e-01 0.1966118813
## [2,] 0.8807971 -1.049936e-01 0.2099871635
## [3,] 0.9525741 -4.517674e-02 0.1355299950
## [4,] 0.9820137 -1.766276e-02 0.0706508160
## [5,] 0.9933071 -6.648064e-03 0.0332403183
## [6,] 0.9975274 -2.466440e-03 0.0147991180
## [7,] 0.9990890 -9.102821e-04 0.0063714981
## [8,] 0.9996643 -3.356934e-04 0.0026817322
## [9,] 0.9998765 -1.235008e-04 0.0011105537
## [10,] 0.9999547 -4.529953e-05 0.0004539490
## [11,] 0.9999828 -1.716614e-05 0.0001831055
## [12,] 0.9999943 -5.722046e-06 0.0000743866
print(sum(ndnls^2))

## [1] 23520.58

tndnls<-microbenchmark(ndnls<-nlspkg::numericDeriv(rexpr, theta, rho=weedenv))
print(tndnls)

## Unit: microseconds
##                                expr    min      lq
## ndnls <- nlspkg::numericDeriv(rexpr, theta, rho = weedenv) 10.37 10.771
##      mean median    uq    max neval
## 11.74108 11.061 11.48 66.357   100

## numericDeriv also has central difference option, as well as choice of eps parameter
## Central diff
ndnlsc<-nlspkg::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE)
print(ndnlsc)

## [1] -4.576941 -6.359203 -8.685426 -11.883986 -16.075693 -22.194473
```

```
## [7] -30.443911 -37.558335 -49.156123 -61.948045 -74.995017 -90.972006
## attr("gradient")
##           [,1]           [,2]           [,3]
## [1,] 0.7310586 -1.966119e-01 1.966119e-01
## [2,] 0.8807971 -1.049936e-01 2.099872e-01
## [3,] 0.9525741 -4.517666e-02 1.355300e-01
## [4,] 0.9820138 -1.766271e-02 7.065082e-02
## [5,] 0.9933071 -6.648057e-03 3.324028e-02
## [6,] 0.9975274 -2.466509e-03 1.479906e-02
## [7,] 0.9990889 -9.102211e-04 6.371548e-03
## [8,] 0.9996647 -3.352378e-04 2.681902e-03
## [9,] 0.9998766 -1.233799e-04 1.110414e-03
## [10,] 0.9999546 -4.539623e-05 4.539581e-04
## [11,] 0.9999833 -1.670090e-05 1.837134e-04
## [12,] 0.9999939 -6.143885e-06 7.372897e-05

print(sum(ndnlsc^2))

## [1] 23520.58

tndnlsc<-microbenchmark(ndnlsc<-nlspkg::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE))
print(tndnlsc)

## Unit: microseconds
##
##           expr
## ndnlsc <- nlspkg::numericDeriv(rexpr, theta, rho = weedenv, central = TRUE)
##   min      lq    mean median      uq    max neval
## 12.957 13.257 13.97593 13.457 13.7985 53.787   100

## Forward diff with smaller eps
ndnlsc<-nlspkg::numericDeriv(rexpr, theta, rho=weedenv, eps=1e-10)
print(ndnlsc)

## [1] -4.576941 -6.359203 -8.685426 -11.883986 -16.075693 -22.194473
## [7] -30.443911 -37.558335 -49.156123 -61.948045 -74.995017 -90.972006
## attr("gradient")
##           [,1]           [,2]           [,3]
## [1,] 0.7310597 -0.1966160568 0.1966071750
## [2,] 0.8807977 -0.1049915710 0.2099920238
## [3,] 0.9525714 -0.0451905180 0.1355182633
## [4,] 0.9820056 -0.0176747506 0.0706457115
## [5,] 0.9933032 -0.0066435746 0.0332534000
## [6,] 0.9975309 -0.0024513724 0.0148148160
## [7,] 0.9990941 -0.0009237056 0.0063593575
## [8,] 0.9996626 -0.0003552714 0.0026290081
## [9,] 0.9998757 -0.0001421085 0.0011368684
## [10,] 0.9999468 0.0000000000 0.0004973799
## [11,] 0.9998757 -0.0001421085 0.0001421085
## [12,] 1.0000178 0.0000000000 0.0001421085

print(sum(ndnlsc^2))

## [1] 23520.58

tndnlsc<-microbenchmark(ndnlsc<-nlspkg::numericDeriv(rexpr, theta, rho=weedenv, eps=1e-10))
print(tndnlsc)

## Unit: microseconds
```

```
##                                     expr   min
## ndnlscx <- nls pkg::numericDeriv(rexpr, theta, rho = weedenv, eps = 1e-10) 9.197
##    lq      mean median    uq      max neval
##  9.41 10.11952 9.5535 9.8585 39.722   100
```

```
## Central diff with smaller eps
```

```
ndnlscx<-nls pkg::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE, eps=1e-10)
print(ndnlscx)
```

```
## [1] -4.576941 -6.359203 -8.685426 -11.883986 -16.075693 -22.194473
## [7] -30.443911 -37.558335 -49.156123 -61.948045 -74.995017 -90.972006
```

```
## attr("gradient")
```

```
##           [,1]           [,2]           [,3]
## [1,] 0.7310597 -1.966116e-01 1.966116e-01
## [2,] 0.8807977 -1.049916e-01 2.099876e-01
## [3,] 0.9525714 -4.518164e-02 1.355271e-01
## [4,] 0.9820145 -1.766587e-02 7.065459e-02
## [5,] 0.9933032 -6.643575e-03 3.325340e-02
## [6,] 0.9975309 -2.451372e-03 1.481482e-02
## [7,] 0.9990941 -9.059420e-04 6.359357e-03
## [8,] 0.9996981 -3.197442e-04 2.664535e-03
## [9,] 0.9998757 -1.421085e-04 1.136868e-03
## [10,] 0.9999468 -3.552714e-05 4.618528e-04
## [11,] 0.9999468 -7.105427e-05 2.131628e-04
## [12,] 1.0000178 0.000000e+00 7.105427e-05
```

```
print(sum(ndnlscx^2))
```

```
## [1] 23520.58
```

```
tndnlscx<-microbenchmark(ndnlscx<-nls pkg::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE, eps=1e-10),
print(tndnlscx))
```

```
## Unit: microseconds
```

```
##                                     expr
## ndnlscx <- nls pkg::numericDeriv(rexpr, theta, rho = weedenv,          central = TRUE, eps = 1e-10)
##    min      lq      mean median    uq      max neval
## 11.854 12.2725 13.06421 12.4415 12.71 44.404   100
```

```
## Add dir parameter -- the direction of the parameter shift
```

```
ndnlscd<-nls pkg::numericDeriv(rexpr, theta, rho=weedenv, dir=-1)
# Does dir make a difference? This might be accidental for forward difference.
max(abs(ndnlscd-ndnlscx))
```

```
## [1] 0
```

```
ndnlscd<-nls pkg::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE, dir=-1)
# Does dir make a difference? For central diff it should NOT!
max(abs(ndnlscd-ndnlscx))
```

```
## [1] 0
```

numericDeriv() alternative pure-R version

This version (see Appendix 2) has C code replaced with R equivalents.

```
## Try ExDerivs.R ??
```

```
suppressMessages(andnls<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv))
# print(andnls); print(sum(andnls^2))
```

```

tandnls<-microbenchmark(andnls<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv))
print(tandnls)

## Unit: microseconds
##                                expr    min      lq
##  andnls <- nlsalt::numericDeriv(rexpr, theta, rho = weedenv) 30.66 31.659
##      mean median      uq    max neval
## 35.76053 32.3275 33.3205 82.424   100

## numericDeriv also has central difference option, as well as choice of eps parameter
## Central diff
andnls<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE)
ndnls<-nls pkg::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE)
# print(andnls); print(sum(andnls^2))
tandnls<-microbenchmark(andnls<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE))
print(tandnls)

## Unit: microseconds
##                                expr
##  andnls <- nlsalt::numericDeriv(rexpr, theta, rho = weedenv,      central = TRUE)
##      min      lq      mean median      uq    max neval
## 40.792 41.5425 43.47624 41.9825 42.7615 89.09   100

## Forward diff with smaller eps
andnlsx<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, eps=1e-10)
ndnlsx<-nls pkg::numericDeriv(rexpr, theta, rho=weedenv, eps=1e-10)
# print(andnlsx); print(sum(andnlsx^2))
tandnlsx<-microbenchmark(andnlsx<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, eps=1e-10))
print(tandnlsx)

## Unit: microseconds
##                                expr
##  andnlsx <- nlsalt::numericDeriv(rexpr, theta, rho = weedenv,      eps = 1e-10)
##      min      lq      mean median      uq    max neval
## 29.715 30.404 31.51655 30.785 31.1455 75.795   100

## Central diff with smaller eps
andnlsx<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE, eps=1e-10)
ndnlsx<-nls pkg::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE, eps=1e-10)
# print(andnlsx) ; print(sum(andnlsx^2))
tandnlsx<-microbenchmark(andnlsx<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE, eps=1e-10))
print(tandnlsx)

## Unit: microseconds
##                                expr
##  andnlsx <- nlsalt::numericDeriv(rexpr, theta, rho = weedenv,      central = TRUE, eps = 1e-10)
##      min      lq      mean median      uq    max neval
## 40.005 41.0585 43.11109 41.58 42.5515 118.096   100

## Comparisons for Jacobian between nls pkg and nlsalt i.e. R&C vs just R
max(abs(attr(ndnls, "gradient")-attr(andnls, "gradient")))

## [1] 0

max(abs(attr(ndnls, "gradient")-attr(andnls, "gradient")))

## [1] 0

```

```

max(abs(attr(ndnlsx, "gradient")-attr(Andnlsx,"gradient")))

## [1] 0

max(abs(attr(ndnlsx, "gradient")-attr(Andnlsx,"gradient")))

## [1] 0

## Using dir
cat("eps (regular) = ",.Machine$double.eps^(1/2),
    "   eps (central) =",.Machine$double.eps^(1/3),"\\n")

## eps (regular) = 1.490116e-08   eps (central) = 6.055454e-06
Andnlsd<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, dir=-1)
max(abs(attr(Andnlsd, "gradient")-attr(ndnls,"gradient")))

## [1] 9.536743e-07

max(abs(attr(Andnlsd, "gradient")-attr(Andnls,"gradient")))

## [1] 9.536743e-07

Andnlsd<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE, dir=-1)
max(abs(attr(Andnlsd, "gradient")-attr(ndnls,"gradient")))

## [1] 0

## Try comparisons over different eps sizes
for (ee in 3:10){
  Andnlsd<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, dir=-1, eps=10^(-ee))
  Andnlsd<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE, dir=-1, eps=10^(-ee))
  Andnlsx<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, eps=10^(-ee))
  Andnlsx<-nlsalt::numericDeriv(rexpr, theta, rho=weedenv, central=TRUE, eps=10^(-ee))
  cat("Regular diff, eps=10^(-",ee,"):",
      max(abs(attr(Andnlsd,"gradient")-attr(Andnlsx,"gradient"))),"\\n")
  cat("Central diff, eps=10^(-",ee,"):",
      max(abs(attr(Andnlsd,"gradient")-attr(Andnlsx,"gradient"))),"\\n")
}

## Regular diff, eps=10^(- 3 ): 0.0003680243
## Central diff, eps=10^(- 3 ): 0
## Regular diff, eps=10^(- 4 ): 3.680242e-05
## Central diff, eps=10^(- 4 ): 0
## Regular diff, eps=10^(- 5 ): 3.680256e-06
## Central diff, eps=10^(- 5 ): 0
## Regular diff, eps=10^(- 6 ): 3.677059e-07
## Central diff, eps=10^(- 6 ): 0
## Regular diff, eps=10^(- 7 ): 1.421085e-07
## Central diff, eps=10^(- 7 ): 0
## Regular diff, eps=10^(- 8 ): 1.421085e-06
## Central diff, eps=10^(- 8 ): 0
## Regular diff, eps=10^(- 9 ): 1.421085e-05
## Central diff, eps=10^(- 9 ): 0
## Regular diff, eps=10^(- 10 ): 0.0001421085
## Central diff, eps=10^(- 10 ): 0

```

The `dir` parameter allows us to use a backward difference for the derivative. This appears in `nlsModel()` for the case where a parameter is on an upper bound for the case `algorithm="port"`. It does not check for

nearness to the bound, and for the lower bound assumes that we are stepping AWAY from the bound in the default direction (`dir=+1`). None of the code addresses the issue where bounds are closer together than the step used for the finite difference, so there are situations where we could crash the code. Nor does the code check if the central difference is specified when near a bound.

- In the case of lower bounds, a central difference can overstep the bound when a parameter is “close” or on the bound.
- In the case of an upper bound, changing the `dir` will not change the central derivative approximation expression and steps in both forward and backward directions of the parameter are taken.

Symbolic methods from `nlsr`

The package `nlsr` has a function `model2rjfun()` that converts an expression describing how the residual functions are computed into an R function that computes the residuals at a particular set of parameters and sets the **attribute** “gradient” of the vector of residual values to the Jacobian at the particular set of parameters.

```
# nlsr has function model2rjfun. We can evaluate just the residuals
res0<-model2rjfun(eunsc, start1, data=weeddata1, jacobian=FALSE)
res0(start1)

## [1] -4.576941 -6.359203 -8.685426 -11.883986 -16.075693 -22.194473
## [7] -30.443911 -37.558335 -49.156123 -61.948045 -74.995017 -90.972006

# or the residuals and jacobian
## nlsr::model2rjfun forms a function with gradient (jacobian) attribute
funsc <- model2rjfun(eunsc, start1, data=weeddata1) # from nlsr: creates a function
tmodel2rjfun <- microbenchmark(model2rjfun(eunsc, start1, data=weeddata1))
print(tmodel2rjfun)

## Unit: microseconds
##                  expr      min       lq      mean median
## model2rjfun(eunsc, start1, data = weeddata1) 81.553 82.785 87.26409 83.616
##          uq      max neval
## 85.263 213.224   100

print(funsc)

## function(prm) {
##   if (is.null(names(prm)))
##     names(prm) <- names(pvec)
##   localdata <- list2env(as.list(prm), parent = data)
##   eval(residexpr, envir = localdata)
##   # Saves Jacobian matrix as "gradient" attribute (consistent with deriv())
## }
## <bytecode: 0x55d5ea5dcae8>
## <environment: 0x55d5f107c1c0>

print(funsc(start1))

## [1] -4.576941 -6.359203 -8.685426 -11.883986 -16.075693 -22.194473
## [7] -30.443911 -37.558335 -49.156123 -61.948045 -74.995017 -90.972006
## attr(,"gradient")
##          b1          b2          b3
## [1,] 0.7310586 -1.966119e-01 1.966119e-01
## [2,] 0.8807971 -1.049936e-01 2.099872e-01
## [3,] 0.9525741 -4.517666e-02 1.355300e-01
## [4,] 0.9820138 -1.766271e-02 7.065082e-02
```



```

## [5,] 0.9933071 -6.648057e-03 3.324028e-02
## [6,] 0.9975274 -2.466509e-03 1.479906e-02
## [7,] 0.9990889 -9.102212e-04 6.371548e-03
## [8,] 0.9996646 -3.352377e-04 2.681901e-03
## [9,] 0.9998766 -1.233793e-04 1.110414e-03
## [10,] 0.9999546 -4.539581e-05 4.539581e-04
## [11,] 0.9999833 -1.670114e-05 1.837126e-04
## [12,] 0.9999939 -6.144137e-06 7.372964e-05

print(environment(funsc))

## <environment: 0x55d5f107c1c0>
print(ls.str(environment(funsc)))

## data : <environment: 0x55d5f128f210>
## jacobian : logi TRUE
## modelformula : Class 'formula' language y ~ b1/(1 + b2 * exp(-b3 * tt))
## pvec : Named num [1:3] 1 1 1
## residexpr : expression({ .expr3 <- exp(-b3 * tt) .expr5 <- 1 + b2 * .expr3 .expr10 <- .expr5^2
## rjfun : function (prm)
## testresult : logi TRUE
print(ls(environment(funsc)$data))

## [1] "tt" "y"
eval(eunsc, environment(funsc))

## y ~ b1/(1 + b2 * exp(-b3 * tt))
vfunsc<-funsc(start1)
print(vfunsc)

## [1] -4.576941 -6.359203 -8.685426 -11.883986 -16.075693 -22.194473
## [7] -30.443911 -37.558335 -49.156123 -61.948045 -74.995017 -90.972006
## attr(,"gradient")
##          b1          b2          b3
## [1,] 0.7310586 -1.966119e-01 1.966119e-01
## [2,] 0.8807971 -1.049936e-01 2.099872e-01
## [3,] 0.9525741 -4.517666e-02 1.355300e-01
## [4,] 0.9820138 -1.766271e-02 7.065082e-02
## [5,] 0.9933071 -6.648057e-03 3.324028e-02
## [6,] 0.9975274 -2.466509e-03 1.479906e-02
## [7,] 0.9990889 -9.102212e-04 6.371548e-03
## [8,] 0.9996646 -3.352377e-04 2.681901e-03
## [9,] 0.9998766 -1.233793e-04 1.110414e-03
## [10,] 0.9999546 -4.539581e-05 4.539581e-04
## [11,] 0.9999833 -1.670114e-05 1.837126e-04
## [12,] 0.9999939 -6.144137e-06 7.372964e-05

tfunsc<-microbenchmark(funsc(start1))
print(tfunsc)

## Unit: microseconds
##          expr    min      lq      mean    median      uq    max neval
## funsc(start1) 15.35 16.699 17.63718 16.8945 17.231 48.403   100

```

numDeriv package

The package `numDeriv` includes a function `jacobian()` that acts on a user function `resid()` to produce the Jacobian at a set of parameters by several choices of approximation.

```
# We use the residual function (without gradient attribute) from nlsc
```

```
jnlsc<-jacobian(res0, start1)
jnlsc
```

```
##           [,1]           [,2]           [,3]
## [1,] 0.7310586 -1.966119e-01 1.966119e-01
## [2,] 0.8807971 -1.049936e-01 2.099872e-01
## [3,] 0.9525741 -4.517666e-02 1.355300e-01
## [4,] 0.9820138 -1.766271e-02 7.065082e-02
## [5,] 0.9933071 -6.648057e-03 3.324028e-02
## [6,] 0.9975274 -2.466509e-03 1.479906e-02
## [7,] 0.9990889 -9.102212e-04 6.371548e-03
## [8,] 0.9996647 -3.352378e-04 2.681902e-03
## [9,] 0.9998766 -1.233791e-04 1.110414e-03
## [10,] 0.9999546 -4.539572e-05 4.539580e-04
## [11,] 0.9999833 -1.670116e-05 1.837129e-04
## [12,] 0.9999939 -6.144205e-06 7.373002e-05
```

```
# Timings of the analytic jacobian calculations
```

```
tjnlsc<-microbenchmark(jnlsc<-jacobian(res0, start1))
print(tjnlsc)
```

```
## Unit: microseconds
```

```
##           expr      min       lq      mean   median      uq
## jnlsc <- jacobian(res0, start1) 344.413 351.9415 360.6021 355.1935 362.016
##           max neval
## 497.917   100
```

Note that the manual pages for `numDeriv` offer many options for the functions in the package. At 2021-5-27 we have yet to explore these.

Comparisons

In the following, we are comparing to `vfunsc`, which is the evaluated residual vector at `start1=c(1,1,1)` with “gradient” attribute (jacobian) included, as developed using package `nlsc`. This is taken as the “correct” result, even though it is possible that the generated order of calculations may introduce inaccuracies in the supposedly analytic derivatives.

`numericDeriv` computes a similar structure (residuals with “gradient” attribute): `ndnlsc`: the forward difference result with default `eps` ($1e-07$ according to manual) `ndnlsc2`: Central difference with default `eps` `ndnlscx`: Forward difference with smaller `eps=1e-10` `ndnlscx2`: Central difference with smaller `eps=1e-10`

`jnlsc`: `numDeriv::jacobian()` result with default settings.

```
## Matrix comparisons
```

```
attr(ndnls, "gradient")-attr(vfunsc, "gradient")
```

```
##           b1           b2           b3
## [1,] -4.066995e-08 -7.619266e-09 -5.198538e-08
## [2,] 1.016833e-08 3.631656e-09 -7.263312e-09
## [3,] 7.050552e-09 -8.473015e-08 1.577186e-08
## [4,] -8.764533e-08 -5.738229e-08 -8.889419e-09
```

```
## [5,] -3.542825e-08 -6.988878e-09 3.494439e-08
## [6,] -1.592723e-08 6.909055e-08 6.229383e-08
## [7,] 5.380365e-08 -6.095489e-08 -5.015294e-08
## [8,] -3.432289e-07 -4.556886e-07 -1.691883e-07
## [9,] -1.062480e-07 -1.214742e-07 1.395936e-07
## [10,] 9.833867e-08 9.627771e-08 -9.102750e-09
## [11,] -4.647158e-07 -4.649948e-07 -6.071033e-07
## [12,] 4.221287e-07 4.220910e-07 6.569545e-07
```

```
attr(ndnls, "gradient")-attr(vfunsc, "gradient")
```

```
##          b1          b2          b3
## [1,] -5.513268e-11 1.371020e-11 5.962686e-11
## [2,] 6.850076e-13 -3.831403e-11 3.291006e-12
## [3,] -2.144829e-11 -1.208666e-10 6.925160e-11
## [4,] -2.665634e-11 4.123477e-11 -1.826495e-11
## [5,] 2.175706e-10 -7.825720e-11 9.793778e-11
## [6,] -2.416068e-10 -1.666460e-10 -1.735172e-10
## [7,] -8.350343e-11 5.415257e-11 -8.571976e-11
## [8,] 3.255913e-10 -9.864836e-11 2.024904e-10
## [9,] 1.379652e-11 -5.685668e-10 -1.631673e-10
## [10,] -9.296786e-11 -4.173983e-10 6.710748e-11
## [11,] -4.266865e-11 2.415372e-10 8.632699e-10
## [12,] -2.738492e-10 2.515432e-10 -6.717320e-10
```

```
attr(ndnlsx, "gradient")-attr(vfunsc, "gradient")
```

```
##          b1          b2          b3
## [1,] 1.078625e-06 -4.123528e-06 -4.758257e-06
## [2,] 5.790545e-07 2.014411e-06 4.852963e-06
## [3,] -2.771694e-06 -1.385826e-05 -1.171591e-05
## [4,] -8.202081e-06 -1.204434e-05 -5.113350e-06
## [5,] -3.931620e-06 4.482091e-06 1.311668e-05
## [6,] 3.569890e-06 1.513685e-05 1.576029e-05
## [7,] 5.191947e-06 -1.348438e-05 -1.219078e-05
## [8,] -2.074929e-06 -2.003370e-05 -5.289324e-05
## [9,] -8.676624e-07 -1.872920e-05 2.645423e-05
## [10,] -7.810096e-06 4.539581e-05 4.342184e-05
## [11,] -1.075608e-04 -1.254074e-04 -4.160402e-05
## [12,] 2.399048e-05 6.144137e-06 6.837890e-05
```

```
attr(ndnlsx, "gradient")-attr(vfunsc, "gradient")
```

```
##          b1          b2          b3
## [1,] 1.078625e-06 3.173646e-07 -3.173646e-07
## [2,] 5.790545e-07 2.014411e-06 4.120706e-07
## [3,] -2.771694e-06 -4.976479e-06 -2.834131e-06
## [4,] 6.797035e-07 -3.162555e-06 3.768434e-06
## [5,] -3.931620e-06 4.482091e-06 1.311668e-05
## [6,] 3.569890e-06 1.513685e-05 1.576029e-05
## [7,] 5.191947e-06 4.279192e-06 -1.219078e-05
## [8,] 3.345221e-05 1.549344e-05 -1.736611e-05
## [9,] -8.676624e-07 -1.872920e-05 2.645423e-05
## [10,] -7.810096e-06 9.868671e-06 7.894701e-06
## [11,] -3.650654e-05 -5.435313e-05 2.945025e-05
## [12,] 2.399048e-05 6.144137e-06 -2.675369e-06
```

```

jnlsc-attr(vfunsc,"gradient")

##           b1           b2           b3
## [1,] -2.239464e-11  7.806283e-12 -1.156686e-12
## [2,] -2.267631e-12  2.974312e-11  2.957756e-11
## [3,] -8.948509e-12  3.630193e-11 -1.256267e-11
## [4,] -1.649125e-12  1.182179e-13  6.369841e-11
## [5,] -4.272493e-11 -1.109757e-11  3.501116e-11
## [6,]  1.867381e-10  1.793287e-11  3.319552e-11
## [7,]  1.090728e-11  1.840947e-11  9.946462e-12
## [8,]  2.035664e-10 -1.520996e-10  1.911593e-10
## [9,] -3.582228e-10  2.039028e-10 -1.905254e-10
## [10,] 3.202474e-10  8.291927e-11 -6.263366e-11
## [11,] 5.931922e-12 -1.779933e-11  3.682277e-10
## [12,] 4.132902e-10 -6.831839e-11  3.817154e-10

## Summary comparisons
max(abs(attr(ndnls, "gradient")-attr(vfunsc,"gradient"))

## [1] 6.569545e-07

max(abs(attr(ndnls, "gradient")-attr(vfunsc,"gradient")))

## [1] 8.632699e-10

max(abs(attr(ndnlsx, "gradient")-attr(vfunsc,"gradient")))

## [1] 0.0001254074

max(abs(attr(ndnls, "gradient")-attr(vfunsc,"gradient")))

## [1] 5.435313e-05

max(abs(jnlsc-attr(vfunsc,"gradient")))

## [1] 4.132902e-10

```

Performance results for different computing environments

Here we present tables of the results, preceded by identified descriptions of the machines we used. We use ideas and functions from the document `MachineSummary` to provide a characterization and identity for each machine used.

M21-LM20.1

?? still to be run

?? What machines provide a range of possibilities.

Discussion of derivative computation for nonlinear least squares

In no particular order, we comment on some issues relating to the Jacobian calculations in nonlinear least squares.

Nomenclature

R is not in step with many other areas of numerical computation when labelling different objects in the nonlinear least squares problem. In particular, R uses the term “gradient” when the object of interest is

the Jacobian matrix. In that it is useful in performing iterations of the Gauss-Newton or related equations to have the Jacobian associated with the residuals, and the rows of the Jacobian matrix are “gradients” of the respective residuals, we can accept the attribute name “gradient” to select the required information. Moreover, as in package `nlsr` it is very useful to have the Jacobian matrix as an attribute of the residual vector, since the main solver function, in this case `nlsr::nlfb()`, can be called with the same input for the arguments `res` and `jac`. These are the functions required to compute the residual and the Jacobian, and using the same function for both is very convenient, but needs some way to return both the residual vector and Jacobian matrix in a coherent fashion.

Numerical approximation near constraints

As far as we are aware there is no software that implements a fully safeguarded system to compute numerical approximation of the Jacobian (or gradients in general optimization) near constraints. The same statement applies even in the case of the much simpler bounds constraints. Users have a perverse tendency to devise ways to foil our best efforts. For example, they may decide that a good way to specify fixed (i.e., masked) parameters that they do not want to vary during a particular calculation is to specify the lower and upper bound of a parameter at the same value. Later runs may want the parameter constraints relaxed.

In `nlsr::nlxb()`, users may, in fact, specify masked parameters this way. This is a case of “if you can’t beat them, join them,” but it does provide an easily understood way for users to fix values.

More tricky is dealing with constraints that are close together. Note that these may arise from, for example, two linear (planar) constraints that approach at a narrow angle. In the apex where these constraints intersect, we will have tight bounds on parameters. If the constraint is not one that is imposed by the nature of the residual or objective function, for example, a `log()` or square root near zero, then we can generally proceed and allow the derivative approximator to evaluate outside the constraints. Things are decidedly nastier if we do have inadmissible values.

The issue of constraints and the need for a step in parameter values for derivative approximations was one of the motivations for trying to find analytic derivatives in package `nlsr` and the continuing effort to bring them into other R tools.

A case where the initial Jacobian is singular

The following example shows that `numericDeriv()` does a reasonable job of computing the Jacobian, but the result is still singular.

```
# File: badJlogmod.R
# A problem illustrating poor numeric Jacobian
form<-y ~ 10*a*(8*b-log(0.075*c*x)) # the model formula
# This model uses log near a small argument, which skirts the dangerous
# value of 0. The parameters a, b, c could all be 1 "safely" as a start.
x<-1:20 # define x
a<-1.01
b<-0.9
c<-0.95
y <- 10*a*(8*b-log(0.075*c*x))+0.2*runif(20) # compute a y
df<-data.frame(x=x, y=y)
# plot(x,y) # for information
st<-c(a=1, b=1,c=1) # set the "default" starting vector
n0<-try(nls(form, start=st, data=df)) # and watch the fun as this fails.
```

```
## Error in nlsModel(formula, mf, start, wts, scaleOffset = scOff, nDcentral = nDcntr) :
##   singular gradient matrix at initial parameter estimates
```

```
library(nlsr) # but this will work
n1<-nlxb(form, start=st, data=df)
```

```
n1
```

```
## nlsr object: x
## residual sumsquares = 0.065093 on 20 observations
## after 5 Jacobian and 6 function evaluations
## name      coeff      SE      tstat      pval      gradient      JSingval
## a          1.00967      NA      NA      NA      -5.161e-08      501.9
## b          0.950581      NA      NA      NA      2.775e-08      25.6
## c          1.40495      NA      NA      NA      -2.469e-09      6.371e-15
```

```
jmod<-model2rjfun(form, pvec=st,data=data.frame(x=x, y=y)) # extract the model
Jatst<-jmod(st) # compute this at the start from package nlsr
Jatst<-attr(Jatst,"gradient") # and extract the Jacobian
#
# Now try to compute Jacobian produced by nls()
env<-environment(form) # We need the environment of the formula
eform<-eval(form, envir=env) # and the evaluated expression
localdata<-list2env(as.list(st), parent=env)
jnlsatst<-numericDeriv(form[[3L]], theta=names(st), rho=localdata)
Jnls<-attr(jnlsatst,"gradient")
Jnls # from nls()
```

```
##      [,1] [,2] [,3]
## [1,] 105.903 80 -10
## [2,] 98.971 80 -10
## [3,] 94.917 80 -10
## [4,] 92.040 80 -10
## [5,] 89.808 80 -10
## [6,] 87.985 80 -10
## [7,] 86.444 80 -10
## [8,] 85.108 80 -10
## [9,] 83.930 80 -10
## [10,] 82.877 80 -10
## [11,] 81.924 80 -10
## [12,] 81.054 80 -10
## [13,] 80.253 80 -10
## [14,] 79.512 80 -10
## [15,] 78.822 80 -10
## [16,] 78.177 80 -10
## [17,] 77.571 80 -10
## [18,] 76.999 80 -10
## [19,] 76.458 80 -10
## [20,] 75.945 80 -10
```

```
Jatst # from nlsr -- analytic derivative
```

```
##      a b c
## [1,] 105.903 80 -10
## [2,] 98.971 80 -10
## [3,] 94.917 80 -10
## [4,] 92.040 80 -10
## [5,] 89.808 80 -10
## [6,] 87.985 80 -10
## [7,] 86.444 80 -10
## [8,] 85.108 80 -10
```

```

## [9,] 83.930 80 -10
## [10,] 82.877 80 -10
## [11,] 81.924 80 -10
## [12,] 81.054 80 -10
## [13,] 80.253 80 -10
## [14,] 79.512 80 -10
## [15,] 78.822 80 -10
## [16,] 78.177 80 -10
## [17,] 77.571 80 -10
## [18,] 76.999 80 -10
## [19,] 76.458 80 -10
## [20,] 75.945 80 -10

max(abs(Jnls-Jatst))

## [1] 9.5367e-07

svd(Jnls)$d

## [1] 5.2370e+02 2.4390e+01 9.0872e-07

svd(Jatst)$d

## [1] 5.2370e+02 2.4390e+01 1.3047e-15
# Even start at the solution?
n0c<-try(nls(form, start=coef(n1), data=data.frame(x=x, y=y), trace=TRUE))

## Error in nlsModel(formula, mf, start, wts, scaleOffset = scOff, nDcentral = nDcntr) :
## singular gradient matrix at initial parameter estimates
## attempts with nlsj
library(nlsj)

##
## Attaching package: 'nlsj'

## The following object is masked from 'package:stats':
##
## numericDeriv
n0jn<-try(nlsj(form, start=st, data=df, trace=TRUE, control=nlsj.control(derivmeth="numericDeriv")))

## Warning in nlsj(form, start = st, data = df, trace = TRUE, control =
## nlsj.control(derivmeth = "numericDeriv")): Forcing numericDeriv

## control:$maxiter
## [1] 500
##
## $tol
## [1] 1e-05
##
## $minFactor
## [1] 0.00097656
##
## $printEval
## [1] FALSE
##
## $warnOnly
## [1] FALSE

```

```

##
## $scaleOffset
## [1] 0
##
## $nDcentral
## [1] FALSE
##
## $watch
## [1] FALSE
##
## $phi
## [1] 1
##
## $lamda
## [1] 0
##
## $offset
## [1] 100
##
## $laminc
## [1] 10
##
## $lamdec
## [1] 0.4
##
## $resmax
## [1] 10000
##
## $rofftest
## [1] TRUE
##
## $smallstest
## [1] TRUE
##
## $derivmeth
## [1] "numericDeriv"
##
## $altderivmeth
## [1] "numericDeriv"
##
## $trace
## [1] FALSE
##
## cont.
## nlsj: Using default algorithm
## maskidx:integer(0)
## lhs has just the variable y
## npar= 3  pnames:[1] "a" "b" "c"
## Top - slam= 0  ssmin= 872.81  at [1] 1 1 1
## npar= 3
## [1] 1 1 1
## [1] 1 1 1
## i= 1  bmi= 1
## i= 2  bmi= 1

```



```

## i= 3  bmi= 1
##      [,1] [,2] [,3]
## [1,] 105.903 80 -10
## [2,] 98.971 80 -10
## [3,] 94.917 80 -10
## [4,] 92.040 80 -10
## [5,] 89.808 80 -10
## [6,] 87.985 80 -10
## [7,] 86.444 80 -10
## [8,] 85.108 80 -10
## [9,] 83.930 80 -10
## [10,] 82.877 80 -10
## [11,] 81.924 80 -10
## [12,] 81.054 80 -10
## [13,] 80.253 80 -10
## [14,] 79.512 80 -10
## [15,] 78.822 80 -10
## [16,] 78.177 80 -10
## [17,] 77.571 80 -10
## [18,] 76.999 80 -10
## [19,] 76.458 80 -10
## [20,] 75.945 80 -10
## Error in nlsj(form, start = st, data = df, trace = TRUE, control = nlsj.control(derivmeth = "numeric")
## Singular jacobian
tmp<-readline("more.")

## more.
n0ja<-try(nlsj(form, start=st, data=df, trace=TRUE, control=nlsj.control(derivmeth="default"))))

## control:$maxiter
## [1] 500
##
## $tol
## [1] 1e-05
##
## $minFactor
## [1] 0.00097656
##
## $printEval
## [1] FALSE
##
## $warnOnly
## [1] FALSE
##
## $scaleOffset
## [1] 0
##
## $nDcentral
## [1] FALSE
##
## $watch
## [1] FALSE
##

```

```

## $phi
## [1] 1
##
## $lamda
## [1] 0
##
## $offset
## [1] 100
##
## $laminc
## [1] 10
##
## $lamdec
## [1] 0.4
##
## $resmax
## [1] 10000
##
## $rofftest
## [1] TRUE
##
## $smallstest
## [1] TRUE
##
## $derivmeth
## [1] "default"
##
## $altderivmeth
## [1] "numericDeriv"
##
## $trace
## [1] FALSE
##
## cont.
## nlsj: Using default algorithm
## maskidx:integer(0)
## lhs has just the variable y
## npar= 3  pnames:[1] "a" "b" "c"
## Top - slam= 0  ssmin= 872.81  at [1] 1 1 1
## npar= 3
## [1] 1 1 1
## [1] 1 1 1
## i= 1  bmi= 1
## i= 2  bmi= 1
## i= 3  bmi= 1
##
##           a  b  c
## [1,] 105.903 80 -10
## [2,]  98.971 80 -10
## [3,]  94.917 80 -10
## [4,]  92.040 80 -10
## [5,]  89.808 80 -10
## [6,]  87.985 80 -10
## [7,]  86.444 80 -10
## [8,]  85.108 80 -10

```

```
## [9,] 83.930 80 -10
## [10,] 82.877 80 -10
## [11,] 81.924 80 -10
## [12,] 81.054 80 -10
## [13,] 80.253 80 -10
## [14,] 79.512 80 -10
## [15,] 78.822 80 -10
## [16,] 78.177 80 -10
## [17,] 77.571 80 -10
## [18,] 76.999 80 -10
## [19,] 76.458 80 -10
## [20,] 75.945 80 -10
## Error in nlsj(form, start = st, data = df, trace = TRUE, control = nlsj.control(derivmeth = "default
## Singular jacobian
```

Appendix 1: Base R numericDeriv code

This code is in two files, nls.R and nls.c and is extracted here.

From nls.R

```
numericDeriv <- function(expr, theta, rho = parent.frame(), dir = 1,
                        eps = .Machine$double.eps ^ (1/if(central) 3 else 2), central = FALSE)
## Note: this expr must be set up as a call to work properly according to JN??
## ?? we set eps conditional on central. But central set AFTER eps. Is this OK.
{
  cat("numericDeriv-Alt\n")
  dir <- rep_len(dir, length(theta))
  stopifnot(is.finite(eps), eps > 0)
  rho1 <- new.env(FALSE, rho, 0)
  if (!is.character(theta) ) {stop("'theta' should be of type character")}
  if (is.null(rho)) {
    stop("use of NULL environment is defunct")
    # rho <- R_BaseEnv;
  } else {
    if(! is.environment(rho)) {stop("'rho' should be an environment")}
    # int nprot = 3;
  }
  if( ! ((length(dir) == length(theta) ) & (is.numeric(dir) ) ) )
    {stop("'dir' is not a numeric vector of the correct length") }
  if(is.na(central)) { stop("'central' is NA, but must be TRUE or FALSE") }
  res0 <- eval(expr, rho) # the base residuals. ?? C has a check for REAL ANS=res0
  if (any(is.infinite(res0)) ) {stop("residuals cannot be evaluated at base point")}
  ## CHECK_FN_VAL(res, ans); ?? how to do this. Is it necessary?
  nt <- length(theta) # number of parameters
  mr <- length(res0) # number of residuals
  JJ <- matrix(NA, nrow=mr, ncol=nt) # Initialize the Jacobian
  for (j in 1:nt){
    origPar<-get(theta[j],rho)
    xx <- abs(origPar)
    delta <- if (xx == 0.0) {eps} else { xx*eps }
    ## JN: I prefer eps*(xx + eps) which is simpler ?? Should we suggest / use a control switch
    prmx<-origPar+delta*dir[j]
    assign(theta[j],prmx,rho)
    res1 <- eval(expr, rho) # new residuals (forward step)
```

```

    if (central) { # compute backward step resids for central diff
      prmb <- origPar - dir[j]*delta
      assign(theta[j], prmb, envir=rho) # may be able to make more efficient later??
      resb <- eval(expr, rho)
      JJ[, j] <- dir[j]*(res1-resb)/(2*delta) # vectorized
    } else { ## forward diff
      JJ[,j] <- dir[j]*(res1-res0)/delta
    } # end forward diff
  } # end loop over the parameters
  attr(res0, "gradient") <- JJ
  return(res0)
}

```

From nls.c

```

#include <stdlib.h>
#include <string.h>
#include <math.h>
#include <float.h>
#include <R.h>
#include <Rinternals.h>
#include "nls.h"
#include "internals.h"

#ifndef MIN
#define MIN(a,b) (((a)<(b))?(a):(b))
#endif

/*
 * call to numeric_deriv from R -
 * .Call("numeric_deriv", expr, theta, rho, dir = 1., eps = .Machine$double.eps, central=FALSE)
 * Returns: ans
 */
SEXP
numeric_deriv(SEXP expr, SEXP theta, SEXP rho, SEXP dir, SEXP eps_, SEXP centr,
              SEXP rho1)
{
  if(!isString(theta))
    error(_("'theta' should be of type character"));
  if (isNull(rho)) {
    error(_("use of NULL environment is defunct"));
    rho = R_BaseEnv;
  } else
    if(!isEnvironment(rho))
      error(_("'rho' should be an environment"));
  int nprot = 3;
  if(TYPEOF(dir) != REALSXP) {
    PROTECT(dir = coerceVector(dir, REALSXP)); nprot++;
  }
  if(LENGTH(dir) != LENGTH(theta))
    error(_("'dir' is not a numeric vector of the correct length"));
  Rboolean central = asLogical(centr);
  if(central == NA_LOGICAL)
    error(_("'central' is NA, but must be TRUE or FALSE"));
}

```

```

//      SEXP rho1 = PROTECT(R_NewEnv(rho, FALSE, 0));
//      nprot++;
SEXP
pars = PROTECT(allocVector(VECSXP, LENGTH(theta))),
ans = PROTECT(duplicate(eval(expr, rho1)));
double *rDir = REAL(dir), *res = NULL; // -Wall
#define CHECK_FN_VAL(_r_, _ANS_) do { \
    if(!isReal(_ANS_)) { \
        SEXP temp = coerceVector(_ANS_, REALSXP); \
        UNPROTECT(1); /*: _ANS_ *must* have been the last PROTECT() ! */ \
        PROTECT(_ANS_ = temp); \
    } \
    _r_ = REAL(_ANS_); \
    for(int i = 0; i < LENGTH(_ANS_); i++) { \
        if (!R_FINITE(_r_[i])) \
            error(_("Missing value or an infinity produced when evaluating the model")); \
    } \
} while(0)

CHECK_FN_VAL(res, ans);

const void *vmax = vmaxget();
int lengthTheta = 0;
for(int i = 0; i < LENGTH(theta); i++) {
    const char *name = translateChar(STRING_ELT(theta, i));
    SEXP s_name = install(name);
    SEXP temp = findVar(s_name, rho1);
    if(isInteger(temp))
        error(_("variable '%s' is integer, not numeric"), name);
    if(!isReal(temp))
        error(_("variable '%s' is not numeric"), name);
    // We'll be modifying the variable, so need to make a copy PR#15849
    defineVar(s_name, temp = duplicate(temp), rho1);
    MARK_NOT_MUTABLE(temp);
    SET_VECTOR_ELT(pars, i, temp);
    lengthTheta += LENGTH(VECTOR_ELT(pars, i));
}
vmaxset(vmax);
SEXP gradient = PROTECT(allocMatrix(REALSXP, LENGTH(ans), lengthTheta));
double *grad = REAL(gradient);
double eps = asReal(eps_); // was hardcoded sqrt(DOUBLE_EPS) { ~= 1.49e-08, typically}
for(int start = 0, i = 0; i < LENGTH(theta); i++) {
    double *pars_i = REAL(VECTOR_ELT(pars, i));
    for(int j = 0; j < LENGTH(VECTOR_ELT(pars, i)); j++, start += LENGTH(ans)) {
        double
        origPar = pars_i[j],
        xx = fabs(origPar),
        delta = (xx == 0) ? eps : xx*eps;
        pars_i[j] += rDir[i] * delta;
        SEXP ans_del = PROTECT(eval(expr, rho1));
        double *rDel = NULL;
        CHECK_FN_VAL(rDel, ans_del);
        if(central) {
            pars_i[j] = origPar - rDir[i] * delta;

```

```

SEXP ans_de2 = PROTECT(eval(expr, rho1));
double *rD2 = NULL;
CHECK_FN_VAL(rD2, ans_de2);
for(int k = 0; k < LENGTH(ans); k++) {
    grad[start + k] = rDir[i] * (rDel[k] - rD2[k])/(2 * delta);
}
} else { // forward difference (previously hardwired):
for(int k = 0; k < LENGTH(ans); k++) {
    grad[start + k] = rDir[i] * (rDel[k] - res[k])/delta;
}
}
UNPROTECT(central ? 2 : 1); // ansDel & possibly ans
pars_i[j] = origPar;
}
}
setAttrib(ans, install("gradient"), gradient);
UNPROTECT(nprot);
return ans;
}

```

Appendix 2: numericDeriv() from nlsalt package (all in R)

```

# File src/library/stats/R/nlsnd.R
# Part of the modified R package, https://www.R-project.org
#
# Copyright (C) 2000-2020 The R Core Team
# Copyright (C) 1999-1999 Saikat DebRoy, Douglas M. Bates, Jose C. Pinheiro
# J C Nash 2021
#
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# https://www.R-project.org/Licenses/
###
###          numeric Jacobian for Nonlinear least squares for R
###

numericDeriv <- function(expr, theta, rho = parent.frame(), dir = 1,
    eps = .Machine$double.eps ^ (1/if(central) 3 else 2), central = FALSE)
## Note: this expr must be set up as a call to work properly according to JN??
## ?? we set eps conditional on central. But central set AFTER eps. Is this OK.
{
    ndtrace<-FALSE
    # if(ndtrace) cat("numericDeriv-Alt\n")
    dir <- rep_len(dir, length(theta))

```

```

stopifnot(is.finite(eps), eps > 0)
rho1 <- new.env(FALSE, rho, 0)
if (!is.character(theta) ) {stop("'theta' should be of type character")}
if (is.null(rho)) {
  stop("use of NULL environment is defunct")
  #      rho <- R_BaseEnv;
} else {
  if(! is.environment(rho)) {stop("'rho' should be an environment")}
  #      int nprot = 3;
}
if( ! ((length(dir) == length(theta) ) & (is.numeric(dir) ) ) )
  {stop("'dir' is not a numeric vector of the correct length") }
if(is.na(central)) { stop("'central' is NA, but must be TRUE or FALSE") }
res0 <- eval(expr, rho) # the base residuals. ?? C has a check for REAL ANS=res0
if (any(is.infinite(res0)) ) {stop("residuals cannot be evaluated at base point")}
## CHECK_FN_VAL(res, ans); ?? how to do this. Is it necessary?
nt <- length(theta) # number of parameters
mr <- length(res0) # number of residuals
JJ <- matrix(NA, nrow=mr, ncol=nt) # Initialize the Jacobian
for (j in 1:nt){
  origPar<-get(theta[j],rho)
  xx <- abs(origPar)
  delta <- if (xx == 0.0) {eps} else { xx*eps }
  ## JN: I prefer eps*(xx + eps) which is simpler ?? Should we suggest / use a control switch
  prmx<-origPar+delta*dir[j]
  assign(theta[j],prmx,rho)
  res1 <- eval(expr, rho) # new residuals (forward step)
  if (central) { # compute backward step resids for central diff
    prmb <- origPar - dir[j]*delta
    assign(theta[j], prmb, envir=rho) # may be able to make more efficient later??
    resb <- eval(expr, rho)
    JJ[, j] <- dir[j]*(res1-resb)/(2*delta) # vectorized
  } else { ## forward diff
    JJ[,j] <- dir[j]*(res1-res0)/delta
  } # end forward diff
  assign(theta[j],origPar,rho) # restore the parameter value !! IMPORTANT
} # end loop over the parameters
attr(res0, "gradient") <- JJ
if (ndtrace){
  cat("par:")
  for (j in 1:nt){ cat(get(theta[j],rho)," ") }
  cat("\n")
  print(res0)
}
return(res0)
}

```

Marquardt, Donald W. 1963. "An Algorithm for Least-Squares Estimation of Nonlinear Parameters." *SIAM Journal on Applied Mathematics* 11 (2): 431–41.

Nash, John C. 1979. *Compact Numerical Methods for Computers : Linear Algebra and Function Minimisation*. Book. Hilger: Bristol.