

Package ‘numDeriv’

June 6, 2019

Version 2016.8-1.1

Title Accurate Numerical Derivatives

Description Methods for calculating (usually) accurate numerical first and second order derivatives. Accurate calculations are done using 'Richardson"s' extrapolation or, when applicable, a complex step derivative is available. A simple difference method is also provided. Simple difference is (usually) less accurate but is much quicker than 'Richardson"s' extrapolation and provides a useful cross-check.
Methods are provided for real scalar and vector valued functions.

Depends R (>= 2.11.1)

LazyLoad yes

ByteCompile yes

License GPL-2

Copyright 2006-2011, Bank of Canada. 2012-2016, Paul Gilbert

Author Paul Gilbert and Ravi Varadhan

Maintainer Paul Gilbert <pgilbert.ttv9z@ncf.ca>

URL <http://optimizer.r-forge.r-project.org/>

NeedsCompilation no

Repository CRAN

Date/Publication 2019-06-06 09:51:09 UTC

R topics documented:

numDeriv-package	2
00.numDeriv.Intro	3
genD	3
grad	5
hessian	8
jacobian	10
Index	12

numDeriv-package *Accurate Numerical Derivatives*

Description

Calculate (accurate) numerical approximations to derivatives.

Details

The main functions are

`grad` to calculate the gradient (first derivative) of a scalar real valued function (possibly applied to all elements of a vector argument).

`jacobian` to calculate the gradient of a real m-vector valued function with real n-vector argument.

`hessian` to calculate the Hessian (second derivative) of a scalar real valued function with real n-vector argument.

`genD` to calculate the gradient and second derivative of a real m-vector valued function with real n-vector argument.

Author(s)

Paul Gilbert, based on work by Xingqiao Liu, and Ravi Varadhan (who wrote complex-step derivative codes)

References

Linfield, G. R. and Penny, J. E. T. (1989) *Microcomputers in Numerical Analysis*. New York: Halsted Press.

Fornberg, B. and Sloan, D. M. (1994) "A review of pseudospectral methods for solving partial differential equations." *Acta Numerica*, 3, 203-267.

Lyness, J. N. and Moler, C. B. (1967) "Numerical Differentiation of Analytic Functions." *SIAM Journal for Numerical Analysis*, 4(2), 202-210.

00.numDeriv.Intro *Accurate Numerical Derivatives*

Description

Calculate (accurate) numerical approximations to derivatives.

Details

See [numDeriv-package](#) (in the help system use `package?numDeriv` or `?numDeriv-package`) for an overview.

genD *Generate Bates and Watts D Matrix*

Description

Generate a matrix of function derivative information.

Usage

```
genD(func, x, method="Richardson",
      method.args=list(), ...)
## Default S3 method:
genD(func, x, method="Richardson",
      method.args=list(), ...)
```

Arguments

func	a function for which the first (vector) argument is used as a parameter vector.
x	The parameter vector first argument to func.
method	one of "Richardson" or "simple" indicating the method to use for the approximation.
method.args	arguments passed to method. See grad . (Arguments not specified remain with their default values.)
...	any additional arguments passed to func. WARNING: None of these should have names matching other arguments of this function.

Details

The derivatives are calculated numerically using Richardson improvement. Methods "simple" and "complex" are not supported in this function. The "Richardson" method calculates a numerical approximation of the first and second derivatives of `func` at the point `x`. For a scalar valued function these are the gradient vector and Hessian matrix. (See [grad](#) and [hessian](#).) For a vector valued function the first derivative is the Jacobian matrix (see [jacobian](#)). For the Richardson method `method.args=list(eps=1e-4, d=0.0001, zero.tol=sqrt(.Machine$double.eps/7e-7), r=4, v=2)` is set as the default. See [grad](#) for more details on the Richardson's extrapolation parameters.

A simple approximation to the first order derivative with respect to x_i is

$$f'_i(x) = \langle f(x_1, \dots, x_i + d, \dots, x_n) - f(x_1, \dots, x_i - d, \dots, x_n) \rangle / (2 * d)$$

A simple approximation to the second order derivative with respect to x_i is

$$f''_i(x) = \langle f(x_1, \dots, x_i + d, \dots, x_n) - 2 * f(x_1, \dots, x_n) + f(x_1, \dots, x_i - d, \dots, x_n) \rangle / (d^2)$$

The second order derivative with respect to x_i, x_j is

$$f''_{i,j}(x) = \langle f(x_1, \dots, x_i + d, \dots, x_j + d, \dots, x_n) - 2 * f(x_1, \dots, x_n) +$$

$$f(x_1, \dots, x_i - d, \dots, x_j - d, \dots, x_n) \rangle / (2 * d^2) - (f''_i(x) + f''_j(x)) / 2$$

Richardson's extrapolation is based on these formula with the `d` being reduced in the extrapolation iterations. In the code, `d` is scaled to accommodate parameters of different magnitudes.

`genD` does $1 + r (N^2 + N)$ evaluations of the function `f`, where `N` is the length of `x`.

Value

A list with elements as follows: `D` is a matrix of first and second order partial derivatives organized in the same manner as `Bates` and `Watts`, the number of rows is equal to the length of the result of `func`, the first `p` columns are the Jacobian, and the next $p(p+1)/2$ columns are the lower triangle of the second derivative (which is the Hessian for a scalar valued `func`). `p` is the length of `x` (dimension of the parameter space). `f0` is the function value at the point where the matrix `D` was calculated. The `genD` arguments `func`, `x`, `d`, `method`, and `method.args` also are returned in the list.

References

- Linfield, G.R. and Penny, J.E.T. (1989) "Microcomputers in Numerical Analysis." Halsted Press.
- Bates, D.M. & Watts, D. (1980), "Relative Curvature Measures of Nonlinearity." J. Royal Statistics Soc. series B, 42:1-25
- Bates, D.M. and Watts, D. (1988) "Non-linear Regression Analysis and Its Applications." Wiley.

See Also

[hessian](#), [grad](#)

Examples

```
func <- function(x){c(x[1], x[1], x[2]^2)}
z <- genD(func, c(2,2,5))
```

grad

*Numerical Gradient of a Function***Description**

Calculate the gradient of a function by numerical approximation.

Usage

```
grad(func, x, method="Richardson", side=NULL, method.args=list(), ...)

## Default S3 method:
grad(func, x, method="Richardson", side=NULL,
      method.args=list(), ...)
```

Arguments

func	a function with a scalar real result (see details).
x	a real scalar or vector argument to func, indicating the point(s) at which the gradient is to be calculated.
method	one of "Richardson", "simple", or "complex" indicating the method to use for the approximation.
method.args	arguments passed to method. Arguments not specified remain with their default values as specified in details
side	an indication of whether one-sided derivatives should be attempted (see details).
...	an additional arguments passed to func. WARNING: None of these should have names matching other arguments of this function.

Details

The function `grad` calculates a numerical approximation of the first derivative of `func` at the point `x`. Any additional arguments in `...` are also passed to `func`, but the gradient is not calculated with respect to these additional arguments. It is assumed `func` is a scalar value function. If a vector `x` produces a scalar result then `grad` returns the numerical approximation of the gradient at the point `x` (which has the same length as `x`). If a vector `x` produces a vector result then the result must have the same length as `x`, and it is assumed that this corresponds to applying the function to each of its arguments (for example, `sin(x)`). In this case `grad` returns the gradient at each of the points in `x` (which also has the same length as `x` – so be careful). An alternative for vector valued functions is provided by [jacobian](#).

If method is "simple", the calculation is done using a simple epsilon difference. For method "simple" `method.args=list(eps=1e-4)` is the default. Only `eps` is used by this method.

If method is "complex", the calculation is done using the complex step derivative approach of Lyness and Moler, described in Squire and Trapp. This method requires that the function be able to handle complex valued arguments and return the appropriate complex valued result, even though the user may only be interested in the real-valued derivatives. It also requires that the complex function be analytic. (This might be thought of as the complex equivalent of the requirement for continuity and smoothness of a real valued function.) So, while this method is extremely powerful it is applicable to a very restricted class of functions. *Avoid this method if you do not know that your function is suitable. Your mistake may not be caught and the results will be spurious.* For cases where it can be used, it is faster than Richardson's extrapolation, and it also provides gradients that are correct to machine precision (16 digits). For method "complex", `method.args` is ignored. The algorithm uses an `eps` of `.Machine$double.eps` which cannot (and should not) be modified.

If method is "Richardson", the calculation is done by Richardson's extrapolation (see e.g. Linfield and Penny, 1989, or Fornberg and Sloan, 1994.) This method should be used if accuracy, as opposed to speed, is important (but see method "complex" above). For this method `method.args=list(eps=1e-4, d=0.0001, zero.tol=0)` is set as the default. `d` gives the fraction of `x` to use for the initial numerical approximation. The default means the initial approximation uses $0.0001 * x$. `eps` is used instead of `d` for elements of `x` which are zero (absolute value less than `zero.tol`). `zero.tol` tolerance used for deciding which elements of `x` are zero. `r` gives the number of Richardson improvement iterations (repetitions with successively smaller `d`). The default 4 general provides good results, but this can be increased to 6 for improved accuracy at the cost of more evaluations. `v` gives the reduction factor. `show.details` is a logical indicating if detailed calculations should be shown.

The general approach in the Richardson method is to iterate for `r` iterations from initial values for interval value `d`, using reduced factor `v`. The the first order approximation to the derivative with respect to x_i is

$$f'_i(x) = \frac{f(x_1, \dots, x_i + d, \dots, x_n) - f(x_1, \dots, x_i - d, \dots, x_n)}{2 * d}$$

This is repeated `r` times with successively smaller `d` and then Richardson extrapolation is applied.

If elements of `x` are near zero the multiplicative interval calculation using `d` does not work, and for these elements an additive calculation using `eps` is done instead. The argument `zero.tol` is used determine if an element should be considered too close to zero. In the iterations, interval is successively reduced to eventual be d/v^r and the square of this value is used in second derivative calculations (see [genD](#)) so the default `zero.tol=sqrt(.Machine$double.eps/7e-7)` is set to ensure the interval is bigger than `.Machine$double.eps` with the default `d`, `r`, and `v`.

If `side` is NULL then it is assumed that the point at which the calculation is being done is interior to the domain of the function. If the point is on the boundary of the domain then `side` can be used to indicate which side of the point `x` should be used for the calculation. If not NULL then it should be a vector of the same length as `x` and have values NA, +1, or -1. NA indicates that the usual calculation will be done, while +1, or -1 indicate adding or subtracting from the parameter point `x`. The argument `side` is not supported for all methods.

Since usual calculation with method "simple" uses only a small `eps` step to one side, the only effect of argument `side` is to determine the direction of the step. The usual calculation with method "Richardson" is symmetric, using steps to both sides. The effect of argument `side` is to take a double sized step to one side, and no step to the other side. This means that the center of the Richardson

extrapolation steps is moving slightly in the reduction, and is not exactly on the boundary. (Warning: I am not aware of theory or published experimental evidence to support this, but the results in my limited testing seem good.)

Value

A real scalar or vector of the approximated gradient(s).

References

Linfield, G. R. and Penny, J. E. T. (1989) *Microcomputers in Numerical Analysis*. New York: Halsted Press.

Fornberg, B. and Sloan, D. M. (1994) "A review of pseudospectral methods for solving partial differential equations." *Acta Numerica*, 3, 203-267.

Lyness, J. N. and Moler, C. B. (1967) "Numerical Differentiation of Analytic Functions." *SIAM Journal for Numerical Analysis*, 4(2), 202-210.

Squire, William and Trapp, George (1998) "Using Complex Variables to Estimate Derivatives of Real Functions." *SIAM Rev*, 40(1), 110-112.

See Also

[jacobian](#), [hessian](#), [genD](#), [numericDeriv](#)

Examples

```
grad(sin, pi)
grad(sin, (0:10)*2*pi/10)
func0 <- function(x){ sum(sin(x)) }
grad(func0 , (0:10)*2*pi/10)

func1 <- function(x){ sin(10*x) - exp(-x) }

curve(func1,from=0,to=5)

x <- 2.04
numd1 <- grad(func1, x)
exact <- 10*cos(10*x) + exp(-x)
c(numd1, exact, (numd1 - exact)/exact)

x <- c(1:10)
numd1 <- grad(func1, x)
numd2 <- grad(func1, x, "complex")
exact <- 10*cos(10*x) + exp(-x)
cbind(numd1, numd2, exact, (numd1 - exact)/exact, (numd2 - exact)/exact)

sc2.f <- function(x){
  n <- length(x)
  sum((1:n) * (exp(x) - x)) / n
}

sc2.g <- function(x){
```

```

n <- length(x)
(1:n) * (exp(x) - 1) / n
}

x0 <- rnorm(100)
exact <- sc2.g(x0)

g <- grad(func=sc2.f, x=x0)
max(abs(exact - g)/(1 + abs(exact)))

gc <- grad(func=sc2.f, x=x0, method="complex")
max(abs(exact - gc)/(1 + abs(exact)))

f <- function(x) if(x[1]<=0) sum(sin(x)) else NA
grad(f, x=c(0,0), method="Richardson", side=c(-1, 1))

```

hessian

Calculate Hessian Matrix

Description

Calculate a numerical approximation to the Hessian matrix of a function at a parameter value.

Usage

```

hessian(func, x, method="Richardson", method.args=list(), ...)

## Default S3 method:
hessian(func, x, method="Richardson",
        method.args=list(), ...)

```

Arguments

func	a function for which the first (vector) argument is used as a parameter vector.
x	the parameter vector first argument to func.
method	one of "Richardson" or "complex" indicating the method to use for the approximation.
method.args	arguments passed to method. See grad . (Arguments not specified remain with their default values.)
...	an additional arguments passed to func. WARNING: None of these should have names matching other arguments of this function.

Details

The function `hessian` calculates an numerical approximation to the $n \times n$ second derivative of a scalar real valued function with n -vector argument.

The argument `method` can be "Richardson" or "complex". Method "simple" is not supported.

For method "complex" the Hessian matrix is calculated as the Jacobian of the gradient. The function `grad` with method "complex" is used, and `method.args` is ignored for this (an `eps` of `.Machine$double.eps` is used). However, `jacobian` is used in the second step, with method "Richardson" and argument `method.args` is used for this. The default is `method.args=list(eps=1e-4, d=0.1, zero.to` (These are the defaults for `hessian` with method "Richardson", which are slightly different from the defaults for `jacobian` with method "Richardson".) See addition comments in `grad` before choosing method "complex".

Methods "Richardson" uses `genD` and extracts the second derivative. For this method `method.args=list(eps=1e-4, d=0.1, zero.to` is set as the default. `hessian` does one evaluation of `func` in order to do some error checking before calling `genD`, so the number of function evaluations will be one more than indicated for `genD`.

The argument `side` is not supported for second derivatives and since ... are passed to `func` there may be no error message if it is specified.

Value

An n by n matrix of the Hessian of the function calculated at the point x .

See Also

[jacobian](#), [grad](#), [genD](#)

Examples

```
sc2.f <- function(x){
  n <- length(x)
  sum((1:n) * (exp(x) - x)) / n
}

sc2.g <- function(x){
  n <- length(x)
  (1:n) * (exp(x) - 1) / n
}

x0 <- rnorm(5)
hess <- hessian(func=sc2.f, x=x0)
hessc <- hessian(func=sc2.f, x=x0, "complex")
all.equal(hess, hessc, tolerance = .Machine$double.eps)

# Hessian = Jacobian of the gradient
jac <- jacobian(func=sc2.g, x=x0)
jacc <- jacobian(func=sc2.g, x=x0, "complex")
all.equal(hess, jac, tolerance = .Machine$double.eps)
all.equal(hessc, jacc, tolerance = .Machine$double.eps)
```

jacobian

*Gradient of a Vector Valued Function***Description**

Calculate the m by n numerical approximation of the gradient of a real m -vector valued function with n -vector argument.

Usage

```
jacobian(func, x, method="Richardson", side=NULL, method.args=list(), ...)

## Default S3 method:
jacobian(func, x, method="Richardson", side=NULL,
         method.args=list(), ...)
```

Arguments

func	a function with a real (vector) result.
x	a real or real vector argument to func, indicating the point at which the gradient is to be calculated.
method	one of "Richardson", "simple", or "complex" indicating the method to use for the approximation.
method.args	arguments passed to method. See grad . (Arguments not specified remain with their default values.)
...	any additional arguments passed to func. WARNING: None of these should have names matching other arguments of this function.
side	an indication of whether one-sided derivatives should be attempted (see details in function grad).

Details

For $f : R^n \rightarrow R^m$ calculate the $m \times n$ Jacobian dy/dx . The function `jacobian` calculates a numerical approximation of the first derivative of `func` at the point `x`. Any additional arguments in `...` are also passed to `func`, but the gradient is not calculated with respect to these additional arguments.

If `method` is "Richardson", the calculation is done by Richardson's extrapolation. See [link{grad}](#) for more details. For this method `method.args=list(eps=1e-4, d=0.0001, zero.tol=sqrt(.Machine$double.eps)/7)` is set as the default.

If `method` is "simple", the calculation is done using a simple epsilon difference. For method "simple" `method.args=list(eps=1e-4)` is the default. Only `eps` is used by this method.

If `method` is "complex", the calculation is done using the complex step derivative approach. See addition comments in [grad](#) before choosing this method. For method "complex", `method.args` is ignored. The algorithm uses an `eps` of `.Machine$double.eps` which cannot (and should not) be modified.

Value

A real m by n matrix.

See Also

[grad](#), [hessian](#), [numericDeriv](#)

Examples

```
func2 <- function(x) c(sin(x), cos(x))
x <- (0:1)*2*pi
jacobian(func2, x)
jacobian(func2, x, "complex")
```

Index

*Topic **multivariate**

genD, [3](#)

grad, [5](#)

hessian, [8](#)

jacobian, [10](#)

*Topic **package**

00.numDeriv.Intro, [3](#)

numDeriv-package, [2](#)

00.numDeriv.Intro, [3](#)

genD, [3](#), [6](#), [7](#), [9](#)

grad, [3](#), [4](#), [5](#), [8–11](#)

hessian, [4](#), [7](#), [8](#), [11](#)

jacobian, [4](#), [5](#), [7](#), [9](#), [10](#)

numDeriv-package, [2](#)

numDeriv.Intro (numDeriv-package), [2](#)

numericDeriv, [7](#), [11](#)