Package deSolve: Solving Initial Value Differential Equations in R

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Abstract

R package deSolve (Soetaert, Petzoldt, and Setzer 2010b,c) the successor of R package odesolve is a package to solve initial value problems (IVP) of:

- ordinary differential equations (ODE),
- differential algebraic equations (DAE),
- partial differential equations (PDE) and
- delay differential equations (DeDE).

The implementation includes stiff and nonstiff integration routines based on the ODEPACK FORTRAN codes (Hindmarsh 1983). It also includes fixed and adaptive time-step explicit Runge-Kutta solvers and the Euler method (Press, Teukolsky, Vetterling, and Flannery 1992), and the implicit Runge-Kutta method RADAU (Hairer and Wanner 2010).

In this vignette we outline how to implement differential equations as R -functions. Another vignette (“compiledCode”) (Soetaert, Petzoldt, and Setzer 2008), deals with differential equations implemented in lower-level languages such as FORTRAN, C, or C++, which are compiled into a dynamically linked library (DLL) and loaded into R (R Development Core Team 2008).

Note that another package, bvpSolve provides methods to solve boundary value problems (Soetaert, Cash, and Mazzia 2010a).

Keywords: differential equations, ordinary differential equations, differential algebraic equations, partial differential equations, initial value problems, R.

1. A simple ODE: chaos in the atmosphere

The Lorenz equations (Lorenz, 1963) were the first chaotic dynamic system to be described. They consist of three differential equations that were assumed to represent idealized behavior of the earth’s atmosphere. We use this model to demonstrate how to implement and solve differential equations in R. The Lorenz model describes the dynamics of three state variables, X, Y and Z. The model equations are:
\[ \frac{dX}{dt} = a \cdot X + Y \cdot Z \]
\[ \frac{dY}{dt} = b \cdot (Y - Z) \]
\[ \frac{dZ}{dt} = -X \cdot Y + c \cdot Y - Z \]

with the initial conditions:
\[ X(0) = Y(0) = Z(0) = 1 \]

Where \( a, b \) and \( c \) are three parameters, with values of -8/3, -10 and 28 respectively.

Implementation of an IVP ODE in R can be separated in two parts: the model specification and the model application. Model specification consists of:

- Defining model parameters and their values,
- Defining model state variables and their initial conditions,
- Implementing the model equations that calculate the rate of change (e.g. \( dX/dt \)) of the state variables.

The model application consists of:

- Specification of the time at which model output is wanted,
- Integration of the model equations (uses R-functions from \texttt{deSolve}),
- Plotting of model results.

Below, we discuss the R-code for the Lorenz model.

1.1. Model specification

\textit{Model parameters}

There are three model parameters: \( a, b, \) and \( c \) that are defined first. Parameters are stored as a vector with assigned names and values:

```r
> parameters <- c(a = -8/3,
+                 b = -10,
+                 c = 28)
```

\textit{State variables}

The three state variables are also created as a vector, and their initial values given:
> state <- c(X = 1,
+     Y = 1,
+     Z = 1)

Model equations

The model equations are specified in a function (Lorenz) that calculates the rate of change of the state variables. Input to the function is the model time (t, not used here, but required by the calling routine), and the values of the state variables (state) and the parameters, in that order. This function will be called by the R routine that solves the differential equations (here we use \texttt{ode}, see below).

The code is most readable if we can address the parameters and state variables by their names. As both parameters and state variables are 'vectors', they are converted into a list. The statement \texttt{with(as.list(c(state, parameters)), ...)} then makes available the names of this list.

The main part of the model calculates the rate of change of the state variables. At the end of the function, these rates of change are returned, packed as a list. Note that it is necessary to return the rate of change in the same ordering as the specification of the state variables. This is very important. In this case, as state variables are specified X first, then Y and Z, the rates of changes are returned as \texttt{dX, dY, dZ}.

> Lorenz<-function(t, state, parameters) {
+   with(as.list(c(state, parameters)),{
+     # rate of change
+     dX <- a*X + Y*Z
+     dY <- b * (Y-Z)
+     dZ <- -X*Y + c*Y - Z
+     +   # return the rate of change
+     +     list(c(dX, dY, dZ))
+   + }) # end with(as.list ...
+ +
+ }

1.2. Model application

Time specification

We run the model for 100 days, and give output at 0.01 daily intervals. R's function \texttt{seq()} creates the time sequence:

> times <- seq(0, 100, by = 0.01)

Model integration

The model is solved using \texttt{deSolve} function \texttt{ode}, which is the default integration routine. Function \texttt{ode} takes as input, a.o. the state variable vector (y), the times at which output is
required (times), the model function that returns the rate of change (func) and the parameter vector (parms).

Function ode returns an object of class deSolve with a matrix that contains the values of the state variables (columns) at the requested output times.

```r
> library(deSolve)
> out <- ode(y = state, times = times, func = Lorenz, parms = parameters)
> head(out)

     time       X       Y       Z
[1,] 0.00 1.000000 1.000000 1.000000
[2,] 0.01 0.984891 1.012567 1.259918
[3,] 0.02 0.973114 1.048823 1.523999
[4,] 0.03 0.965159 1.107207 1.798314
[5,] 0.04 0.961737 1.186866 2.088545
[6,] 0.05 0.963807 1.287555 2.400161
```

Plotting results

Finally, the model output is plotted. We use the plot method designed for objects of class deSolve, which will neatly arrange the figures in two rows and two columns; before plotting, the size of the outer upper margin (the third margin) is increased (oma), such as to allow writing a figure heading (mtext). First all model variables are plotted versus time, and finally Z versus X:

```r
> par(oma = c(0, 0, 3, 0))
> plot(out, xlab = "time", ylab = "-")
> plot(out[, "X"], out[, "Z"], pch = ".")
> mtext(outer = TRUE, side = 3, "Lorenz model", cex = 1.5)
```
Lorenz model

Figure 1: Solution of the ordinary differential equation - see text for R-code
2. Solvers for initial value problems of ordinary differential equations

Package `deSolve` contains several IVP ordinary differential equation solvers, that belong to the most important classes of solvers. Most functions are based on original (FORTRAN) implementations, e.g. the Backward Differentiation Formulae and Adams methods from ODEPACK (Hindmarsh 1983), or from (Brown, Byrne, and Hindmarsh 1989; Petzold 1983), the implicit Runge-Kutta method RADAU (Hairer and Wanner 2010). The package contains also a de novo implementation of several Runge-Kutta methods (Butcher 1987; Press et al. 1992; Hairer, Norsett, and Wanner 2009).

All integration methods\(^1\) can be triggered from function `ode`, by setting `ode`'s argument `method`), or can be run as stand-alone functions. Moreover, for each integration routine, several options are available to optimise performance.

For instance, the next statements will use integration method `radau` to solve the model, and set the tolerances to a higher value than the default. Both statements are the same:

```r
> outb <- radau(state, times, Lorenz, parameters, atol = 1e-4, rtol = 1e-4)
> outc <- ode(state, times, Lorenz, parameters, method = "radau",
  + atol = 1e-4, rtol = 1e-4)
```

The default integration method, based on the FORTRAN code LSODA is one that switches automatically between stiff and non-stiff systems (Petzold 1983). This is a very robust method, but not necessarily the most efficient solver for one particular problem. See (Soetaert et al. 2010b) for more information about when to use which solver in `deSolve`. For most cases, the default solver, `ode` and using the default settings will do. Table 1 also gives a short overview of the available methods.

To show how to trigger the various methods, we solve the model with several integration routines, each time printing the time it took (in seconds) to find the solution:

```r
> print(system.time(out1 <- rk4 (state, times, Lorenz, parameters)))
  user  system elapsed
  0.75   0.00   0.75
> print(system.time(out2 <- lsode (state, times, Lorenz, parameters)))
  user  system elapsed
  0.27   0.02   0.28
> print(system.time(out <- lsoda (state, times, Lorenz, parameters)))
  user  system elapsed
  0.39   0.00   0.39
> print(system.time(out <- lsodes(state, times, Lorenz, parameters)))
```

\(^1\)except `zvode`, the solver used for systems containing complex numbers.
2.1. Runge-Kutta methods and Euler

The explicit Runge-Kutta methods are de novo implementations in C, based on the Butcher tables (Butcher 1987). They comprise simple Runge-Kutta formulae (Euler’s method `euler`, Heun’s method `rk2`, the classical 4th order Runge-Kutta, `rk4`) and several Runge-Kutta pairs of order 3(2) to order 8(7). The embedded, explicit methods are according to Fehlberg (1967) (`rk...f`, `ode45`), Dormand and Prince (1980, 1981) (`rk..dp.`), Bogacki and Shampine (1989) (`rk23bs`, `ode23`) and Cash and Karp (1990) (`rk45ck`), where `ode23` and `ode45` are aliases for the popular methods `rk23bs` resp. `rk45dp7`.

With the following statement all implemented methods are shown:

```r
> rkMethod()

[1] "euler" "rk2" "rk4" "rk23" "rk23bs" "rk34f"
[7] "rk45f" "rk45ck" "rk45e" "rk45dp6" "rk45dp7" "rk78dp"
[13] "rk78f" "irk3r" "irk5r" "irk4hh" "irk6kb" "irk4l"
[19] "irk6l" "ode23" "ode45"
```

This list also contains implicit Runge-Kutta’s (`irk..`), but they are not yet optimally coded. The only well-implemented implicit Runge-Kutta is the `radau` method (Hairer and Wanner 2010) that will be discussed in the section dealing with differential algebraic equations.

The properties of a Runge-Kutta method can be displayed as follows:

```r
> rkMethod("rk23")
```

```
$ID
[1] "rk23"

$varstep
[1] TRUE

$FSAL
```
Here \texttt{varstep} informs whether the method uses a variable time-step; \texttt{FSAL} whether the first same as last strategy is used, while \texttt{stage} and \texttt{Qerr} give the number of function evaluations needed for one step, and the order of the local truncation error. \texttt{A, b1, b2, c} are the coefficients of the Butcher table. Two formulae (\texttt{rk45dp7, rk45ck}) support dense output.

It is also possible to modify the parameters of a method (be very careful with this) or define and use a new Runge-Kutta method:

```r
> func <- function(t, x, parms) {
+   with(as.list(c(parms, x)),{
+     dP <- a * P - b * C * P
+     dC <- b * P * C - c * C
+     res <- c(dP, dC)
+     list(res)
+   })
+ }
> rKnew <- rkMethod(ID = "midpoint",
+   varstep = FALSE,
+   A = c(0, 1/2),
+   b1 = c(0, 1),
+   c = c(0, 1/2),
+   stage = 2,
```
\begin{verbatim}
+ Qerr = 1
+
> out <- ode(y = c(P = 2, C = 1), times = 0:100, func,
+ parms = c(a = 0.1, b = 0.1, c = 0.1), method = rKnew)
> head(out)

time P C
[1,] 0 2.000000 1.000000
[2,] 1 1.990000 1.105000
[3,] 2 1.958387 1.218598
[4,] 3 1.904734 1.338250
[5,] 4 1.830060 1.460298
[6,] 5 1.736925 1.580136

Fixed time-step methods

There are two explicit methods that do not adapt the time step: the euler method and the rk4 method.

They are implemented in two ways:

- as a rkMethod of the general rk solver. In this case the time step used can be specified independently from the times argument, by setting argument hini. Function ode uses this general code.

- as special solver codes euler and rk4. These implementations are simplified and with less options to avoid overhead. The timestep used is determined by the time increment in the times argument.

For example, the next two statements both trigger the Euler method, the first using the "special" code with a time step = 1, as imposed by the times argument, the second using the generalized method with a time step set by hini. Unsurprisingly, the first solution method completely fails (the time step = 1 is much too large for this problem).

out <- euler(y = state, times = 0:40, func = Lorenz, parms = parameters)
outb <- ode(y = state, times = 0:40, func = Lorenz, parms = parameters,
method = "euler", hini = 0.01)

2.2. Model diagnostics and summaries

Function diagnostics prints several diagnostics of the simulation to the screen. For the Runge-Kutta and lsode routine called above they are:

> diagnostics(out1)

---------------------
rk return code
\end{verbatim}
return code (idid) = 0
Integration was successful.

INTEGER values

1 The return code : 0
2 The number of steps taken for the problem so far: 10000
3 The number of function evaluations for the problem so far: 40001
18 The order (or maximum order) of the method: 4

> diagnostics(out2)

lsode return code

return code (idid) = 2
Integration was successful.

INTEGER values

1 The return code : 2
2 The number of steps taken for the problem so far: 12778
3 The number of function evaluations for the problem so far: 16633
5 The method order last used (successfully): 5
6 The order of the method to be attempted on the next step: 5
7 If return flag =-4,-5: the largest component in error vector 0
8 The length of the real work array actually required: 58
9 The length of the integer work array actually required: 23
14 The number of Jacobian evaluations and LU decompositions so far: 721

RSTATE values

1 The step size in t last used (successfully): 0.01
2 The step size to be attempted on the next step: 0.01
3 The current value of the independent variable which the solver has reached: 100.0072
4 Tolerance scale factor > 1.0 computed when requesting too much accuracy: 0

There is also a summary method for deSolve objects. This is especially handy for multi-
dimensional problems (see below)
```
> summary(out1)

          X           Y           Z
Min.    9.617372e-01 -17.965128 -24.107629
1st Qu. 1.702231e+01  -7.347550 -7.151654
Median  2.305675e+01  -1.946728 -1.450773
Mean    2.368979e+01  -1.385164 -1.401846
3rd Qu. 3.020200e+01  3.606680  2.984168
Max.    4.783395e+01  19.555041 27.183473
N        1.000100e+04 10001.000000 10001.000000
sd      8.501340e+00  7.846889  8.929121
```
3. Partial differential equations

As package deSolve includes integrators that deal efficiently with arbitrarily sparse and banded Jacobians, it is especially well suited to solve initial value problems resulting from 1, 2 or 3-dimensional partial differential equations (PDE), using the method-of-lines approach. The PDEs are first written as ODEs, using finite differences. This can be efficiently done with functions from R-package ReacTran (Soetaert and Meysman 2010). However, here we will create the finite differences in R-code.

Several special-purpose solvers are included in deSolve:

- ode.band integrates 1-dimensional problems comprizing one species,
- ode.1D integrates 1-dimensional problems comprizing one or many species,
- ode.2D integrates 2-dimensional problems,
- ode.3D integrates 3-dimensional problems.

As an example, consider the Aphid model described in Soetaert and Herman (2009). It is a model where aphids (a pest insect) slowly diffuse and grow on a row of plants. The model equations are:

\[
\frac{\partial N}{\partial t} = -\frac{\partial Flux}{\partial x} + g \cdot N
\]

and where the diffusive flux is given by:

\[
Flux = -D \frac{\partial N}{\partial x}
\]

with boundary conditions

\[N_{x=0} = N_{x=60} = 0\]

and initial condition

\[N_x = 0 \text{ for } x \neq 30 \]
\[N_x = 1 \text{ for } x = 30\]

In the method of lines approach, the spatial domain is subdivided in a number of boxes and the equation is discretized as:

\[
\frac{dN_i}{dt} = -\frac{Flux_{i,i+1} - Flux_{i-1,i}}{\Delta x_i} + g \cdot N_i
\]

with the flux on the interface equal to:

\[
Flux_{i-1,i} = -D_{i-1,i} \cdot \frac{N_i - N_{i-1}}{\Delta x_{i-1,i}}
\]
Note that the values of state variables (here densities) are defined in the centre of boxes (i), whereas the fluxes are defined on the box interfaces. We refer to Soetaert and Herman (2009) for more information about this model and its numerical approximation.

Here is its implementation in R. First the model equations are defined:

```r
> Aphid <- function(t, APHIDS, parameters) {
+   deltax <- c(0.5, rep(1, numboxes - 1), 0.5)
+   Flux <- -D * diff(c(0, APHIDS, 0)) / deltax
+   dAPHIDS <- -diff(Flux) / delx + APHIDS * r
+   # the return value
+   list(dAPHIDS)
+ } # end
```

Then the model parameters and spatial grid are defined:

```r
> D     <- 0.3      # m2/day diffusion rate
> r     <- 0.01     # /day net growth rate
> delx  <- 1        # m thickness of boxes
> numboxes <- 60
> Distance <- seq(from = 0.5, by = delx, length.out = numboxes)
```

Aphids are initially only present in two central boxes:

```r
> # Initial conditions: # ind/m2
> APHIDS     <- rep(0, times = numboxes)
> APHIDS[30:31] <- 1
> state <- c(APHIDS = APHIDS)      # initialise state variables
```

The model is run for 200 days, producing output every day; the time elapsed in seconds to solve this 60 state-variable model is estimated (system.time):

```r
> times     <- seq(0, 200, by = 1)
> print(system.time(
+   out <- ode.1D(state, times, Aphid, parms = 0, nspec = 1, names = "Aphid")
+ ))
```

```
user    system   elapsed
 0.02     0.00     0.02
```

Matrix `out` consist of times (1st column) followed by the densities (next columns).

```r
> head(out[,1:5])
```
Package *desolve*: Solving Initial Value Differential Equations in R

<table>
<thead>
<tr>
<th>time</th>
<th>APHIDS1</th>
<th>APHIDS2</th>
<th>APHIDS3</th>
<th>APHIDS4</th>
</tr>
</thead>
<tbody>
<tr>
<td>[1,]</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>[2,]</td>
<td>1</td>
<td>1.667</td>
<td>9.555</td>
<td>2.555</td>
</tr>
<tr>
<td>[3,]</td>
<td>2</td>
<td>3.630</td>
<td>4.865</td>
<td>5.394</td>
</tr>
<tr>
<td>[4,]</td>
<td>3</td>
<td>2.051</td>
<td>9.208</td>
<td>3.723</td>
</tr>
<tr>
<td>[5,]</td>
<td>4</td>
<td>1.307</td>
<td>3.719</td>
<td>9.635</td>
</tr>
<tr>
<td>[6,]</td>
<td>5</td>
<td>6.839</td>
<td>1.465</td>
<td>2.860</td>
</tr>
</tbody>
</table>

The *summary* method gives the mean, min, max, ... of the entire 1-D variable:

```r
> summary(out)

Aphid

       Min. 1st Qu.  Median       Mean 3rd Qu.       Max. N      sd
Aphid 0.000000e+00 1.705086e-03 4.051383e-02 1.062271e-01 1.931426e-01 1.000000e+00 1.303048e-01
```

Finally, the output is plotted. It is simplest to do this with *desolve*’s S3-method *image*

```r
image(out, method = "filled.contour", grid = Distance, 
      xlab = "time, days", ylab = "Distance on plant, m", 
      main = "Aphid density on a row of plants")
```

As this is a 1-D model, it is best solved with *desolve* function *ode.1D*. A multi-species IVP example can be found in *Soetaert and Herman* (2009). For 2-D and 3-D problems, we refer to the help-files of functions *ode.2D* and *ode.3D*.

The output of one-dimensional models can also be plotted using S3-method *plot.1D* and *matplot.1D*. In both cases, we can simply take a *subset* of the output, and add observations.

```r
> data <- cbind(dist = c(0,10, 20, 30, 40, 50, 60), 
               Aphid = c(0,0.1,0.25,0.5,0.25,0.1,0))
> par (mfrow = c(1,2))
> matplot.1D(out, grid = Distance, type = "l", mfrow = NULL, 
             subset = time %in% seq(0, 200, by = 10), 
             obs = data, obspar = list(pch = 18, cex = 2, col="red"))
> plot.1D(out, grid = Distance, type = "l", mfrow = NULL, 
         subset = time == 100, 
         obs = data, obspar = list(pch = 18, cex = 2, col="red"))
```
Figure 2: Solution of the 1-dimensional aphid model - see text for R-code
Figure 3: Solution of the Aphid model - plotted with matplot.1D, plot.1D - see text for R-code
4. Differential algebraic equations

Package deSolve contains two functions that solve initial value problems of differential algebraic equations. They are:

- `radau` which implements the implicit Runge-Kutta RADAU5 (Hairer and Wanner 2010),
- `daspk`, based on the backward differentiation code DASPK (Brenan, Campbell, and Petzold 1996).

Function `radau` needs the input in the form \( My' = f(t, y, y') \) where \( M \) is the mass matrix. Function `daspk` also supports this input, but can also solve problems written in the form \( F(t, y, y') = 0 \).

`radau` solves problems up to index 3; `daspk` solves problems of index \( \leq 1 \).

4.1. DAEs of index maximal 1

Function `daspk` from package deSolve solves (relatively simple) DAEs of index\(^2\) maximal 1. The DAE has to be specified by the residual function instead of the rates of change (as in ODE). Consider the following simple DAE:

\[
\begin{align*}
\frac{dy_1}{dt} &= -y_1 + y_2 \\
y_1 \cdot y_2 &= t
\end{align*}
\]

where the first equation is a differential, the second an algebraic equation. To solve it, it is first rewritten as residual functions:

\[
\begin{align*}
0 &= \frac{dy_1}{dt} + y_1 - y_2 \\
0 &= y_1 \cdot y_2 - t
\end{align*}
\]

In R we write:

```r
> daefun <- function(t, y, dy, parameters) {
+   return(list(c(res1, res2))
+ )
> library(deSolve)
> yini <- c(1, 0)
> dyini <- c(1, 0)
> times <- seq(0, 10, 0.1)
> ## solver
> system.time(out <- daspk(y = yini, dy = dyini,
+   times = times, res = daefun, parms = 0))
```

\(^2\)note that many – apparently simple – DAEs are higher-index DAEs
Figure 4: Solution of the differential algebraic equation model - see text for R-code

\begin{verbatim}
> matplot(out[,1], out[,2:3], type = "l", lwd = 2,
+        main = "dae", xlab = "time", ylab = "y")
\end{verbatim}

4.2. DAEs of index up to three

Function \texttt{radau} from package \texttt{deSolve} can solve DAEs of index up to three provided that they can be written in the form $M \frac{dy}{dt} = f(t, y)$.

Consider the well-known pendulum equation:

\begin{align*}
x' & = u \\
y' & = v \\
u' & = -\lambda x \\
v' & = -\lambda y - 9.8 \\
0 & = x^2 + y^2 - 1
\end{align*}

where the dependent variables are $x, y, u, v$ and $\lambda$.

Implemented in R to be used with function \texttt{radau} this becomes:

\begin{verbatim}
> pendulum <- function (t, Y, parms) {
+   with (as.list(Y),
+   list(c(u,
+           v,
+           -lam * x,
+           -lam * y - 9.8,
+           x^2 + y^2 - 1
+   ))
\end{verbatim}
A consistent set of initial conditions are:

```r
d yini <- c(x = 1, y = 0, u = 0, v = 1, lam = 1)
```

and the mass matrix $M$:

```r
d M <- diag(nrow = 5)
> M[5, 5] <- 0
> M

[1,] 1 0 0 0 0
[2,] 0 1 0 0 0
[3,] 0 0 1 0 0
[4,] 0 0 0 1 0
[5,] 0 0 0 0 0
```

Function `radau` requires that the index of each equation is specified; there are 2 equations of index 1, two of index 2, one of index 3:

```r
d index <- c(2, 2, 1)
> times <- seq(from = 0, to = 10, by = 0.01)
> out <- radau (y = yini, func = pendulum, parms = NULL,
+ times = times, mass = M, nind = index)

> plot(out, type = "l", lwd = 2)
> plot(out[, c("x", "y")], type = "l", lwd = 2)
```
Figure 5: Solution of the pendulum problem, an index 3 differential algebraic equation using \texttt{radau} - see text for R-code
5. Integrating systems containing complex numbers, function zvode

Function \texttt{zvode} solves ODEs that are composed of complex variables. We use \texttt{zvode} to solve the following system of 2 ODEs:

\[
\frac{dz}{dt} = i \cdot z \\
\frac{dw}{dt} = -i \cdot w \cdot w \cdot z
\]

where

\[w(0) = 1/2.1\]
\[z(0) = 1\]

on the interval \(t = [0, 2\pi]\)

\[
\text{ZODE2} \leftarrow \text{function}(\text{Time}, \text{State}, \text{Pars}) \{
  \text{with(as.list(State), \{}
    \text{df} <- 1i * f \\
    \text{dg} <- -1i * g * g * f \\
    \text{return(list(c(df, dg)))}
  \})
\}
\]

\[
yini \leftarrow \text{c}(f = 1+0i, g = 1/2.1+0i)
\]

\[
times \leftarrow \text{seq}(0, 2 * \pi, \text{length} = 100)
\]

\[
\text{out} \leftarrow \text{zvode(func = ZODE2, y = yini, pars = NULL, times = times,}
  + \text{atol = 1e-10, rtol = 1e-10})
\]

The analytical solution is:

\[
f(t) = \exp(1i \cdot t)
\]

and

\[
g(t) = 1/(f(t) + 1.1)
\]

The numerical solution, as produced by \texttt{zvode} matches the analytical solution:

\[
\text{analytical} \leftarrow \text{cbind}(f = \exp(1i*times), g = 1/(\exp(1i*times) + 1.1))
\]

\[
\text{tail(cbind(out[,2], analytical[,1]))}
\]

\[
[,1] [,2]
[95,] 0.9500711-0.3120334i 0.9500711-0.3120334i
[96,] 0.9679487-0.2511480i 0.9679487-0.2511480i
[97,] 0.9819287-0.1892512i 0.9819287-0.1892512i
[98,] 0.9919548-0.1265925i 0.9919548-0.1265925i
[99,] 0.9979867-0.0634239i 0.9979867-0.0634239i
[100,] 1.0000000+0.0000000i 1.0000000-0.0000000i
\]
6. Making good use of the integration options

The solvers from ODEPACK can be fine-tuned if it is known whether the problem is stiff or
non-stiff, or if the structure of the Jacobian is sparse. We repeat the example from lsode to
show how we can make good use of these options.

The model describes the time evolution of 5 state variables:

```r
> f1 <- function (t, y, parms) {
+   ydot <- vector(len = 5)
+   return(list(ydot))
+ }
```

and the initial conditions and output times are:

```r
> yini <- 1:5
> times <- 1:20
```

The default solution, using lsode assumes that the model is stiff, and the integrator generates
the Jacobian, which is assumed to be full:

```r
> out <- lsode(yini, times, f1, parms = 0, jactype = "fullint")
```

It is possible for the user to provide the Jacobian. Especially for large problems this can
result in substantial time savings. In a first case, the Jacobian is written as a full matrix:

```r
> fulljac <- function (t, y, parms) {
+   jac <- matrix(nrow = 5, ncol = 5, byrow = TRUE,
+                 data = c(0.1, -0.2, 0 , 0 , 0 ,
+                           -0.3, 0.1, -0.2, 0 , 0 ,
+                           0 , -0.3, 0.1, -0.2, 0 ,
+                           0 , 0 , -0.3, 0.1, -0.2,
+                           0 , 0 , 0 , -0.3, 0.1))
+   return(jac)
+ }
```

and the model solved as:

```r
> out2 <- lsode(yini, times, f1, parms = 0, jactype = "fullusr",
+               jacfunc = fulljac)
```
The Jacobian matrix is banded, with one nonzero band above (up) and one below (down) the diagonal. First we let `lsode` estimate the banded Jacobian internally (`jactype = "bandint"`):

```r
> out3 <- lsode(yini, times, f1, parms = 0, jactype = "bandint",
+                bandup = 1, banddown = 1)
```

It is also possible to provide the nonzero bands of the Jacobian in a function:

```r
> bandjac <- function (t, y, parms) {
+   jac <- matrix(nrow = 3, ncol = 5, byrow = TRUE,
+                  data = c( 0 , -0.2, -0.2, -0.2, -0.2,
+                     0.1, 0.1, 0.1, 0.1, 0.1,
+                     -0.3, -0.3, -0.3, -0.3, 0))
+   return(jac)
+ }
```

in which case the model is solved as:

```r
> out4 <- lsode(yini, times, f1, parms = 0, jactype = "bandusr",
+                jacfunc = bandjac, bandup = 1, banddown = 1)
```

Finally, if the model is specified as “non-stiff” (by setting `mf=10`), there is no need to specify the Jacobian:

```r
> out5 <- lsode(yini, times, f1, parms = 0, mf = 10)
```
7. Events and roots

As from version 1.6, events are supported. Events occur when the values of state variables are instantaneously changed. They can be specified as a data.frame, or in a function. Events can also be triggered by a root function.

Several integrators (lsoda, lsodar, lsode, lsodes and radau) can estimate the root of one or more functions. For the first 4 integration methods, the root finding algorithm is based on the algorithm in solver LSODAR, and implemented in FORTRAN. For radau, the root solving algorithm is written in C-code, and it works slightly different. Thus, some problems involving roots may be more efficient to solve with either lsoda, lsode, or lsodes, while other problems are more efficiently solved with radau.

If a root is found, then the integration will be terminated, unless an event function is defined. A help file with information on roots and events can be opened by typing ?events or ?roots.

7.1. Event specified in a data.frame

In this example, two state variables with constant decay are modeled:

```r
> eventmod <- function(t, var, parms) {
+   list(dvar = -0.1*var)
+ }
> yini <- c(v1 = 1, v2 = 2)
> times <- seq(0, 10, by = 0.1)
```

At time 1 and 9 a value is added to variable v1, at time 1 state variable v2 is multiplied with 2, while at time 5 the value of v2 is replaced with 3. These events are specified in a data.frame, eventdat:

```r
> eventdat <- data.frame(var = c("v1", "v2", "v2", "v1"), time = c(1, 1, 5, 9),
+   value = c(1, 2, 3, 4), method = c("add", "mult", "rep", "add"))
> eventdat
                 var time value method
1          v1     1     1      add
2          v2     1     2     mult
3          v2     5     3      rep
4          v1     9     4      add
```

The model is solved with ode:

```r
> out <- ode(func = eventmod, y = yini, times = times, parms = NULL,
+   events = list(data = eventdat))
> plot(out, type = "l", lwd = 2)
```

7.2. Event triggered by a root function

This model describes the position (y1) and velocity (y2) of a bouncing ball:
An event is triggered when the ball hits the ground (height = 0) then velocity (y2) is reversed and reduced by 10 percent. The root function, y[1] = 0, triggers the event:

```r
> root <- function(t, y, parms) y[1]
```

The event function imposes the bouncing of the ball

```r
> event <- function(t, y, parms) {
+   y[1]<- 0
+   y[2]<- -0.9 * y[2]
+   return(y)
+ }
```

After specifying the initial values and times, the model is solved, here using `lsode`.

```r
> yini <- c(height = 0, v = 20)
> times <- seq(from = 0, to = 20, by = 0.01)
> out <- lsode(times = times, y = yini, func = ballode, parms = NULL,
+   events = list(func = event, root = TRUE), rootfun = root)
> plot(out, which = "height", type = "l", lwd = 2,
+   main = "bouncing ball", ylab = "height")
```
7.3. Events and time steps

The use of events requires that all event times are contained in the output time steps, otherwise such events would be skipped. This sounds easy but sometimes problems can occur due to the limited accuracy of floating point arithmetics of the computer. To make things work as expected, two requirements have to be fulfilled:

1. all event times have to be contained exactly in times, i.e. with the maximum possible accuracy of floating point arithmetics.
2. two time steps should not be too close together, otherwise numerical problems would occur during the integration.

Starting from version 1.10 of deSolve this is now checked (and if necessary also fixed) automatically by the solver functions. A warning is issued to inform the user about possible problems, especially that the output time steps were now adjusted and therefore different from the ones originally specified by the user. This means that all values of eventtimes are now contained but only the subset of times that have no exact or “rather close” neighbors in eventtimes.

Instead of relying on this automatism, matching times and eventtimes can also be managed by the user, either by appropriate rounding or by using function cleanEventTimes shown below.

Let’s assume we have a vector of time steps times and another vector of event times eventtimes:

```r
> times <- seq(0, 1, 0.1)
> eventtimes <- c(0.7, 0.9)
```

If we now check whether the eventtimes are in times:

```r
> eventtimes %in% times
```
we get the surprising answer that this is only partly the case, because seq made small numerical errors. The easiest method to get rid of this is rounding:

```r
> times2 <- round(times, 1)
> times - times2
```

```
[1] 0.000000e+00 0.000000e+00 0.000000e+00 5.551115e-17 0.000000e+00
[6] 0.000000e+00 1.110223e-16 1.110223e-16 0.000000e+00 0.000000e+00
[11] 0.000000e+00
```

The last line shows us that the error was always smaller than, say $10^{-15}$, what is typical for ordinary double precision arithmetics. The accuracy of the machine can be determined with `Machine$double.eps`.

To check if all `eventtimes` are now contained in the new times vector `times2`, we use:

```r
> eventtimes %in% times2
```

```
[1] TRUE TRUE
```

or

```r
> all(eventtimes %in% times2)
```

```
[1] TRUE
```

and see that everything is o.k. now.

In few cases, rounding may not work properly, for example if a pharmacokinetic model is simulated with a daily time step, but drug injection occurs at precisely fixed times within the day. Then one has to add all additional event times to the ordinary time stepping:

```r
> times <- 1:10
> eventtimes <- c(1.3, 3.4, 4, 7.9, 8.5)
> newtimes <- sort(unique(c(times, eventtimes)))
```

If, however, an event and a time step are almost (but not exactly) the same, then it is more safe to use:

```r
> times <- 1:10
> eventtimes <- c(1.3, 3.4, 4, 7.9999999999999999, 8.5)
> newtimes <- sort(c(eventtimes, cleanEventTimes(times, eventtimes)))
```

because `cleanEventTimes` removes not only the doubled 4 (like `unique`, but also the “almost doubled” 8, while keeping the exact event time. The tolerance of `cleanEventTimes` can be adjusted using an optional argument `eps`.

As said, this is normally done automatically by the differential equation solvers and in most cases appropriate rounding will be sufficient to get rid of the warnings.
8. Delay differential equations

As from deSolve version 1.7, time lags are supported, and a new general solver for delay differential equations, dede has been added.

We implement the lemming model, example 6 from (Shampine and Thompson 2000).

Function lagvalue calculates the value of the state variable at $t = 0.74$. As long as these lag values are not known, the value 19 is assigned to the state variable. Note that the simulation starts at time $= -0.74$.

```r
> library(deSolve)
> #-----------------------------
> # the derivative function
> #-----------------------------
> derivs <- function(t, y, parms) {
+   if (t < 0)
+     lag <- 19
+   else
+     lag <- lagvalue(t - 0.74)
+   dy <- r * y * (1 - lag/m)
+   list(dy, dy = dy)
+ }
> #-----------------------------
> # parameters
> #-----------------------------
> r <- 3.5; m <- 19
> #-----------------------------
> # initial values and times
> #-----------------------------
> yinit <- c(y = 19.001)
> times <- seq(-0.74, 40, by = 0.01)
> #-----------------------------
> # solve the model
> #-----------------------------
> yout <- dede(y = yinit, times = times, func = derivs,
+     parms = NULL, atol = 1e-10)
> plot(yout, which = 1, type = "l", lwd = 2,
+     main = "Lemming model", mfrow = c(1,2))
> plot(yout[,2], yout[,3], xlab = "y", ylab = "dy", type = "l", lwd = 2)
```
Figure 8: A delay differential equation model
9. Discrete time models, difference equations

There is one special-purpose solver, triggered with method = "iteration" which can be used in cases where the new values of the state variables are directly estimated by the user, and need not be found by numerical integration.

This is for instance useful when the model consists of difference equations, or for 1-D models when transport is implemented by an implicit or a semi-implicit method.

We give here an example of a discrete time model, represented by a difference equation: the Teasel model as from Soetaert and Herman (2009, p287).

The dynamics of this plant is described by 6 stages and the transition from one stage to another is in a transition matrix:

We define the stages and the transition matrix first:

```r
> Stages <- c("DS 1yr", "DS 2yr", "R small", "R medium", "R large", "F")
> NumStages <- length(Stages)
> # Population matrix
> A <- matrix(nrow = NumStages, ncol = NumStages, byrow = TRUE, data = c(
+ 0, 0, 0, 0, 0, 322.38,
+ 0.966, 0, 0, 0, 0, 0,
+ 0.013, 0.01, 0.125, 0, 0, 3.448,
+ 0.007, 0, 0.125, 0.238, 0, 30.170,
+ 0.008, 0, 0.038, 0.245, 0.167, 0.862,
+ 0, 0, 0, 0, 0.023, 0.75,
), byrow = TRUE)
```

The difference function is defined as usual, but does not return the “rate of change” but rather the new relative stage densities are returned. Thus, each time step, the updated values are divided by the summed densities:

```r
> Teasel <- function (t, y, p) {
+ yNew <- A %*% y
+ list (yNew / sum(yNew))
+ }
```

The model is solved using method “iteration”:

```r
> out <- ode(func = Teasel, y = c(1, rep(0, 5) ), times = 0:50,
+ parms = 0, method = "iteration")
```

and plotted using R-function matplot:

```r
> matplot(out[,1], out[-1], main = "Teasel stage distribution", type = "l")
> legend("topright", legend = Stages, lty = 1:6, col = 1:6)
```

10. Plotting deSolve Objects

There are S3 plot and image methods for plotting 0-D (plot), and 1-D and 2-D model output (image) as generated with ode, ode.1D, ode.2D.
How to use it and examples can be found by typing \texttt{?plot.deSolve}.

10.1. Plotting Multiple Scenario’s

The \texttt{plot} method for \texttt{deSolve} objects can also be used to compare different scenarios, e.g. from the same model but with different sets of parameters or initial values, with one single call to \texttt{plot}.

As an example we implement the simple combustion model, which can be found on \url{https://www.scholarpedia.org/article/Stiff_systems}:

$$y' = y^2 \cdot (1 - y)$$

The model is run with 4 different values of the initial conditions: $y = 0.01, 0.02, 0.03, 0.04$ and written to \texttt{deSolve} objects \texttt{out}, \texttt{out2}, \texttt{out3}, \texttt{out4}.

\begin{verbatim}
> library(deSolve)
> combustion <- function (t, y, parms)
+   list(y^2 * (1-y) )

> yini <- 0.01
> times <- 0 : 200

> out <- ode(times = times, y = yini, parms = 0, func = combustion)
> out2 <- ode(times = times, y = yini*2, parms = 0, func = combustion)
\end{verbatim}
The different scenarios are plotted at once, and a suitable legend is written.

> plot(out, out2, out3, out4, main = "combustion")
> legend("bottomright", lty = 1:4, col = 1:4, legend = 1:4, title = "yini*i")

### 10.2. Plotting Output with Observations

With the help of the optional argument `obs` it is possible to specify observed data that should be added to a `deSolve` plot.

We exemplify this using the `ccl4model` in package `deSolve`. (see `?ccl4model` for what this is about). This model example has been implemented in compiled code. An observed data set is also available, called `ccl4data`. It contains toxicant concentrations in a chamber where rats were dosed with CCl4.

> head(ccl4data)

<table>
<thead>
<tr>
<th>time</th>
<th>initconc</th>
<th>animal</th>
<th>ChamberConc</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.083</td>
<td>1000</td>
<td>828.4376</td>
</tr>
<tr>
<td>2</td>
<td>0.167</td>
<td>1000</td>
<td>779.6795</td>
</tr>
<tr>
<td>3</td>
<td>0.333</td>
<td>1000</td>
<td>713.8045</td>
</tr>
<tr>
<td>4</td>
<td>0.500</td>
<td>1000</td>
<td>672.0502</td>
</tr>
<tr>
<td>5</td>
<td>0.667</td>
<td>1000</td>
<td>631.9522</td>
</tr>
<tr>
<td>6</td>
<td>0.833</td>
<td>1000</td>
<td>600.6975</td>
</tr>
</tbody>
</table>
We select the data from animal “A”:

```r
> obs <- subset(ccl4data, animal == "A", c(time, ChamberConc))
> names(obs) <- c("time", "CP")
> head(obs)

         time    CP
1  0.0833333 828.4376
2  0.1666667 779.6795
3  0.3333333 713.8045
4  0.5000000 672.0502
5  0.6666667 631.9522
6  0.8333333 600.6975
```

After assigning values to the parameters and providing initial conditions, the `ccl4model` can be run. We run the model three times, each time with a different value for the first parameter. Output is written to matrices `out`, `out2`, and `out3`.

```r
> parms <- c(0.182, 4.0, 4.0, 0.08, 0.04, 0.74, 0.05, 0.15, 0.32, 16.17,
+ 281.48, 13.3, 16.17, 5.487, 153.8, 0.04321671,
+ 0.40272550, 951.46, 0.02, 1.0, 3.8000000)
> yini <- c(AI = 21, AAM = 0, AT = 0, AF = 0, AL = 0, CLT = 0, AM = 0)
> out <- ccl4model(times = seq(0, 6, by = 0.05), y = yini, parms = parms)
> par2 <- parms
> par2[1] <- 0.1
> out2 <- ccl4model(times = seq(0, 6, by = 0.05), y = yini, parms = par2)
> par3 <- parms
> par3[1] <- 0.05
> out3 <- ccl4model(times = seq(0, 6, by = 0.05), y = yini, parms = par3)

We plot all these scenarios and the observed data at once:

```r
> plot(out, out2, out3, which = c("AI", "MASS", "CP"),
+ col = c("black", "red", "green"), lwd = 2,
+ obs = obs, obspar = list(pch = 18, col = "blue", cex = 1.2))
> legend("topright", lty = c(1,2,3,NA), pch = c(NA, NA, NA, 18),
+ col = c("black", "red", "green", "blue"), lwd = 2,
+ legend = c("par1", "par2", "par3", "obs"))
```

If we do not select specific variables, then only the ones for which there are observed data are plotted. Assume we have measured the total mass at the end of day 6. We put this in a second data set:

```r
> obs2 <- data.frame(time = 6, MASS = 12)
> obs2

     time MASS
1      6   12
```
Figure 11: Plotting output and observations in one figure
then we plot the data together with the three model runs as follows:

```r
> plot(out, out2, out3, lwd = 2,
+       obs = list(obs, obs2),
+       obspar = list(pch = c(16, 18), col = c("blue", "black"),
+                     cex = c(1.2 , 2))
+     )
```

### 10.3. Plotting Summary Histograms

The `hist` function plots the histogram for each variable; all plot parameters can be set individually (here for `col`).

To generate the next plot, we overrule the default `mfrow` setting which would plot the figures in 3 rows and 3 columns (and hence plot one figure in isolation)

```r
> hist(out, col = grey(seq(0, 1, by = 0.1)), mfrow = c(3, 4))
```

### 10.4. Plotting multi-dimensional output

The `image` function plots time versus x images for models solved with `ode.1D`, or generates x-y plots for models solved with `ode.2D`.

**1-D model output**

We exemplify its use by means of a Lotka-Volterra model, implemented in 1-D. The model describes a predator and its prey diffusing on a flat surface and in concentric circles. This is a 1-D model, solved in the cylindrical coordinate system.
Figure 13: Plotting histograms of all output variables
Note that it is simpler to implement this model in R-package ReacTran (Soetaert and Meysman 2010).

We start by defining the derivative function

\[
\begin{align*}
lvmod & \leftarrow \text{function} \ (\text{time, state, parms, N, rr, ri, dr, dri}) \{ \\
& \text{with} \ (\text{as.list(parms)}, \ {}} \\
& \ \ \text{PREY} \leftarrow \text{state}[1: \text{N}] \\
& \ \ \text{PRED} \leftarrow \text{state}[(\text{N+1}): (2* \text{N})] \\
& \end{align*}
\]

\[
\begin{align*}
\text{## Fluxes due to diffusion} \\
\text{FluxPrey} & \leftarrow -\text{Da} \times \text{diff(c(PREY[1], PREY, PREY[N]))}/\text{dri} \\
\text{FluxPred} & \leftarrow -\text{Da} \times \text{diff(c(PRED[1], PRED, PRED[N]))}/\text{dri} \\
\text{## Biology: Lotka-Volterra model} \\
\text{Ingestion} & \leftarrow \text{rIng} \times \text{PREY} \times \text{PRED} \\
\text{GrowthPrey} & \leftarrow \text{rGrow} \times \text{PREY} \times (1 - \text{PREY/cap}) \\
\text{MortPredator} & \leftarrow \text{rMort} \times \text{PRED} \\
\text{## Rate of change = Flux gradient + Biology} \\
\text{dPREY} & \leftarrow -\text{diff(ri} \times \text{FluxPrey)/rr/dr} + \\
& \text{GrowthPrey} - \text{Ingestion} \\
\text{dPRED} & \leftarrow -\text{diff(ri} \times \text{FluxPred)/rr/dr} + \\
& \text{Ingestion} \times \text{assEff} - \text{MortPredator} \\
\text{return} \ (\text{list(c(dPREY, dPRED)))} \\
\}
\)
\]

Then we define the parameters, which we put in a list

\[
\begin{align*}
\text{R} & \leftarrow 20 \qquad \# \text{total radius of surface, m} \\
\text{N} & \leftarrow 100 \quad \# \text{100 concentric circles} \\
\text{dr} & \leftarrow \text{R}/\text{N} \quad \# \text{thickness of each layer} \\
\text{r} & \leftarrow \text{seq(dr/2, by = dr, len = N)} \quad \# \text{distance of center to mid-layer} \\
\text{ri} & \leftarrow \text{seq(0, by = dr, len = N+1)} \quad \# \text{distance to layer interface} \\
\text{dri} & \leftarrow \text{dr} \quad \# \text{dispersion distances} \\
\text{parms} & \leftarrow \text{c(Da = 0.05,} \quad \# \text{m2/d, dispersion coefficient} \\
& \qquad \text{rIng = 0.2,} \quad \# \text{/day, rate of ingestion} \\
& \qquad \text{rGrow = 1.0,} \quad \# \text{/day, growth rate of prey} \\
& \qquad \text{rMort = 0.2,} \quad \# \text{/day, mortality rate of pred} \\
& \qquad \text{assEff = 0.5,} \quad \# \text{- , assimilation efficiency} \\
& \qquad \text{cap = 10)} \quad \# \text{density, carrying capacity}
\end{align*}
\]

After defining initial conditions, the model is solved with routine \texttt{ode.1D}

\[
\begin{align*}
\text{state} & \leftarrow \text{rep(0, 2*N)} \\
\text{state}[1] & \leftarrow \text{state[N + 1] \leftarrow 10}
\end{align*}
\]
Package `deSolve`: Solving Initial Value Differential Equations in R

times <- seq(0, 200, by = 1)  # output wanted at these time intervals
print(system.time(
  out <- ode.1D(y = state, times = times, func = lvmod, parms = parms,
                nspec = 2, names = c("PREY", "PRED"),
                N = N, rr = r, ri = ri, dr = dr, dri = dri)
))

user  system elapsed
0.18 0.03 0.21

The `summary` method provides summaries for both 1-dimensional state variables:

```r
summary(out)
```

<table>
<thead>
<tr>
<th></th>
<th>PREY</th>
<th>PRED</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min.</td>
<td>0.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>1.996668</td>
<td>3.970746</td>
</tr>
<tr>
<td>Median</td>
<td>2.000000</td>
<td>4.000000</td>
</tr>
<tr>
<td>Mean</td>
<td>2.094254</td>
<td>3.33339</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>2.000066</td>
<td>4.000008</td>
</tr>
<tr>
<td>Max.</td>
<td>10.000000</td>
<td>10.000000</td>
</tr>
<tr>
<td>N</td>
<td>20100.000000</td>
<td>20100.000000</td>
</tr>
<tr>
<td>sd</td>
<td>1.648847</td>
<td>1.526742</td>
</tr>
</tbody>
</table>

while the S3-method `subset` can be used to extract only specific values of the variables:

```r
p10 <- subset(out, select = "PREY", subset = time == 10)
head(p10, n = 5)
```

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>[8]</td>
<td>[9]</td>
<td>[10]</td>
<td>[11]</td>
<td>[12]</td>
<td>[13]</td>
<td>[14]</td>
</tr>
<tr>
<td>[15]</td>
<td>[16]</td>
<td>[17]</td>
<td>[18]</td>
<td>[19]</td>
<td>[20]</td>
<td>[21]</td>
</tr>
<tr>
<td>[1,]</td>
<td>5.054634</td>
<td>3.947258</td>
<td>2.876796</td>
<td>1.946159</td>
<td>1.22074</td>
<td>0.7120999</td>
</tr>
<tr>
<td>[22]</td>
<td>[23]</td>
<td>[24]</td>
<td>[25]</td>
<td>[26]</td>
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</tr>
<tr>
<td>[1,]</td>
<td>0.1996948</td>
<td>0.09733824</td>
<td>0.04526957</td>
<td>0.02018686</td>
<td>0.00866459</td>
<td></td>
</tr>
<tr>
<td>[27]</td>
<td>[28]</td>
<td>[29]</td>
<td>[30]</td>
<td>[31]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1,]</td>
<td>0.003590384</td>
<td>0.001439632</td>
<td>0.0005595871</td>
<td>0.0002111643</td>
<td>7.745135e-05</td>
<td></td>
</tr>
<tr>
<td>[32]</td>
<td>[33]</td>
<td>[34]</td>
<td>[35]</td>
<td>[36]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1,]</td>
<td>2.763954e-05</td>
<td>9.605149e-06</td>
<td>3.252992e-06</td>
<td>1.074404e-06</td>
<td>3.462836e-07</td>
<td></td>
</tr>
<tr>
<td>[37]</td>
<td>[38]</td>
<td>[39]</td>
<td>[40]</td>
<td>[41]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1,]</td>
<td>1.089753e-07</td>
<td>3.350363e-08</td>
<td>1.006801e-08</td>
<td>2.958638e-09</td>
<td>8.506159e-10</td>
<td></td>
</tr>
<tr>
<td>[42]</td>
<td>[43]</td>
<td>[44]</td>
<td>[45]</td>
<td>[46]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1,]</td>
<td>2.393626e-10</td>
<td>6.595368e-11</td>
<td>1.780133e-11</td>
<td>4.708254e-12</td>
<td>1.220725e-12</td>
<td></td>
</tr>
<tr>
<td>[47]</td>
<td>[48]</td>
<td>[49]</td>
<td>[50]</td>
<td>[51]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1,]</td>
<td>3.103673e-13</td>
<td>7.740666e-14</td>
<td>1.894361e-14</td>
<td>4.550522e-15</td>
<td>1.07325e-15</td>
<td></td>
</tr>
</tbody>
</table>
We first plot both 1-dimensional state variables at once; we specify that the figures are arranged in two rows, and 2 columns; when we call `image`, we overrule the default `mfrow` setting using `mfrow = NULL`. Next we plot "PREY" again, once with the default `xlim` and `ylim`, and next zooming in. Note that `xlim` and `ylim` are a list here. When we call `image` for the second time, we overrule the default `mfrow` setting by specifying `mfrow = NULL`.

```
image(out, grid = r, mfrow = c(2, 2), method = "persp", border = NA, ticktype = "detailed", legend = TRUE)
image(out, grid = r, which = c("PREY", "PREY"), mfrow = NULL, xlim = list(NULL, c(0, 10)), ylim = list(NULL, c(0, 5)), add.contour = c(FALSE, TRUE))
```

### 2-D model output

When using `image` with a 2-D model, then the 2-D values at all output times will be plotted. Sometimes we want only output at a specific time value. We then use S3-method `subset` to extract 2-D variables at suitable time-values and use R's `image`, `filled.contour` or `contour` method to depict them.

Consider the very simple 2-D model (100*100), containing just 1-st order consumption, at a rate `r_x2y2`, where `r_x2y2` depends on the position along the grid. First the derivative function is defined:

```r
Simple2D <- function(t, Y, par) {
    y <- matrix(nrow = nx, ncol = ny, data = Y) # vector to 2-D matrix
dY <- - r_x2y2 * y # consumption
}
```
Figure 14: image plots
return(list(dY))
}

Then the grid is created, and the consumption rate made a function of grid position (outer).

\[
dy \leftarrow dx \leftarrow 1 \quad \# \text{grid size}
\]
\[
nx \leftarrow ny \leftarrow 100
\]
\[
x \leftarrow \text{seq(dx/2, by = dx, len = nx)}
\]
\[
y \leftarrow \text{seq(dy/2, by = dy, len = ny)}
\]
\[
\# \text{in each grid cell: consumption depending on position}
\]
\[
r_{x2y2} \leftarrow \text{outer}(x, y, \text{FUN=function}(x,y) ((x-50)^2 + (y-50)^2)*1e-4)
\]

After defining the initial values, the model is solved using solver ode2D. We use Runge-Kutta method ode45.

\[
C \leftarrow \text{matrix(nrow = nx, ncol = ny, 1)}
\]
\[
\text{ODE3} \leftarrow \text{ode2D}(y = C, \text{times} = 1:100, \text{func} = \text{Simple2D}, \text{parms} = \text{NULL},
\text{dimens} = c(nx, ny), \text{names} = "C", \text{method} = "ode45")
\]

We print a summary, and extract the 2-D variable at time = 50

\[
\text{summary(ODE3)}
\]

\[
\begin{align*}
\text{C} \\
\text{Min.} & \quad 8.522667e-22 \\
\text{1st Qu.} & \quad 4.331846e-06 \\
\text{Median} & \quad 2.630735e-03 \\
\text{Mean} & \quad 1.311539e-01 \\
\text{3rd Qu.} & \quad 1.202539e-01 \\
\text{Max.} & \quad 1.000000e+00 \\
\text{N} & \quad 1.000000e+06 \\
\text{sd} & \quad 2.489394e-01
\end{align*}
\]

\[
t_{50} \leftarrow \text{matrix(nrow = nx, ncol = ny},
\text{data} = \text{subset(ODE3, select = "C", subset = (time == 50))}
\]

We use function contour to plot both the consumption rate and the values of the state variables at time = 50.

\[
\text{par(mfrow = c(1, 2))}
\]
\[
\text{contour}(x, y, \_r_{x2y2}, \text{main = "consumption"})
\]
\[
\text{contour}(x, y, t_{50}, \text{main = "Y(t = 50)"})
\]
Figure 15: Contour plot of 2-D variables
11. Troubleshooting

11.1. Avoiding numerical errors

The solvers from ODEPACK should be first choice for any problem and the defaults of the control parameters are reasonable for many practical problems. However, there are cases where they may give dubious results. Consider the following Lotka-Volterra type of model:

```r
PCmod <- function(t, x, parms) {
  with(as.list(c(parms, x)), {
    dP <- c*P - d*C*P # producer
    dC <- e*P*C - f*C # consumer
    res <- c(dP, dC)
    list(res)
  })
}
```

and with the following (biologically not very realistic)\(^3\) parameter values:

```r
c <- 10, d = 0.1, e = 0.1, f = 0.1
```

After specification of initial conditions and output times, the model is solved – using `lsoda`

```r
xstart <- c(P = 0.5, C = 1)
times <- seq(0, 200, 0.1)
out <- ode(y = xstart, times = times,
  func = PCmod, parms = parms)
```

DLSODA - At T(=R1) and step size H(=R2), the error test failed repeatedly or with ABS(H) = HMIN.
In above message, R1 = 89.9566, R2 = 1.40508e-10

```r
tail(out)

<table>
<thead>
<tr>
<th>time</th>
<th>P</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>[896,</td>
<td>89.50000</td>
<td>-5.437180e+10</td>
</tr>
<tr>
<td>[897,</td>
<td>89.60000</td>
<td>-1.477988e+11</td>
</tr>
<tr>
<td>[898,</td>
<td>89.70000</td>
<td>-4.017604e+11</td>
</tr>
<tr>
<td>[899,</td>
<td>89.80000</td>
<td>-1.092102e+12</td>
</tr>
<tr>
<td>[900,</td>
<td>89.90000</td>
<td>-2.968659e+12</td>
</tr>
<tr>
<td>[901,</td>
<td>89.95657</td>
<td>-5.226781e+12</td>
</tr>
</tbody>
</table>
```

\(^3\)they are not realistic because producers grow unlimited with a high rate and consumers with 100 % efficiency
We see that the simulation was stopped before reaching the final simulation time and both producers and consumer values may have negative values.

What has happened? Being an implicit method, \texttt{lsoda} generates very small negative values for producers, from day 40 on; these negative values, small at first grow in magnitude until they become infinite or even NaNs (not a number). This is because the model equations are not intended to be used with negative numbers, as negative concentrations are not realistic.

A quick-and-dirty solution is to reduce the maximum time step to a considerably small value (e.g. \texttt{hmax = 0.02} which, of course, reduces computational efficiency. However, a much better solution is to think about the reason of the failure, i.e in our case the \textbf{absolute} accuracy because the states can reach very small absolute values. Therefore, it helps here to reduce \texttt{atol} to a very small number or even to zero:

\begin{verbatim}
out <- ode(y = xstart, times = times, func = PCmod, 
        parms = parms, atol = 0)
matplot(out[,1], out[,2:3], type = "l", 
        xlab = "time", ylab = "Producer, Consumer")
\end{verbatim}

It is, of course, not possible to set both, \texttt{atol} and \texttt{rtol} simultaneously to zero. As we see from this example, it is always a good idea to test simulation results for plausibility. This can be done by theoretical considerations or by comparing the outcome of different ODE solvers and parametrizations.

\section*{11.2. Checking model specification}

If a model outcome is obviously unrealistic or one of the \texttt{deSolve} functions complains about numerical problems it is even more likely that the “numerical problem” is in fact a result of an unrealistic model or a programming error. In such cases, playing with solver parameters will not help. Here are some common mistakes we observed in our models and the codes of our students:

\begin{itemize}
  \item The function with the model definition must return a list with the derivatives of all state variables in correct order (and optionally some global values). Check if the number and order of your states is identical in the initial states \texttt{y} passed to the solver, in the assignments within your model equations and in the returned values. Check also whether the return value is the last statement of your model definition.
  \item The order of function arguments in the model definition is \texttt{t, y, parms, ...}. This order is strictly fixed, so that the \texttt{deSolve} solvers can pass their data, but naming is flexible and can be adapted to your needs, e.g. \texttt{time, init, params}. Note also that all three arguments must be given, even if \texttt{t} is not used in your model.
  \item Mixing of variable names: if you use the \texttt{with()}-construction explained above, you must ensure to avoid naming conflicts between parameters (\texttt{parms}) and state variables (\texttt{y}).
\end{itemize}

The solvers included in package \texttt{deSolve} are thoroughly tested, however they come with \textbf{no warranty} and the user is solely responsible for their correct application. If you encounter unexpected behavior, first check your model and read the documentation. If this doesn’t
help, feel free to ask a question to an appropriate mailing list, e.g. r-help@r-project.org or, more specific, r-sig-dynamic-models@r-project.org.

11.3. Making sense of deSolve’s error messages

As many of deSolve’s functions are wrappers around existing FORTRAN codes, the warning and error messages are derived from these codes. Whereas these codes are highly robust, well tested, and efficient, they are not always as user-friendly as we would like. Especially some of the warnings/error messages may appear to be difficult to understand.

Consider the first example on the ode function:

```
LVmod <- function(Time, State, Pars) {
  with(as.list(c(State, Pars)), {
    Ingestion    <- rIng  * Prey  * Predator
    GrowthPrey   <- rGrow * Prey * (1 - Prey/K)  
    MortPredator <- rMort * Predator

    dPrey       <- GrowthPrey - Ingestion
    dPredator   <- Ingestion * assEff - MortPredator

    return(list(c(dPrey, dPredator)))
  })
}

pars <- c(rIng  = 0.2,  # /day, rate of ingestion
          rGrow = 1.0,  # /day, growth rate of prey
          rMort = 0.2 ,  # /day, mortality rate of predator
          assEff = 0.5,  # -, assimilation efficiency
          K    = 10)    # mmol/m3, carrying capacity

yini <- c(Prey = 1, Predator = 2)
times <- seq(0, 200, by = 1)
out  <- ode(func = LVmod, y = yini,
            parms = pars, times = times)
```

This model is easily solved by the default integration method, lsoda.

Now we change one of the parameters to an unrealistic value: rIng is set to 100. This means that the predator ingests 100 times its own body-weight per day if there are plenty of prey. Needless to say that this is very unhealthy, if not lethal.

Also, lsoda cannot solve the model anymore. Thus, if we try:

```
pars["rIng"] <- 100
out2 <- ode(func = LVmod, y = yini,
            parms = pars, times = times)
```

A lot of seemingly incomprehensible messages will be written to the screen. We repeat the latter part of them:
DLSODA- Warning..Internal T (=R1) and H (=R2) are
such that in the machine, T + H = T on the next step
(H = step size). Solver will continue anyway.
In above message, R1 = 53.4272, R2 = 2.44876e-15

DLSODA- Above warning has been issued I1 times.
It will not be issued again for this problem.
In above message, I1 = 10

DLSODA- At current T (=R1), MXSTEP (=I1) steps
taken on this call before reaching TOUT
In above message, I1 = 5000
In above message, R1 = 53.4272

Warning messages:
1: In lsoda(y, times, func, parms, ...) :
an excessive amount of work (> maxsteps ) was done,
but integration was not successful - increase maxsteps
2: In lsoda(y, times, func, parms, ...) :
Returning early. Results are accurate, as far as they go

The first sentence tells us that at T = 53.4272, the solver used a step size H = 2.44876e-15.
This step size is so small that it cannot tell the difference between T and T + H. Nevertheless,
the solver tried again.

The second sentence tells that, as this warning has been occurring 10 times, it will not be
outputted again.

As expected, this error did not go away, so soon the maximal number of steps (5000) has
been exceeded. This is indeed what the next message is about:

The third sentence tells that at T = 53.4272, maxstep = 5000 steps have been done.
The one before last message tells why the solver returned prematurely, and suggests a solution.
Simply increasing maxsteps will not work and it makes more sense to first see if the output
tells what happens:

\[
\text{plot(out2, type = "l", lwd = 2, main = "corrupt Lotka-Volterra model")}
\]

You may, of course, consider to use another solver:

\[
\text{pars["rIng"] <- 100}
\text{out3 <- ode(func = LVmod, y = yini, parms = pars,}
   \quad \text{times = times, method = "ode45", atol = 1e-14, rtol = 1e-14)}
\]

but don’t forget to think about this too and, for example, increase simulation time to 1000
and try different values of \texttt{atol} and \texttt{rtol}. We leave this open as an exercise to the reader.
Figure 16: A model that cannot be solved correctly
References


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R. Woodrow Setzer  
National Center for Computational Toxicology  
US Environmental Protection Agency
Table 1: Summary of the functions that solve differential equations

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>ode</code></td>
<td>integrates systems of ordinary differential equations, assumes a full, banded or arbitrary sparse Jacobian</td>
</tr>
<tr>
<td><code>ode.1D</code></td>
<td>integrates systems of ODEs resulting from 1-dimensional reaction-transport problems</td>
</tr>
<tr>
<td><code>ode.2D</code></td>
<td>integrates systems of ODEs resulting from 2-dimensional reaction-transport problems</td>
</tr>
<tr>
<td><code>ode.3D</code></td>
<td>integrates systems of ODEs resulting from 3-dimensional reaction-transport problems</td>
</tr>
<tr>
<td><code>ode.band</code></td>
<td>integrates systems of ODEs resulting from unicomponent 1-dimensional reaction-transport problems</td>
</tr>
<tr>
<td><code>dede</code></td>
<td>integrates systems of delay differential equations</td>
</tr>
<tr>
<td><code>daspk</code></td>
<td>solves systems of differential algebraic equations, assumes a full or banded Jacobian</td>
</tr>
<tr>
<td><code>radau</code></td>
<td>solves systems of ordinary or differential algebraic equations, assumes a full or banded Jacobian; includes a root solving procedure</td>
</tr>
<tr>
<td><code>lsoda</code></td>
<td>integrates ODEs, automatically chooses method for stiff or non-stiff problems, assumes a full or banded Jacobian</td>
</tr>
<tr>
<td><code>lsodar</code></td>
<td>same as <code>lsoda</code>, but includes a root-solving procedure</td>
</tr>
<tr>
<td><code>lsode</code> or <code>vode</code></td>
<td>integrates ODEs, user must specify if stiff or non-stiff assumes a full or banded Jacobian; Note that, as from version 1.7, <code>lsode</code> includes a root finding procedure, similar to <code>lsodar</code>.</td>
</tr>
<tr>
<td><code>lsodes</code></td>
<td>integrates ODEs, using stiff method and assuming an arbitrary sparse Jacobian. Note that, as from version 1.7, <code>lsodes</code> includes a root finding procedure, similar to <code>lsodar</code>.</td>
</tr>
<tr>
<td><code>rk</code></td>
<td>integrates ODEs, using Runge-Kutta methods (includes Runge-Kutta 4 and Euler as special cases)</td>
</tr>
<tr>
<td><code>rk4</code></td>
<td>integrates ODEs, using the classical Runge-Kutta 4th order method (special code with less options than <code>rk</code>)</td>
</tr>
<tr>
<td><code>euler</code></td>
<td>integrates ODEs, using Euler’s method (special code with less options than <code>rk</code>)</td>
</tr>
<tr>
<td><code>zvode</code></td>
<td>integrates ODEs composed of complex numbers, full, banded, stiff or nonstiff</td>
</tr>
</tbody>
</table>
Table 2: Meaning of the integer return parameters in the different integration routines. If `out` is the output matrix, then this vector can be retrieved by function `attributes(out)$istate`; its contents is displayed by function `diagnostics(out)`. Note that the number of function evaluations, is without the extra evaluations needed to generate the output for the ordinary variables.

<table>
<thead>
<tr>
<th>Nr</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>the return flag; the conditions under which the last call to the solver returned. For <code>lsoda, lsodar, lsode, lsodes, vode, rk, rk4, euler</code> these are: 2: the solver was successful, -1: excess work done, -2: excess accuracy requested, -3: illegal input detected, -4: repeated error test failures, -5: repeated convergence failures, -6: error weight became zero</td>
</tr>
<tr>
<td>2</td>
<td>the number of steps taken for the problem so far</td>
</tr>
<tr>
<td>3</td>
<td>the number of function evaluations for the problem so far</td>
</tr>
<tr>
<td>4</td>
<td>the number of Jacobian evaluations so far</td>
</tr>
<tr>
<td>5</td>
<td>the method order last used (successfully)</td>
</tr>
<tr>
<td>6</td>
<td>the order of the method to be attempted on the next step</td>
</tr>
<tr>
<td>7</td>
<td>If return flag = -4,-5: the largest component in the error vector</td>
</tr>
<tr>
<td>8</td>
<td>the length of the real work array actually required. (FORTRAN code)</td>
</tr>
<tr>
<td>9</td>
<td>the length of the integer work array actually required. (FORTRAN code)</td>
</tr>
<tr>
<td>10</td>
<td>the number of matrix LU decompositions so far</td>
</tr>
<tr>
<td>11</td>
<td>the number of nonlinear (Newton) iterations so far</td>
</tr>
<tr>
<td>12</td>
<td>the number of convergence failures of the solver so far</td>
</tr>
<tr>
<td>13</td>
<td>the number of error test failures of the integrator so far</td>
</tr>
<tr>
<td>14</td>
<td>the number of Jacobian evaluations and LU decompositions so far</td>
</tr>
<tr>
<td>15</td>
<td>the method indicator for the last succesful step, 1 = adams (nonstiff), 2 = bdf (stiff)</td>
</tr>
<tr>
<td>17</td>
<td>the number of nonzero elements in the sparse Jacobian</td>
</tr>
<tr>
<td>18</td>
<td>the current method indicator to be attempted on the next step, 1 = adams (nonstiff), 2 = bdf (stiff)</td>
</tr>
<tr>
<td>19</td>
<td>the number of convergence failures of the linear iteration so far</td>
</tr>
</tbody>
</table>
Table 3: Meaning of the double precision return parameters in the different integration routines. If `out` is the output matrix, then this vector can be retrieved by function `attributes(out)$rstate`; its contents is displayed by function `diagnostics(out)`

<table>
<thead>
<tr>
<th>Nr</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>the step size in t last used (successfully)</td>
</tr>
<tr>
<td>2</td>
<td>the step size to be attempted on the next step</td>
</tr>
<tr>
<td>3</td>
<td>the current value of the independent variable which the solver has actually reached</td>
</tr>
<tr>
<td>4</td>
<td>a tolerance scale factor, greater than 1.0, computed when a request for too much accuracy was detected</td>
</tr>
<tr>
<td>5</td>
<td>the value of t at the time of the last method switch, if any (only <code>lsoda</code>, <code>lsodar</code>)</td>
</tr>
</tbody>
</table>