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Dynamic simulation models – is R powerful enough?



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 $\frac{dN}{dt} = r \cdot N \cdot \left(1 - \frac{N}{K}\right) =$

- ... models that respect time explicitly.
- used in many fields:

mathematics, physics, chemistry, biology, ecology, engineering, economics...

 "What makes using system dynamics different from other approaches to studying complex systems is the use of feedback loops and stocks and flows. These elements help describe how even seemingly simple systems display baffling nonlinearity.

http://en.wikipedia.org/wiki/System_dynamics

Example 1: A Lotka-Volterra-type model



```
lvmodel <- function(t, x, parms, input) {</pre>
  with(as.list(c(parms, x)), {
    import <- input(t)</pre>
    dS <- import - b*S*P
    dP <- c*S*P - d*K*P
    dK <- e*P*K - f*K
    list(c(dS, dP, dK))
  })
}
# parameters, initial values time steps ...
# ... and some data, e.g. rectangular signal
sigimp <- approxfun(signal$times, signal$import)</pre>
out <- ls@da(init, times, lvmodel, parms, input=sigimp)</pre>
             package deSolve (Soetaert, Petzoldt, Setzer)
```

Benchmark



3 equations (ODEs) in R, 1000 (external) timesteps

CPU time

- case A: interpolated input (approxfun) 1.4 s
- case B: import <- if (trunc(t) %% 2 == 0) 0 else 0.1 0.8 s

Time is ok for this toy model, but is R suited for more complex simulations?

3 ODEs = 1 s → spatial system with 10.000 ODEs > 1 hour?

Example 2: A stream model

Experimentally manipulated small stream of our limnological workgroup



Downward drift of water insects in the stream (Mayflies)

Is buffer stretch sufficiently long?



Can be described by a basic PDE model



The drift model in R: simple structure but 1300 eqs.

```
drift <- function(time, state, parms) {</pre>
                                        # sessile
  S <- state[1:N]</pre>
 M <- state[(N+1):(2*N)]
                                        # mobile
  dM < -v * diff(c(0, M))/dx - down * M + up * S
                              + down * M - up * S - mort * S
  ds <-
 list(c(ds, dm))
}
dx <- 1
                                          # grid size [m]
v <- 10000
                                          # velocity. m/day
                                          # experimental strech 650 m
x <- seq(dx/2, 650, by = dx)
N < - length(x)
up <- c(rep(6.1, 200), rep(1.4, N-200)) # drift rate, 1/d
down <- 8000
                                          # settlement rate, 1/d
                                          # mortality rate 1/d
mort <-1e-2
## initial conditions (abundance of mayfly larvae)
state <- c(S=rep(500, N), M=rep(0, N))</pre>
times <- seq(0, 60, length=101)  # two months</pre>
out <- ode.1D(y = state, times, drift, parms = NULL, nspec = 2)
```

Total Abundance (mobile + sessile)

Individuals 1/m²



time, days

- 2 simulated months, 100 external time steps
- model with 2 x 650 = 1300 equations; computation time of ode.1D: 0.6s
 AMD Athlon AM2 X2 6000+, 3000 MHz, 2MB RAM, Windows XP, R-2.10-devel
- → buffer stretch long enough
- → R much faster than expected

Chromatography model

Similar approach like insect drift fixed phase, mobile phase

Example:

- 5 chemical species,
- 500...5000 grid cells
- 100 external time steps



Computational Effort:

Grid cells	Equations	model in C	model in R
500	500 * 2 * 5 = 5,000	0.8 s	1.95 s
5000	5,000 * 2 * 5 = 50,000	59 s	66 s

Example 3: Population dynamics of Daphnia (water flea)



Agent-based Daphnia simulation (ABM) with bioenergetic growth model (ODE)



Effort needed per 100 simulation days:

100 ABM time steps 1000 ODE time steps

1000 ...2000 individuals → 4000 ... 8000 equations





The Lotka-Volterra-type model revisited

Calling a small model many times

Remember:

3 equations (resource, producer, consumer) Rectangular external signal (import of resource)

Now 10,000 time steps

```
\frac{dS}{dt} = import - b \cdot S \cdot P\frac{dP}{dt} = c \cdot S \cdot P - d \cdot P \cdot K\frac{dK}{dt} = e \cdot P \cdot K - f \cdot K
```

Model in:	R signal with if else in model function	8 s
R with approxfun (10,000 rows in data table)		

C, bisectioning, similar to approxfun	0.16 s
C, sequential search in ordered forcings	0.03 s

The integrator (lsoda) and the model are able to communicate directly at the machine code level.

➔ Simulation without "friction"

Programming in R:

- ➤more convenient than C or Fortran
- ➤... more interactive, more compact code, ...

High-level statistical algorithms and graphics
 I can do almost everything in one system
 no need to export / import data to other software
 stats, ... deSolve, FME, ... Sweave
 support data analysis and report writing

Open Source

- >Allows to work with talented people on a global scale
- >Enables me to share my code with others (and use theirs)
 - \rightarrow model collection package simecolModels

Conclusion: R is powerful for system dynamics



A few rules:

Vectorization! Matrix algebra!

- Large models with identical equations = fast in pure R
- > ABMs are efficient with data frames and subset()

Avoid unnecessary copying of large objects.

- > Sometimes it helps to prefer matrices over data frames.
- > Avoid interpolation (i.e. approx),
- \succ If approx is unavoidable, minimize the tables.

Complex systems of equations or frequent calls to small models:

- > considerable performance gain if core functions in C or Fortran
- consider direct communication between deSolve and compiled code

R is a good investment even in that cases:

- It handles my input and output data
- \succ so I can concentrate on the equations.







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Karline Soetaert, Woodrow Setzer, Carola Winkelmann

and

Thank You!

package **deSolve** (Soetaert, Petzoldt, Setzer): http://cran.r-project.org/web/packages/deSolve/

packages **simecol** and **simecolModels** http://www.simecol.de

http://r-forge.r-project.org/projects/simecol/