Package: GillespieSSA (via r-universe)

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Type Package

Title Gillespie's Stochastic Simulation Algorithm (SSA)

Version 0.6.2

Description Provides a simple to use, intuitive, and extensible interface to several stochastic simulation algorithms for generating simulated trajectories of finite population continuous-time model. Currently it implements Gillespie's exact stochastic simulation algorithm (Direct method) and several approximate methods (Explicit tau-leap, Binomial tau-leap, and Optimized tau-leap). The package also contains a library of template models that can be run as demo models and can easily be customized and extended. Currently the following models are included, 'Decaying-Dimerization' reaction set, linear chain system, logistic growth model, 'Lotka' predator-prey model, Rosenzweig-MacArthur predator-prey model, 'Kermack-McKendrick' SIR model, and a 'metapopulation' SIRS model. Pineda-Krch et al. (2008) [<doi:10.18637/jss.v025.i12>](https://doi.org/10.18637/jss.v025.i12).

Depends $R (= 2.0.0)$

Imports grDevices, graphics, methods, stats, utils Suggests knitr, rmarkdown, testthat

URL <https://github.com/rcannood/GillespieSSA>

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GillespieSSA-package *Gillespie Stochastic Simulation Algorithm package*

Description

Package description and overview of basic SSA theory

GillespieSSA is a versatile and extensible framework for stochastic simulation in R and provides a simple interface to a number of Monte Carlo implementations of the stochastic simulation algorithm (SSA). The methods currently implemented are: the Direct method, Explicit tau-leaping (ETL), Binomial tau-leaping (BTL), and Optimized tau-leaping (OTL). The package also provides a library of ecological, epidemiological, and evolutionary continuous-time (demo) models that can easily be customized and extended. Currently the following models are included, Decaying-Dimerization Reaction Set, Linear Chain System, single-species logistic growth model, Lotka predator-prey model, Rosenzweig-MacArthur predator-prey model, Kermack-McKendrick SIR model, and a metapopulation SIRS model.

The stochastic simulation algorithm

The stochastic simulation algorithm (SSA) is a procedure for constructing simulated trajectories of finite populations in continuous time. If $X_i(t)$ is the number of individuals in population i $(i = 1, \ldots, N)$ at time t the SSA estimates the state vector $\mathbf{X}(t) \equiv (X_1(t), \ldots, X_N(t))$, given that the system initially (at time t_0) was in state $\mathbf{X}(t_0) = \mathbf{x_0}$. Reactions, single instantaneous events changing at least one of the populations (e.g. birth, death, movement, collision, predation, infection, etc), cause the state of the system to change over time. The SSA procedure samples the time τ to the next reaction R_j ($j = 1, ..., M$) and updates the system state $X(t)$ accordingly. Each reaction R_j is characterized mathematically by two quantities; its state-change vector $\nu_j \equiv (\nu_{1j}, \dots, \nu_{Nj}),$ where ν_{ij} is the change in the number of individuals in population i caused by one reaction of type j and its propensity function $a_i(\mathbf{x})$, where $a_i(\mathbf{x})dt$ is the probability that a particular reaction j will occur in the next infinitesimal time interval $[t, t + dt]$.

SSA implementations

There are numerous exact Monte Carlo procedures implementing the SSA. Perhaps the simplest is the Direct method of Gillespie (1977. The Direct method is an exact continuous-time numerical realization of the corresponding stochastic time-evolution equation. Because the Direct method

simulates one reaction at a time it is often, however, computationally too slow for practical applications.

Approximate implementations of the SSA sacrifices exactness for large improvements in computational efficiency. The most common technique used is tau-leaping where reaction-bundles are attempted in coarse-grained time increments τ . Speed-ups of several orders of magnitude compared to the Direct method are common. Tau-leaping must be used with care, however, as it is not as foolproof as the Direct method.

Example models

Individual demo models can be run by issuing demo(<model name>), alternatively all of the demo models can be run using demo(GillespieSSA). The following example models are available:

Decaying-Dimerization Reaction Set (Gillespie, 2001) vignette("decaying_dimer", package = "GillespieSSA")

SIRS metapopulation model (Pineda-Krch, 2008) vignette("epi_chain", package = "GillespieSSA")

Linear Chain System (Cao et al., 2004) vignette("linear_chain", package = "GillespieSSA")

Pearl-Verhulst Logistic growth model (Kot, 2001, Pineda-Krch, 2008) vignette("logistic_growth", package = "GillespieSSA")

Lotka predator-prey model (Gillespie, 1977; Kot, 2001) vignette("lotka_predator_prey", package = "GillespieSSA")

```
Radioactive decay model (Gillespie, 1977)
vignette("radioactive_decay", package = "GillespieSSA")
```
Rosenzweig-MacArthur predator-prey model (Pineda-Krch et al., 2007, Pineda-Krch, 2008) vignette("rm_predator_prey", package = "GillespieSSA")

Kermack-McKendrick SIR model (Brown & Rothery, 1993) vignette("sir", package = "GillespieSSA")

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- Thomas Petzoldt for comments on the package, the JSS manuscript and for preparing version $0.5 - 4.$
- Three anonymous referees whose comments substantially improved some of the functionality.

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See Also

[ssa\(\)](#page-3-1), [ssa.d\(\)](#page-9-1), [ssa.etl\(\)](#page-10-1), [ssa.btl\(\)](#page-8-1), [ssa.otl\(\)](#page-10-2), [ssa.plot\(\)](#page-11-1)

ssa *Invoking the stochastic simulation algorithm*

Description

Main interface function to the implemented SSA methods. Runs a single realization of a predefined system.

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Usage

ssa(

```
x0, # initial state vector
                a, \qquad # propensity vector
               nu, # state-change matrix
            parms = NULL, # model parameters
               tf, # final time
           method = ssa.d(), # SSA method
          simName = "",tau = 0.3, # deprecated<br>
f = 10, # deprecated
                             # deprecated
          epsilon = 0.03, # deprecated
               nc = 10, # deprecated
              hor = NA_real_, # deprecated
              dt f = 10, # deprecated
               nd = 100, # deprecated
ignoreNegativeState = TRUE,
   consoleInterval = 0,censusInterval = 0,verbose = FALSE,
       maxWallTime = Inf
```

```
Arguments
```
)

Details

Although ssa can be invoked by only specifying the system arguments (initial state vector x0, propensity vector a, state-change matrix nu), the final time (tf), and the SSA method to use, substantial improvements in speed and accuracy can be obtained by adjusting the additional (and optional) ssa arguments. By default ssa (tries to) use conservative default values for the these arguments, prioritizing computational accuracy over computational speed. These default values are, however, not fool proof for the approximate methods, and occasionally one will have to hand tweak them in order for a stochastic model to run appropriately.

Value

Returns a list object with the following elements,

• data: a numerical matrix object of the simulation time series where the first column is the time vector and subsequent columns are the state frequencies.

- stats: sub-list object with elements containing various simulation statistics. The of the sublist are:
- stats\$startWallTime: start wall clock time (YYYY-mm-dd HH:MM:SS).
- stats\$endWallTime: end wall clock time (YYYY-mm-dd HH:MM:SS).
- stats\$elapsedWallTime: elapsed wall time in seconds.
- stats\$terminationStatus: string vector listing the reason(s) for the termination of the realization in 'plain words'. The possible termination statuses are:
	- finalTime = if the simulation reached the maximum simulation time tf,
	- extinction = if the population size of all states is zero,
	- negativeState = if one or several states have a negative population size (can occur in the ETL method),
	- zeroProp = if all the states have a zero propensity function,
	- $-$ maxWallTime $=$ if the maximum wall time has been reached. Note the termination status may have more than one message.
- 'stats\$nSteps" total number of time steps (or tau-leaps) executed.
- stats\$meanStepSize: mean step (or tau-leap) size.
- stats\$sdStepSize: one standard deviation of the step (or tau-leap) size.
- stats\$SuspendedTauLeaps: number of steps performed using the Direct method due to OTL suspension (only applicable for the OTL method).
- arg\$...: sub-list with elements containing all the arguments and their values used to invoke ssa (see Usage and Arguments list above).

Preparing a run

In order to invoke SSA the stochastic model needs at least four components, the initial state vector $(x0)$, state-change matrix (nu), propensity vector (a), and the final time of the simulation (tf). The initial state vector defines the population sizes in all the states at $t = 0$, e.g. for a system with two species X1 and X2 where both have an initial population size of 1000 the initial state vector is defined as $x0 < -c(X1=1000, X2=1000)$. The elements of the vector have to be labelled using the same notation as the state variables used in the propensity functions. The state-change matrix defines the change in the number of individuals in each state (rows) as caused by one reaction of a given type (columns). For example, the state-change matrix for system with the species S_1 and S_2 with two reactions

$$
S_1 \xrightarrow{c_1} S_2
$$

$$
S_2 \xrightarrow{c_2} 0
$$

is defined as nu <- matrix(c(-1,0,+1,-1),nrow=2,byrow=TRUE) where c_1 and c_2 are the per capita reaction probabilities. The propensity vector, a, defines the probabilities that a particular reaction will occur over the next infinitesimal time interval $[t, t + dt]$. For example, in the previous example the propensity vector is defined as $a \leq c$ ("c1*X1", "c2*X2"). The propensity vector consists of character elements of each reaction's propensity function where each state variable requires the corresponding named element label in the initial state vector $(x0)$.

Example

Irreversible isomerization: Perhaps the simplest model that can be formulated using the SSA is the irreversible isomerization (or radioactive decay) model. This model is often used as a first pedagogic example to illustrate the SSA (see e.g. Gillespie 1977). The deterministic formulation of this model is

$$
\frac{dX}{dt} = -cX
$$

where the single reaction channel is

 $S \stackrel{c}{\longrightarrow} 0$

By setting $X_0 = 1000$ and $c = 0.5$ it is now simple to define this model and run it for 10 time steps using the Direct method,

```
out \leq ssa(x0=c(X=1000), a=c("c*X"), nu=matrix(-1), parms=c(c=0.5), tf=10)
```
The resulting time series can then be displayed by,

ssa.plot(out)

Note

Selecting the appropriate SSA method is a trade-off between computational speed, accuracy of the results, and which SSA actually works for a given scenario. This depends on the characteristics of the defined system (e.g. number of reaction channels, number of species, and the absolute and relative magnitude of the propensity functions). Not all methods are appropriate for all models. When selecting a SSA method all of these factors have to be taken into consideration. The various tau-leap methods accept a number of additional arguments. While the default values of these arguments may work for some scenarios they may have to be adjusted for others. The default values for the tau-leap methods are conservative in terms of computational speed and substantial increase in efficiency may be gained by optimizing their values for a specific system.

See Also

[GillespieSSA-package,](#page-1-1) [ssa.d\(\)](#page-9-1), [ssa.etl\(\)](#page-10-1), [ssa.btl\(\)](#page-8-1), [ssa.otl\(\)](#page-10-2)

Examples

```
## Irreversible isomerization
## Large initial population size (X=1000)
parms <-c(c=0.5)x0 <- c(X=10000)
a \langle -c("c*X")nu \leq matrix(-1)
out <- ssa(x0,a,nu,parms,tf=10,method=ssa.d(),simName="Irreversible isomerization") # Direct method
plot(out$data[,1],out$data[,2]/10000,col="red",cex=0.5,pch=19)
```

```
## Smaller initial population size (X=100)
```
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```
x0 < -c(X=100)out <- ssa(x0,a,nu,parms,tf=10,method=ssa.d()) # Direct method
points(out$data[,1],out$data[,2]/100,col="green",cex=0.5,pch=19)
## Small initial population size (X=10)
x0 < -c(X=10)out <- ssa(x0,a,nu,parms,tf=10,method=ssa.d()) # Direct method
points(out$data[,1],out$data[,2]/10,col="blue",cex=0.5,pch=19)
## Logistic growth
parms <- c(b=2, d=1, K=1000)
x0 <- c(N=500)
a \leftarrow c("b*N", "(d+(b-d)*N/K)*N")nu \leq matrix(c(+1,-1),ncol=2)
out <- ssa(x0,a,nu,parms,tf=10,method=ssa.d(),maxWallTime=5,simName="Logistic growth")
ssa.plot(out)
## Kermack-McKendrick SIR model
parms <- c(beta=0.001, gamma=0.1)
x0 <- c(S=499,I=1,R=0)
a <- c("beta*S*I","gamma*I")
nu <- matrix(c(-1,0,+1,-1,0,+1),nrow=3,byrow=TRUE)
out <- ssa(x0,a,nu,parms,tf=100,method=ssa.d(),simName="SIR model")
ssa.plot(out)
## Lotka predator-prey model
parms <- c(c1=10, c2=.01, c3=10)
x0 <- c(Y1=1000,Y2=1000)
a <- c("c1*Y1","c2*Y1*Y2","c3*Y2")
nu <- matrix(c(+1,-1,0,0,+1,-1),nrow=2,byrow=TRUE)
out <- ssa(x0,a,nu,parms,tf=100,method=ssa.etl(),simName="Lotka predator-prey model")
ssa.plot(out)
```


ssa.btl *Binomial tau-leap method (BTL)*

Description

Binomial tau-leap method implementation of the SSA as described by Chatterjee et al. (2005). Should be passed as method argument for ssa().

Usage

 $ssa.btl(f = 10)$

Arguments

f coarse-graining factor (see page 4 in Chatterjee et al. 2005).

Details

Performs one time step using the Binomial tau-leap method. Intended to be invoked by [ssa\(\)](#page-3-1).

References

Chatterjee et al. (2005)

See Also

[GillespieSSA-package,](#page-1-1) [ssa\(\)](#page-3-1)

Examples

 $ssa.btl(f = 40)$

ssa.d *Direct method (D)*

Description

Direct method implementation of the SSA as described by Gillespie (1977). Should be passed as method argument for ssa().

Usage

ssa.d()

References

Gillespie (1977)

See Also

[GillespieSSA-package,](#page-1-1) [ssa\(\)](#page-3-1)

Examples

ssa.d()

Description

Explicit tau-leap method implementation of the SSA as described by Gillespie (2001). Should be passed as method argument for ssa().

Usage

ssa.etl $(tau = 0.3)$

Arguments

tau tau-leap.

Details

Performs one time step using the Explicit tau-leap method. Intended to be invoked by [ssa\(\)](#page-3-1).

References

Gillespie (2001)

See Also

[GillespieSSA-package,](#page-1-1) [ssa\(\)](#page-3-1)

Examples

ssa.etl(tau = .1)

ssa.otl *Optimized tau-leap method (OTL)*

Description

Optimized tau-leap method implementation of the SSA as described by Cao et al. (2006). Should be passed as method argument for ssa().

Usage

```
ssa.otl(epsilon = 0.03, nc = 10, hor = NA_{real}, dtf = 10, nd = 100)
```
Arguments

Note

Third order-reactions $(S_1 + S_2 + S_3 \rightarrow ...)$ are not supported currently since they are approximations to sets of coupled first- and second-order reactions). See Cao et al. (2006) for more details.

References

Cao et al. (2006)

See Also

[GillespieSSA-package,](#page-1-1) [ssa\(\)](#page-3-1)

Examples

```
ssa.otl(
 hor = 1,
  nc = 10,epsilon = .03,
  dtf = 10,
  nd = 100
\mathcal{L}
```
ssa.plot *Simple plotting of ssa output*

Description

Provides basic functionally for simple and quick time series plot of simulation output from [ssa\(\)](#page-3-1).

Usage

```
ssa.plot(
 out = stop("requires simulation output object"),
 file = "ssaplot",
 by = 1,plot.from = 2,
 plot.to = ncol(out$data),
```
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```
plot.by = 1,
  show.title = TRUE,
  show.legend = TRUE
\lambda
```
Arguments

Note

The options by, plot.from, plot.to, and plot.by can be used to plot a sparser sequence of data points. To plot the population sizes using a larger time interval the by option can be set, e.g. to plot only every 10th time point by=10. To plot only specific populations the plot.from, plot.to, and plot.by options can be set to subset the state vector. Note that the indexing of the populations is based on the (t, X) vector, i.e. the first column is the time vector while the first population is index by 2 and the last population by $N + 1$. Display of a plot title above the plot and legend is optional (and are set with the arguments show.title and show.legend. Above the plot panel miscellaneous information for the simulation are displayed, i.e. method, elapsed wall time, number of time steps executed, and the number of time steps per data point.

See Also

[GillespieSSA-package,](#page-1-1) [ssa\(\)](#page-3-1)

Examples

```
## Define the Kermack-McKendrick SIR model and run once using the Direct method
parms <- c(beta=.001, gamma=.100)
x0 <- c(S=500, I=1, R=0) # Initial state vector
nu <- matrix(c(-1,0,1,-1,0,1),nrow=3,byrow=TRUE) # State-change matrix
a <- c("beta*S*I", "gamma*I") # Propensity vector
tf <- 100 # Final time
simName <- "Kermack-McKendrick SIR"
out <- ssa(x0,a,nu,parms,tf,method="D",simName,verbose=TRUE,consoleInterval=1)
## Basic ssa plot
ssa.plot(out)
# Plot only the infectious class
ssa.plot(out,plot.from=3,plot.to=3)
```
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