Package ‘pomp’

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Title Statistical Inference for Partially Observed Markov Processes
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Description Tools for data analysis with partially observed Markov process (POMP) models (also known as stochastic dynamical systems, hidden Markov models, and nonlinear, non-Gaussian, state-space models). The package provides facilities for implementing POMP models, simulating them, and fitting them to time series data by a variety of frequentist and Bayesian methods. It is also a versatile platform for implementation of inference methods for general POMP models.
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  'parameter_trans.R' 'covariate_table.R' 'skeleton_spec.R'
  'rprocess_spec.R' 'safecall.R' 'pomp_class.R' 'load.R'
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Description

The **pomp** package provides facilities for inference on time series data using partially-observed Markov process (**POMP**) models. These models are also known as state-space models, hidden Markov models, or nonlinear stochastic dynamical systems. One can use **pomp** to fit nonlinear, non-Gaussian dynamic models to time-series data. The package is both a set of tools for data analysis and a platform upon which statistical inference methods for **POMP** models can be implemented.

Data analysis using pomp

**pomp** provides algorithms for:

1. Simulation of stochastic dynamical systems; see `simulate`.
2. Particle filtering (AKA sequential Monte Carlo or sequential importance sampling); see `pfilter` and `wpfilter`.
4. The nonlinear forecasting algorithm of Kendall et al. (2005); see `nonlinear forecasting`.
5. The particle MCMC approach of Andrieu et al. (2010); see `pmcmc`.
7. Synthetic likelihood a la Wood (2010); see `probe`.
9. Approximate Bayesian computation (Toni et al. 2009); see `abc`.
10. The approximate Bayesian sequential Monte Carlo scheme of Liu & West (2001); see `bsmc2`.
11. Ensemble and ensemble adjusted Kalman filters; see `kalman`.
12. Simple trajectory matching; see `trajectory matching`.

The package also provides various tools for plotting and extracting information on models and data.

Structure of the package

**pomp** algorithms are arranged on several levels. At the top level, **estimation algorithms** estimate model parameters and return information needed for other aspects of inference. **Elementary algorithms** perform common operations on **POMP** models, including simulation, filtering, and application of diagnostic probes; these functions may be useful in inference, but they do not themselves perform estimation. At the lowest level, **workhorse functions** provide the interface to **basic POMP model components**. Beyond these, **pomp** provides a variety of auxiliary functions for manipulating and extracting information from `pomp` objects, producing diagnostic plots, facilitating reproducible computations, and so on.
Implementing a model

The basic structure at the heart of the package is the ‘pomp object’. This is a container holding a time series of data (possibly multivariate) and a model. The model is specified by specifying some or all of its basic model components. One does this using the basic component arguments to the pomp constructor. One can also add, modify, or delete basic model components “on the fly” in any pomp function that accepts them.

Documentation and examples

The package contains a number of examples. Some of these are included in the help pages. In addition, several pre-built POMP models are included with the package. Tutorials and other documentation, including a package FAQ, are available from the package website.

Useful links

- pomp homepage: https://kingaa.github.io/pomp/
- Report bugs to: https://github.com/kingaa/pomp/issues
- Frequently asked questions: https://kingaa.github.io/pomp/FAQ.html
- User guides and tutorials: https://kingaa.github.io/pomp/docs.html
- pomp news: https://kingaa.github.io/pomp/blog.html

Citing pomp

Execute `citation("pomp")` to view the correct citation for publications.

Author(s)

Aaron A. King

References


See the package website for more references, including many publications that use pomp.

See Also

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification

More on pomp workhorse functions: dmeasure(), dprior(), dprocess(), emeasure(), flow(), partrans(), rinit(), rmeasure(), rprior(), rprocess(), skeleton(), vmeasure(), workhorses

More on pomp estimation algorithms: approximate Bayesian computation, bsmc2(), estimation algorithms, mif2(), nonlinear forecasting, pmcmc(), probe matching, spectrum matching
More on **pomp** elementary algorithms: `elementary algorithms, kalman, pfilter()`, `probe()`, `simulate()`, `spect()`, `trajectory()`, `wpfilter()`

---

**Description**

Latent state variables that accumulate quantities through time.

**Details**

In formulating models, one sometimes wishes to define a state variable that will accumulate some quantity over the interval between successive observations. **pomp** provides a facility to make such features more convenient. Specifically, variables named in the pomp's `accumvars` argument will be set to zero immediately following each observation. See `sir` and the tutorials on the package website for examples.

**See Also**

`sir`

More on implementing POMP models: `Csnippet, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification`

**Examples**

```r
## A simple SIR model.

ewmeas |> subset(time < 1952) |> pomp(
  times="time", t0=1948,
  rprocess=euler(
    Csnippet("
    int nrate = 6;
    double rate[nrate];       // transition rates
    double trans[nrate];       // transition numbers
    double dW;

    // gamma noise, mean=dt, variance=(sigma^2 dt)
    dW = rgammawn(sigma,dt);

    // compute the transition rates
    rate[0] = mu*pop;        // birth into susceptible class
    rate[1] = (iota+Beta*I*dW/dt)/pop; // force of infection
  
```

```
accumulator variables

rate[2] = mu;  // death from susceptible class
rate[3] = gamma;  // recovery
rate[4] = mu;  // death from infectious class
rate[5] = mu;  // death from recovered class

// compute the transition numbers
trans[0] = rpois(rate[0]*dt);  // births are Poisson
reulermultinom(2, S, &rate[1], dt, &trans[1]);
reulermultinom(2, I, &rate[3], dt, &trans[3]);
reulermultinom(1, R, &rate[5], dt, &trans[5]);

// balance the equations
S += trans[0]-trans[1]-trans[2];
I += trans[1]-trans[3]-trans[4];
R += trans[3]-trans[5];

delta.t=1/52/20

rinit=Csnippet("double m = pop/(S_0+I_0+R_0);
S = nearbyint(m*S_0);
I = nearbyint(m*I_0);
R = nearbyint(m*R_0);
"),
paramnames=c("mu","pop","iota","gamma","Beta","sigma",
"S_0","I_0","R_0"),
statenames=c("S","I","R"),
params=c(mu=1/50,iota=10,pop=50e6,gamma=26,Beta=400,sigma=0.1,
S_0=0.07,I_0=0.001,R_0=0.93)

## A simple SIR model that tracks cumulative incidence.

ew1 |> simulate() |> plot(variables=c("S","I","R"))
rate[3] = gamma;  // recovery
rate[4] = mu;    // death from infectious class
rate[5] = mu;    // death from recovered class

// compute the transition numbers
trans[0] = rpois(rate[0]*dt);  // births are Poisson
reulermultinom(2,S,&rate[1],dt,&trans[1]);
reulermultinom(2,I,&rate[3],dt,&trans[3]);
reulermultinom(1,R,&rate[5],dt,&trans[5]);

// balance the equations
S += trans[0]-trans[1]-trans[2];
I += trans[1]-trans[3]-trans[4];
R += trans[3]-trans[5];     // cumulative incidence
H += trans[3];

delta.t=1/52/20
rmeasure=Csnippet("double mean = H*rho;
double size = 1/tau;
reports = rnbinom_mu(size,mean);"))
rinit=Csnippet("double m = pop/(S_0+I_0+R_0);
S = nearbyint(m*S_0);
I = nearbyint(m*I_0);
R = nearbyint(m*R_0);
H = 0;
")
paramnames=c("mu", "pop", "iota", "gamma", "Beta", "sigma", "tau", "rho",
"S_0", "I_0", "R_0")
statenames=c("S", "I", "R", "H")
params=c(mu=1/50,iota=10,pop=50e6,gamma=26,Beta=400,sigma=0.1,tau=0.001,rho=0.6,
S_0=0.07,I_0=0.001,R_0=0.93)

## A simple SIR model that tracks weekly incidence.

ew2 |> simulate() |> plot()

ew2 |> pomp(accumvars="H") -> ew3

ew3 |> simulate() |> plot()
approximate Bayesian computation

Approximate Bayesian computation

Description

The approximate Bayesian computation (ABC) algorithm for estimating the parameters of a partially-observed Markov process.

Usage

```r
## S4 method for signature 'data.frame'
abc(
  data,
  Nabc = 1,
  proposal,
  scale,
  epsilon,
  probes,
  params,
  rinit,
  rprocess,
  rmeasure,
  dprior,
  ..., 
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'
abc(
  data,
  Nabc = 1,
  proposal,
  scale,
  epsilon,
  probes,
  ..., 
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'probed_pomp'
abc(data, probes, ..., verbose = getOption("verbose", FALSE))

## S4 method for signature 'abcd_pomp'
abc(
  data,
  Nabc,
```
approximate Bayesian computation

proposal, scale, epsilon, probes, ...
verbose = getOption("verbose", FALSE)
)

Arguments

data
Nabc
proposal
scale
epsilon
probes
params
rinit
rprocess
rmeasure
dprior
...

either a data frame holding the time series data, or an object of class `pomp`, i.e., the output of another pomp calculation. Internally, data will be internally coerced to an array with storage-mode double.

the number of ABC iterations to perform.

optional function that draws from the proposal distribution. Currently, the proposal distribution must be symmetric for proper inference: it is the user’s responsibility to ensure that it is. Several functions that construct appropriate proposal function are provided: see MCMC proposals for more information.
	named numeric vector of scales.

ABC tolerance.
	a single probe or a list of one or more probes. A probe is simply a scalar- or vector-valued function of one argument that can be applied to the data array of a ‘pomp’. A vector-valued probe must always return a vector of the same size. A number of useful probes are provided with the package: see basic probes.

optional; named numeric vector of parameters. This will be coerced internally to storage mode double.

simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator to its default. For more information, see rinit specification.

simulator of the latent state process, specified using one of the rprocess plugins. Setting rprocess=NULL removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

simulator of the measurement model, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rmeasure=NULL removes the measurement model simulator. For more information, see rmeasure specification.

optional; prior distribution density evaluator, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. For more information, see prior specification. Setting dprior=NULL resets the prior distribution to its default, which is a flat improper prior.

additional arguments supply new or modify existing model characteristics or components. See pomp for a full list of recognized arguments.
When named arguments not recognized by pomp are provided, these are made available to all basic components via the so-called userdata facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (covar) and model parameters (params). See userdata for information on how to use this facility.

verbose logical; if TRUE, diagnostic messages will be printed to the console.

Running ABC

abc returns an object of class ‘abcd_pomp’. One or more ‘abcd_pomp’ objects can be joined to form an ‘abcList’ object.

Re-running ABC iterations

To re-run a sequence of ABC iterations, one can use the abc method on a ‘abcd_pomp’ object. By default, the same parameters used for the original ABC run are re-used (except for verbose, the default of which is shown above). If one does specify additional arguments, these will override the defaults.

Continuing ABC iterations

One can continue a series of ABC iterations from where one left off using the continue method. A call to abc to perform Nabc=m iterations followed by a call to continue to perform Nabc=n iterations will produce precisely the same effect as a single call to abc to perform Nabc=m+n iterations. By default, all the algorithmic parameters are the same as used in the original call to abc. Additional arguments will override the defaults.

Methods

The following can be applied to the output of an abc operation:

abc repeats the calculation, beginning with the last state
continue continues the abc calculation
plot produces a series of diagnostic plots
traces produces an mcmc object, to which the various coda convergence diagnostics can be applied

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the cdir and cfile options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Author(s)

Edward L. Ionides, Aaron A. King
basic components

References


See Also

More on methods based on summary statistics: basic probes, nonlinear forecasting, probe matching, probe(), spectrum matching, spect()

More on pomp estimation algorithms: bsmc2(), estimation algorithms, mif2(), nonlinear forecasting, pmcmc(), pomp-package, probe matching, spectrum matching

More on Markov chain Monte Carlo methods: pmcmc(), proposals

More on Bayesian methods: bsmc2(), dprior(), pmcmc(), prior specification, rprior()

basic components  
*Basic POMP model components.*

Description

Mathematically, the parts of a POMP model include the latent-state process transition distribution, the measurement-process distribution, the initial-state distribution, and possibly a prior parameter distribution. Algorithmically, each of these corresponds to at least two distinct operations. In particular, for each of the above parts, one sometimes needs to make a random draw from the distribution and sometimes to evaluate the density function. Accordingly, for each such component, there are two basic model components, one prefixed by a ‘r’, the other by a ‘d’, following the usual R convention.

Details

In addition to the parts listed above, pomp includes two additional basic model components: the deterministic skeleton, and parameter transformations that can be used to map the parameter space onto a Euclidean space for estimation purposes.

There are thus altogether eleven basic model components:

1. rprocess, which samples from the latent-state transition distribution,
2. dprocess, which evaluates the latent-state transition density,
3. rmeasure, which samples from the measurement distribution,
4. emeasure, which computes the conditional expectation of the measurements, given the latent states,
5. \texttt{vmeasure}, which computes the conditional covariance matrix of the measurements, given the latent states,
6. \texttt{dmeasure}, which evaluates the measurement density,
7. \texttt{rprior}, which samples from the prior distribution,
8. \texttt{dprior}, which evaluates the prior density,
9. \texttt{rinit}, which samples from the initial-state distribution,
10. \texttt{skeleton}, which evaluates the deterministic skeleton,
11. \texttt{partrans}, which evaluates the forward or inverse parameter transformations.

Each of these can be set or modified in the \texttt{pomp} constructor function or in any of the \texttt{pomp elementary algorithms} or \texttt{estimation algorithms} using an argument that matches the basic model component. A basic model component can be unset by passing \texttt{NULL} in the same way.

Help pages detailing each basic model component are provided.

\textbf{See Also}

workhorse functions, elementary algorithms, estimation algorithms.

More on implementing POMP models: \texttt{Csnippet}, \texttt{accumulator variables}, \texttt{betabinomial}, \texttt{covariates}, \texttt{distributions}, \texttt{dmeasure specification}, \texttt{dprocess specification}, \texttt{emmeasure specification}, \texttt{parameter transformations}, \texttt{pomp-package}, \texttt{pomp}, \texttt{prior specification}, \texttt{rinit specification}, \texttt{rmeasure specification}, \texttt{rprocess specification}, \texttt{skeleton specification}, \texttt{transformations}, \texttt{userdata}, \texttt{vmeasure specification}

---

**basic probes**

Useful probes for partially-observed Markov processes

---

**Description**

Several simple and configurable probes are provided with in the package. These can be used directly and as templates for custom probes.

**Usage**

\begin{verbatim}
probe_mean(var, trim = 0, transform = identity, na.rm = TRUE)
probe_median(var, na.rm = TRUE)
probe_var(var, transform = identity, na.rm = TRUE)
probe_sd(var, transform = identity, na.rm = TRUE)
probe_period(var, kernel.width, transform = identity)
probe_quantile(var, probs, ...)
\end{verbatim}
probe_acf(
  var,
  lags,
  type = c("covariance", "correlation"),
  transform = identity
)

probe_ccf(
  vars,
  lags,
  type = c("covariance", "correlation"),
  transform = identity
)

probe_marginal(var, ref, order = 3, diff = 1, transform = identity)

probe_nlar(var, lags, powers, transform = identity)

Arguments

var, vars character; the name(s) of the observed variable(s).
trim the fraction of observations to be trimmed (see mean).
transform transformation to be applied to the data before the probe is computed.
na.rm if TRUE, remove all NA observations prior to computing the probe.
kernel.width width of modified Daniell smoothing kernel to be used in power-spectrum computation: see kernel.
probs the quantile or quantiles to compute: see quantile.
... additional arguments passed to the underlying algorithms.
lags In probe_ccf, a vector of lags between time series. Positive lags correspond to x advanced relative to y; negative lags, to the reverse.
In probe_nlar, a vector of lags present in the nonlinear autoregressive model that will be fit to the actual and simulated data. See Details, below, for a precise description.
type Compute autocorrelation or autocovariance?
ref empirical reference distribution. Simulated data will be regressed against the values of ref, sorted and, optionally, differenced. The resulting regression coefficients capture information about the shape of the marginal distribution. A good choice for ref is the data itself.
order order of polynomial regression.
diff order of differencing to perform.
powers the powers of each term (corresponding to lags) in the the nonlinear autoregressive model that will be fit to the actual and simulated data. See Details, below, for a precise description.
Value

A call to any one of these functions returns a probe function, suitable for use in `probe` or `probe_objfun`. That is, the function returned by each of these takes a data array (such as comes from a call to `obs`) as input and returns a single numerical value.

Author(s)

Daniel C. Reuman, Aaron A. King

References


See Also

More on methods based on summary statistics: approximate Bayesian computation, nonlinear forecasting, probe matching, probe(), spectrum matching, spect()

---

betabinomial  
*Beta-binomial distribution*

**Description**

Density and random generation for the Beta-binomial distribution with parameters `size`, `mu`, and `theta`.

**Usage**

```r
rbetabinom(n = 1, size, prob, theta)
dbetabinom(x, size, prob, theta, log = FALSE)
```

**Arguments**

- `n` integer; number of random variates to generate.
- `size` size parameter of the binomial distribution
- `prob` mean of the Beta distribution
- `theta` Beta distribution dispersion parameter
- `x` vector of non-negative integer quantiles
- `log` logical; if TRUE, return logarithm(s) of probabilities.
Details

A variable \( X \) is Beta-binomially distributed if \( X \sim \text{Binomial}(n, P) \) where \( P \sim \text{Beta}(\mu, \theta) \). Using the standard \((a, b)\) parameterization, \( a = \mu \theta \) and \( b = (1 - \mu) \theta \).

Value

\texttt{rbetabinom}  
Returns a vector of length \( n \) containing random variates drawn from the Beta-binomial distribution.

\texttt{dbetabinom}  
Returns a vector (of length equal to the number of columns of \( x \)) containing the probabilities of observing each column of \( x \) given the specified parameters (size, prob, theta).

C API

An interface for C codes using these functions is provided by the package. Visit the package homepage to view the \texttt{pomp} C API document.

See Also

More on implementing POMP models: \texttt{Csnippet}, \texttt{accumulator variables}, \texttt{basic components}, \texttt{covariates}, \texttt{distributions}, \texttt{dmeasure specification}, \texttt{dprocess specification}, \texttt{emeasure specification}, \texttt{parameter transformations}, \texttt{pomp-package}, \texttt{pomp}, \texttt{prior specification}, \texttt{rinit specification}, \texttt{rmeasure specification}, \texttt{rprocess specification}, \texttt{skeleton specification}, \texttt{transformations}, \texttt{userdata}, \texttt{vmeasure specification}

\begin{verbatim}
blowflies

blowflies is a data frame containing the data from several of Nicholson’s classic experiments with the Australian sheep blowfly, \textit{Lucilia cuprina}.

Usage

\texttt{blowflies1(}
  \texttt{P = 3.2838,}
  \texttt{delta = 0.16073,}
  \texttt{N0 = 679.94,}
  \texttt{sigma.P = 1.3512,}
  \texttt{sigma.d = 0.74677,}
  \texttt{sigma.y = 0.026649}
\texttt{)}

\texttt{blowflies2(}
  \texttt{P = 2.7319,}
  \texttt{delta = 0.17377,}
\texttt{)}
\end{verbatim}
\[ N0 = 800.31, \]
\[ \text{sigma.P} = 1.442, \]
\[ \text{sigma.d} = 0.76033, \]
\[ \text{sigma.y} = 0.010846 \]

Arguments

- \( \text{P} \) reproduction parameter
- \( \text{delta} \) death rate
- \( N0 \) population scale factor
- \( \text{sigma.P} \) intensity of \( e \) noise
- \( \text{sigma.d} \) intensity of \( \epsilon \) noise
- \( \text{sigma.y} \) measurement error s.d.

Details

\text{blowflies1()} and \text{blowflies2()} construct ‘pomp’ objects encoding stochastic delay-difference equation models. The data for these come from "population I", a control culture. The experiment is described on pp. 163–4 of Nicholson (1957). Unlimited quantities of larval food were provided; the adult food supply (ground liver) was constant at 0.4g per day. The data were taken from the table provided by Brillinger et al. (1980).

The models are discrete delay equations:

\[
\begin{align*}
R(t+1) &\sim \text{Poisson}(PN(t-\tau)\exp(-N(t-\tau)/N0)e(t+1)\Delta t) \\
S(t+1) &\sim \text{Binomial}(N(t), \exp(-\delta \epsilon(t+1)\Delta t)) \\
N(t) &= R(t) + S(t)
\end{align*}
\]

where \( e(t) \) and \( \epsilon(t) \) are Gamma-distributed i.i.d. random variables with mean 1 and variances \( \sigma^2_P/\Delta t, \sigma^2_\delta/\Delta t \), respectively. \text{blowflies1()} has a timestep \( \Delta t \) of 1 day; \text{blowflies2()} has a timestep of 2 days. The process model in \text{blowflies1()} thus corresponds exactly to that studied by Wood (2010). The measurement model in both cases is taken to be

\[
y(t) \sim \text{NegBin}(N(t), 1/\sigma^2_y)\]

i.e., the observations are assumed to be negative-binomially distributed with mean \( N(t) \) and variance \( N(t) + (\sigma^2_y N(t))^2 \).

Default parameter values are the MLEs as estimated by Ionides (2011).

Value

\text{blowflies1()} and \text{blowflies2()} return ‘pomp’ objects containing the actual data and two variants of the model.
bsflu

References


See Also

More examples provided with pomp: SIR models, childhood disease data, dacca(), ebola, gompertz(), ou2(), pomp examples, ricker(), rw2(), verhulst()

More data sets provided with pomp: bsflu, childhood disease data, dacca(), ebola, parus

Examples

```r
plot(blowflies1())
plot(blowflies2())
```

bsflu  
*Influenza outbreak in a boarding school*

Description

An outbreak of influenza in an all-boys boarding school.

Details

Data are recorded from a 1978 flu outbreak in a closed population. The variable ‘B’ refers to boys confined to bed on the corresponding day and ‘C’ to boys in convalescence, i.e., not yet allowed back to class. In total, 763 boys were at risk of infection and, over the course of the outbreak, 512 boys spent between 3 and 7 days away from class (either in bed or convalescent). The index case was a boy who arrived at school from holiday six days before the next case.

References

See Also

SIR models

More data sets provided with pomp: blowflies, childhood disease data, dacca(), ebola, parus

Examples

```r
if (require(tidyverse) && require(ggplot2)) {
  bsflu |>
    gather(variable,value,-date,-day) |>
    ggplot(aes(x=date,y=value,color=variable))+
    geom_line()+
    labs(y="number of boys",title="boarding school flu outbreak")+
    theme_bw()
}
```

bsmc2

The Liu and West Bayesian particle filter

Description


Usage

```r
## S4 method for signature 'data.frame'
bsmc2(
  data,
  Np,
  smooth = 0.1,
  params,
  rprior,
  rinit,
  rprocess,
  dmeasure,
  partrans,
  ...,
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'
bsmc2(data, Np, smooth = 0.1, ..., verbose = getOption("verbose", FALSE))
```
Arguments
data

either a data frame holding the time series data, or an object of class 'pomp', i.e., the output of another pomp calculation. Internally, data will be internally coerced to an array with storage-mode double.

Np

the number of particles to use. This may be specified as a single positive integer, in which case the same number of particles will be used at each timestep. Alternatively, if one wishes the number of particles to vary across timesteps, one may specify Np either as a vector of positive integers of length

\[ \text{length(time(object,t0=TRUE))} \]

or as a function taking a positive integer argument. In the latter case, Np(k) must be a single positive integer, representing the number of particles to be used at the k-th timestep: Np(0) is the number of particles to use going from timezero(object) to time(object)[1], Np(1), from timezero(object) to time(object)[1], and so on, while when T=length(time(object)), Np(T) is the number of particles to sample at the end of the time-series.

smooth

Kernel density smoothing parameter. The compensating shrinkage factor will be \( \sqrt{1 - \text{smooth}^2} \). Thus, smooth=0 means that no noise will be added to parameters. The general recommendation is that the value of smooth should be chosen close to 0 (e.g., shrink ~ 0.1).

params

optional; named numeric vector of parameters. This will be coerced internally to storage mode double.

r prior

optional; prior distribution sampler, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. For more information, see prior specification. Setting rprior=NULL removes the prior distribution sampler.

rinit

simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator to its default. For more information, see rinit specification.

r process

simulator of the latent state process, specified using one of the rprocess plugins. Setting rprocess=NULL removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

d measure

evaluator of the measurement model density, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting dmeasure=NULL removes the measurement density evaluator. For more information, see dmeasure specification.

partrans

optional parameter transformations, constructed using parameter_trans. Many algorithms for parameter estimation search an unconstrained space of parameters. When working with such an algorithm and a model for which the parameters are constrained, it can be useful to transform parameters. One should supply the partrans argument via a call to parameter_trans. For more information, see parameter_trans. Setting partrans=NULL removes the parameter transformations, i.e., sets them to the identity transformation.
... additional arguments supply new or modify existing model characteristics or components. See pomp for a full list of recognized arguments.

When named arguments not recognized by pomp are provided, these are made available to all basic components via the so-called userdata facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (covar) and model parameters (params). See userdata for information on how to use this facility.

verbose logical; if TRUE, diagnostic messages will be printed to the console.

Details

bsmc2 uses a version of the original algorithm (Liu & West 2001), but discards the auxiliary particle filter. The modification appears to give superior performance for the same amount of effort.

Samples from the prior distribution are drawn using the rprior component. This is allowed to depend on elements of params, i.e., some of the elements of params can be treated as “hyperparameters”. Np draws are made from the prior distribution.

Value

An object of class ‘bsmcd_pomp’. The following methods are available:

plot produces diagnostic plots
as.data.frame puts the prior and posterior samples into a data frame

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the cdir and cfile options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Author(s)

Michael Lavine, Matthew Ferrari, Aaron A. King, Edward L. Ionides

References


See Also

More on Bayesian methods: approximate Bayesian computation, dprior(), pmcmc(), prior specification, rprior()
More on full-information (i.e., likelihood-based) methods: mif2(), pfilter(), pmcmc(), wpfilter()
More on sequential Monte Carlo methods: `cond_logLik()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `kalman.mif2()`, `pfilter()`, `pmcmc()`, `pred_mean()`, `pred_var()`, `saved_states()`, `wpfilter()`.

More on `pomp` estimation algorithms: approximate Bayesian computation, estimation algorithms, `mif2()`, nonlinear forecasting, `pmcmc()`, `pomp-package`, probe matching, spectrum matching.

<table>
<thead>
<tr>
<th>bsplines</th>
<th>B-spline bases</th>
</tr>
</thead>
</table>

**Description**

These functions generate B-spline basis functions. `bspline_basis` gives a basis of spline functions. `periodic_bspline_basis` gives a basis of periodic spline functions.

**Usage**

```r
bspline_basis(x, nbasis, degree = 3, deriv = 0, names = NULL, rg = range(x))

periodic_bspline_basis(
  x,
  nbasis,
  degree = 3,
  period = 1,
  deriv = 0,
  names = NULL
)
```

**Arguments**

- `x` Vector at which the spline functions are to be evaluated.
- `nbasis` The number of basis functions to return.
- `degree` Degree of requested B-splines.
- `deriv` The order of the derivative required.
- `names` optional; the names to be given to the basis functions. These will be the column-names of the matrix returned. If the names are specified as a format string (e.g., "basis%d"), `sprintf` will be used to generate the names from the column number. If a single non-format string is specified, the names will be generated by `paste`-ing name to the column number. One can also specify each column name explicitly by giving a length-`nbasis` string vector. By default, no column-names are given.
- `rg` numeric of length 2; range of the B-spline basis. To be properly specified, we must have `rg[1] < rg[2].`
- `period` The period of the requested periodic B-splines.
Value

bspline_basis  Returns a matrix with length(x) rows and nbasis columns. Each column contains the values one of the spline basis functions.

periodic_bspline_basis  Returns a matrix with length(x) rows and nbasis columns. The basis functions returned are periodic with period period. If deriv>0, the derivative of that order of each of the corresponding spline basis functions are returned.

C API

Access to the underlying C routines is available: see the pomp C API document. for definition and documentation of the C API.

Author(s)

Aaron A. King

See Also

More on interpolation: covariates, lookup()

Examples

```r
x <- seq(0,2,by=0.01)
y <- bspline_basis(x,degree=3,nbasis=9,names="basis")
matplot(x,y,type='l',ylim=c(0,1.1))
lines(x,apply(y,1,sum),lwd=2)

x <- seq(-1,2,by=0.01)
y <- periodic_bspline_basis(x,nbasis=5,names="spline%d")
matplot(x,y,type='l')
```

childhood disease data

Historical childhood disease incidence data

Description

LondonYorke is a data frame containing the monthly number of reported cases of chickenpox, measles, and mumps from two American cities (Baltimore and New York) in the mid-20th century (1928–1972).

ewmeas and ewcitmeas are data frames containing weekly reported cases of measles in England and Wales. ewmeas records the total measles reports for the whole country, 1948–1966. One questionable data point has been replaced with an NA. ewcitmeas records the incidence in seven English
childhood disease data

cities 1948–1987. These data were kindly provided by Ben Bolker, who writes: “Most of these data have been manually entered from published records by various people, and are prone to errors at several levels. All data are provided as is; use at your own risk.”

References


See Also

SIR models, bsflu

More data sets provided with pomp: blowflies, bsflu, dacca(), ebola, parus

More examples provided with pomp: SIR models, blowflies, dacca(), ebola, gompertz(), ou2(), pomp examples, ricker(), rw2(), verhulst()

Examples

```r
plot(cases~time, data=LondonYorke, subset=disease=="measles", type='n',main="measles", bty='l')
lines(cases~time, data=LondonYorke, subset=disease=="measles"&town=="Baltimore", col="red")
lines(cases~time, data=LondonYorke, subset=disease=="measles"&town=="New York", col="blue")
legend("topright", legend=c("Baltimore", "New York"), lty=1, col=c("red", "blue"), bty='n')

plot(
cases~time,
data=LondonYorke,
subset=disease=="chickenpox"&town=="New York",
type='l', col="blue", main="chickenpox, New York",
bty='l'
)

plot(
cases~time,
data=LondonYorke,
subset=disease=="mumps"&town=="New York",
type='l', col="blue", main="mumps, New York",
bty='l'
)

plot(reports~time, data=ewmeas, type='l')

plot(reports~date, data=ewcitmeas, subset=city=="Liverpool", type='l')
```
### coef

Extract, set, or alter coefficients

**Description**

Extract, set, or modify the estimated parameters from a fitted model.

**Usage**

```r
## S4 method for signature 'listie'
coef(object, ...)  

## S4 method for signature 'pomp'
coef(object, pars, transform = FALSE, ...)

## S4 replacement method for signature 'pomp'
coef(object, pars, transform = FALSE, ...) <- value

## S4 method for signature 'objfun'
coef(object, ...)

## S4 replacement method for signature 'objfun'
coef(object, pars, transform = FALSE, ...) <- value
```

**Arguments**

- `object`: an object of class ‘pomp’, or of a class extending ‘pomp’
- `...`: ignored or passed to the more primitive function
- `pars`: optional character; names of parameters to be retrieved or set.
- `transform`: logical; perform parameter transformation?
- `value`: numeric vector or list; values to be assigned. If `value = NULL`, the parameters are unset.

**Details**

- `coef` allows one to extract the parameters from a fitted model.
- `coef(object, transform=TRUE)` returns the parameters transformed onto the estimation scale.
- `coef(object) <- value` sets or alters the coefficients of a ‘pomp’ object.
- `coef(object, transform=TRUE) <- value` assumes that value is on the estimation scale, and applies the “from estimation scale” parameter transformation from `object` before altering the coefficients.
See Also

Other extraction methods: `cond_logLik()`, `covmat()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `forecast()`, `logLik`, `obs()`, `pred_mean()`, `pred_var()`, `saved_states()`, `spy()`, `states()`, `summary()`, `timezero()`, `time()`, `traces()`

---

**concat**

Concatenate

**Description**

Concatenate two or more 'pomp' objects into a list-like 'listie'.

**Usage**

```r
## S3 method for class 'Pomp'
c(...)
concat(...)```

**Arguments**

... elements to be recursively combined into a 'listie'

**Details**

`concat` applied to one or more 'pomp' objects or lists of 'pomp' objects converts the list into a 'listie'. In particular, `concat(A,B,C)` is equivalent to `do.call(c,unlist(list(A,B,C)))`.

**Examples**

```r
gompertz(sigma=2,tau=1) -> g
Np <- c(low=100,med=1000,high=10000)
lapply(
  Np,
  \(np\) pfilter(g,Np=np)
) |> concat() -> pfs

pfs
c_coef(pfs)
logLik(pfs)
 eff_sample_size(pfs)
 cond_logLik(pfs)

pfs |> plot()```
cond_logLik

**Conditional log likelihood**

**Description**

The estimated conditional log likelihood from a fitted model.

**Usage**

```r
## S4 method for signature 'kalmand_pomp'
cond_logLik(object, ..., format = c("numeric", "data.frame"))

## S4 method for signature 'pfilterd_pomp'
cond_logLik(object, ..., format = c("numeric", "data.frame"))

## S4 method for signature 'wpfilterd_pomp'
cond_logLik(object, ..., format = c("numeric", "data.frame"))

## S4 method for signature 'bsmc2_pomp'
cond_logLik(object, ..., format = c("numeric", "data.frame"))

## S4 method for signature 'pfilterList'
cond_logLik(object, ..., format = c("numeric", "data.frame"))
```

**Arguments**

- `object` result of a filtering computation
- `...` ignored
- `format` format of the returned object

**Details**

The conditional likelihood is defined to be the value of the density of

\[
Y(t_k)|Y(t_1), \ldots, Y(t_{k-1})
\]

evaluated at \(Y(t_k) = y^*_k\). Here, \(Y(t_k)\) is the observable process, and \(y^*_k\) the data, at time \(t_k\).

Thus the conditional log likelihood at time \(t_k\) is

\[
\ell_k(\theta) = \log f[Y(t_k) = y^*_k|Y(t_1) = y^*_1, \ldots, Y(t_{k-1}) = y^*_{k-1}],
\]

where \(f\) is the probability density above.

**Value**

The numerical value of the conditional log likelihood. Note that some methods compute not the log likelihood itself but instead a related quantity. To keep the code simple, the `cond_logLik` function is nevertheless used to extract this quantity.

When `object` is of class `bsmc2_pomp` (i.e., the result of a bsmc2 computation), `cond_logLik` returns the conditional log “evidence” (see bsmc2).
See Also

More on sequential Monte Carlo methods: `bsmc2()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `kalman`, `mif2()`, `pfilter()`, `pmcmc()`, `pred_mean()`, `pred_var()`, `saved_states()`, `wpfilter()

Other extraction methods: `coef()`, `covmat()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `forecast()`, `logLik`, `obs()`, `pred_mean()`, `pred_var()`, `saved_states()`, `spy()`, `states()`, `summary()`, `timezero()`, `time()`, `traces()`

### Description

Continue an iterative computation where it left off.

### Usage

```r
## S4 method for signature 'abcd_pomp'
continue(object, Nabc = 1, ...)

## S4 method for signature 'pmcmcd_pomp'
continue(object, Nmcmc = 1, ...)

## S4 method for signature 'mif2d_pomp'
continue(object, Nmif = 1, ...)
```

### Arguments

- **object**: the result of an iterative `pomp` computation
- **Nabc**: positive integer; number of additional ABC iterations to perform
- **...**: additional arguments will be passed to the underlying method. This allows one to modify parameters used in the original computations.
- **Nmcmc**: positive integer; number of additional PMCMC iterations to perform
- **Nmif**: positive integer; number of additional filtering iterations to perform

### See Also

`mif2` `pmcmc` `abc`
**Description**

Incorporating time-varying covariates using lookup tables.

**Usage**

```r
## S4 method for signature 'numeric'
covariate_table(..., order = c("linear", "constant"), times)
```

```r
## S4 method for signature 'character'
covariate_table(..., order = c("linear", "constant"), times)
```

**Arguments**

- `...`: numeric vectors or data frames containing time-varying covariates. It must be possible to bind these into a data frame.
- `order`: the order of interpolation to be used. Options are "linear" (the default) and "constant". Setting `order="linear"` treats the covariates as piecewise linear functions of time; `order="constant"` treats them as right-continuous piecewise constant functions.
- `times`: the times corresponding to the covariates. This may be given as a vector of (non-decreasing, finite) numerical values. Alternatively, one can specify by name which of the given variables is the time variable.

**Details**

If the `pomp` object contains covariates (specified via the `covar` argument), then interpolated values of the covariates will be available to each of the model components whenever it is called. In particular, variables with names as they appear in the `covar` covariate table will be available to any C snippet. When a basic component is defined using an R function, that function will be called with an extra argument, `covars`, which will be a named numeric vector containing the interpolated values from the covariate table.

An exception to this rule is the prior (`rprior` and `dprior`): covariate-dependent priors are not allowed. Nor are parameter transformations permitted to depend upon covariates.

**See Also**

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification

More on interpolation: bsplines, lookup()
covmat

Estimate a covariance matrix from algorithm traces

Description

A helper function to extract a covariance matrix.

Usage

```r
## S4 method for signature 'pmcmcd_pomp'
covmat(object, start = 1, thin = 1, expand = 2.38, ...)

## S4 method for signature 'pmcmcList'
covmat(object, start = 1, thin = 1, expand = 2.38, ...)

## S4 method for signature 'abcd_pomp'
covmat(object, start = 1, thin = 1, expand = 2.38, ...)

## S4 method for signature 'abcList'
covmat(object, start = 1, thin = 1, expand = 2.38, ...)

## S4 method for signature 'probed_pomp'
covmat(object, ...)
```

Arguments

- `object`: an object extending `pomp`
- `start`: the first iteration number to be used in estimating the covariance matrix. Setting `thin > 1` allows for a burn-in period.
- `thin`: factor by which the chains are to be thinned
- `expand`: the expansion factor
- `...`: ignored

Value

When `object` is the result of a `pmcmc` or `abc` computation, `covmat(object)` gives the covariance matrix of the chains. This can be useful, for example, in tuning the proposal distribution.

When `object` is a `probed_pomp` object (i.e., the result of a probe computation), `covmat(object)` returns the covariance matrix of the probes, as applied to simulated data.

See Also

MCMC proposals.

Other extraction methods: `coef()`, `cond_logLik()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `forecast()`, `logLik`, `obs()`, `pred_mean()`, `pred_var()`, `saved_states()`, `spy()`, `states()`, `summary()`, `timezero()`, `time()`, `traces()`
Csnippet  C snippets

Description

Accelerating computations through inline snippets of C code

Usage

Csnippet(text)

Arguments

text character; text written in the C language

Details

pomp provides a facility whereby users can define their model’s components using inline C code. C snippets are written to a C file, by default located in the R session’s temporary directory, which is then compiled (via R CMD SHLIB) into a dynamically loadable shared object file. This is then loaded as needed.

Note to Windows and Mac users

By default, your R installation may not support R CMD SHLIB. The package website contains installation instructions that explain how to enable this powerful feature of R.

General rules for writing C snippets

In writing a C snippet one must bear in mind both the goal of the snippet, i.e., what computation it is intended to perform, and the context in which it will be executed. These are explained here in the form of general rules. Additional specific rules apply according to the function of the particular C snippet. Illustrative examples are given in the tutorials on the package website.

1. C snippets must be valid C. They will be embedded verbatim in a template file which will then be compiled by a call to R CMD SHLIB. If the resulting file does not compile, an error message will be generated. Compiler messages will be displayed, but no attempt will be made by pomp to interpret them. Typically, compilation errors are due to either invalid C syntax or undeclared variables.

2. State variables, parameters, observables, and covariates must be left undeclared within the snippet. State variables and parameters are declared via the statenames or paramnames arguments to pomp, respectively. Compiler errors that complain about undeclared state variables or parameters are usually due to failure to declare these in statenames or paramnames, as appropriate.

3. A C snippet can declare local variables. Be careful not to use names that match those of state variables, observables, or parameters. One must never declare state variables, observables, covariates, or parameters within a C snippet.
4. Names of observables must match the names given in the data. They must be referred to in measurement model C snippets (\texttt{rmeasure} and \texttt{dmeasure}) by those names.

5. If the ‘pomp’ object contains a table of covariates (see above), then the variables in the covariate table will be available, by their names, in the context within which the C snippet is executed.

6. Because the dot ‘\.’ has syntactic meaning in C, \texttt{R} variables with names containing dots (‘\.’) are replaced in the C codes by variable names in which all dots have been replaced by underscores (‘\_’).

7. The headers ‘\texttt{R.h}’ and ‘\texttt{Rmath.h}’, provided with \texttt{R}, will be included in the generated C file, making all of the \texttt{R C API} available for use in the C snippet. This makes a great many useful functions available, including all of \texttt{R}’s \textit{statistical distribution functions}.

8. The header ‘\texttt{pomp.h}’, provided with \texttt{pomp}, will also be included, making all of the \texttt{pomp C API} available for use in every C snippet.

9. Snippets of C code passed to the \texttt{globals} argument of \texttt{pomp} will be included at the head of the generated C file. This can be used to declare global variables, define useful functions, and include arbitrary header files.

\section*{Linking to precompiled libraries}

It is straightforward to link C snippets with precompiled C libraries. To do so, one must make sure the library’s header files are included; the \texttt{globals} argument can be used for this purpose. The \texttt{shlib.args} argument can then be used to specify additional arguments to be passed to \texttt{R CMD SHLIB}. \texttt{FAQ 3.7} gives an example.

\section*{C snippets are salted}

To prevent collisions in parallel computations, a ‘pomp’ object built using C snippets is “salted” with the current time and a random number. A result is that two ‘pomp’ objects, built on identical codes and data, will \textbf{not} be identical as \texttt{R} objects, though they will be functionally identical in every respect.

\section*{Note for Windows users}

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the \texttt{cdir} and \texttt{cfile} options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

\section*{See Also}

\texttt{spy}

More on implementing POMP models: \texttt{accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification}
dacca

Model of cholera transmission for historic Bengal.

Description

dacca constructs a ‘pomp’ object containing census and cholera mortality data from the Dacca district of the former British province of Bengal over the years 1891 to 1940 together with a stochastic differential equation transmission model. The model is that of King et al. (2008). The parameters are the MLE for the SIRS model with seasonal reservoir.

Usage

dacca(
  gamma = 20.8,
  eps = 19.1,
  rho = 0,
  delta = 0.02,
  deltaI = 0.06,
  clin = 1,
  alpha = 1,
  beta_trend = -0.00498,
  logbeta = c(0.747, 6.38, -3.44, 4.23, 3.33, 4.55),
  logomega = log(c(0.184, 0.0786, 0.0584, 0.00917, 0.000208, 0.0124)),
  sd_beta = 3.13,
  tau = 0.23,
  S_0 = 0.621,
  I_0 = 0.378,
  Y_0 = 0,
  R1_0 = 0.000843,
  R2_0 = 0.000972,
  R3_0 = 1.16e-07
)

Arguments

gamma  recovery rate
go  rate of waning of immunity for severe infections
rho  rate of waning of immunity for inapparent infections
delta  baseline mortality rate
deltaI  cholera mortality rate
clin  fraction of infections that lead to severe infection
alpha  transmission function exponent
beta_trend  slope of secular trend in transmission
logbeta  seasonal transmission rates
logomega  seasonal environmental reservoir parameters
sd_beta   environmental noise intensity
tau       measurement error s.d.
S_0       initial susceptible fraction
I_0       initial fraction of population infected
Y_0       initial fraction of the population in the Y class
R1_0, R2_0, R3_0 initial fractions in the respective R classes

Details

Data are provided courtesy of Dr. Menno J. Bouma, London School of Tropical Medicine and
Hygiene.

Value
dacca returns a ‘pomp’ object containing the model, data, and MLE parameters, as estimated by
King et al. (2008).

References

Nature 454, 877-880, 2008

See Also

More examples provided with pomp: SIR models, blowflies, childhood disease data, ebola,
gompertz(), ou2(), pomp examples, ricker(), rw2(), verhulst()

More data sets provided with pomp: blowflies, bsflu, childhood disease data, ebola, parus

Examples

# takes too long for R CMD check
po <- dacca()
plot(po)
## MLE:
coef(po)
plot(simulate(po))
Design matrices for pomp calculations

Description

These functions are useful for generating designs for the exploration of parameter space.

profile_design generates a data-frame where each row can be used as the starting point for a profile likelihood calculation.

runif_design generates a design based on random samples from a multivariate uniform distribution.

slice_design generates points along slices through a specified point.

sobol_design generates a Latin hypercube design based on the Sobol’ low-discrepancy sequence.

Usage

profile_design(
  ..., 
  lower, 
  upper, 
  nprof, 
  type = c("runif", "sobol"), 
  stringsAsFactors = getOption("stringsAsFactors", FALSE)
)

runif_design(lower = numeric(0), upper = numeric(0), nseq)

slice_design(center, ...)

sobol_design(lower = numeric(0), upper = numeric(0), nseq)

Arguments

... In profile_design, additional arguments specify the parameters over which to profile and the values of these parameters. In slice_design, additional numeric vector arguments specify the locations of points along the slices.

lower, upper named numeric vectors giving the lower and upper bounds of the ranges, respectively.

nprof The number of points per profile point.

type the type of design to use. type="runif" uses runif_design. type="sobol" uses sobol_design;

stringsAsFactors should character vectors be converted to factors?

nseq Total number of points requested.

center center is a named numeric vector specifying the point through which the slice(s) is (are) to be taken.
Details
The Sobol’ sequence generation is performed using codes from the NLopt library by S. Johnson.

Value
- `profile_design` returns a data frame with `nprof` points per profile point.
- `runif_design` returns a data frame with `nseq` rows and one column for each variable named in `lower` and `upper`.
- `slice_design` returns a data frame with one row per point. The ‘slice’ variable indicates which slice the point belongs to.
- `sobol_design` returns a data frame with `nseq` rows and one column for each variable named in `lower` and `upper`.

Author(s)
Aaron A. King

References


Examples
```r
## Sobol' low-discrepancy design
plot(sobol_design(lower=c(a=0,b=100),upper=c(b=200,a=1),nseq=100))

## Uniform random design
plot(runif_design(lower=c(a=0,b=100),upper=c(b=200,a=1),100))

## A one-parameter profile design:
x <- profile_design(p=1:10,lower=c(a=0,b=0),upper=c(a=1,b=5),nprof=20)
dim(x)
plot(x)

## A two-parameter profile design:
x <- profile_design(p=1:10,q=3:5,lower=c(a=0,b=0),upper=c(b=5,a=1),nprof=200)
dim(x)
plot(x)

## A two-parameter profile design with random points:
```
x <- profile_design(p=1:10, q=3:5, lower=c(a=0, b=0), upper=c(b=5, a=1), nprof=200, type="runif")
dim(x)
plot(x)

## A single 11-point slice through the point c(A=3,B=8,C=0) along the B direction.
x <- slice_design(center=c(A=3, B=8, C=0), B=seq(0, 10, by=1))
dim(x)
plot(x)

## Two slices through the same point along the A and C directions.
x <- slice_design(c(A=3, B=8, C=0), A=seq(0, 5, by=1), C=seq(0, 5, length=11))
dim(x)
plot(x)

---

distributions

**Probability distributions**

**Description**

* pomp provides a number of probability distributions that have proved useful in modeling partially observed Markov processes. These include the Euler-multinomial family of distributions and the Gamma white-noise processes.

**Usage**

```r
reulermultinom(n = 1, size, rate, dt)
deulermultinom(x, size, rate, dt, log = FALSE)
rgammawn(n = 1, sigma, dt)
```

**Arguments**

- `n` integer; number of random variates to generate.
- `size` scalar integer; number of individuals at risk.
- `rate` numeric vector of hazard rates.
- `dt` numeric scalar; duration of Euler step.
- `x` matrix or vector containing number of individuals that have succumbed to each death process.
- `log` logical; if TRUE, return logarithm(s) of probabilities.
- `sigma` numeric scalar; intensity of the Gamma white-noise process.
Details

If \( N \) individuals face constant hazards of death in \( K \) ways at rates \( r_1, r_2, \ldots, r_K \), then in an interval of duration \( \Delta t \), the number of individuals remaining alive and dying in each way is multinomially distributed:

\[
(\Delta n_0, \Delta n_1, \ldots, \Delta n_K) \sim \text{Multinomial}(N; p_0, p_1, \ldots, p_K),
\]

where \( \Delta n_0 = N - \sum_{k=1}^{K} \Delta n_k \) is the number of individuals remaining alive and \( \Delta n_k \) is the number of individuals dying in way \( k \) over the interval. Here, the probability of remaining alive is

\[
p_0 = \exp\left(-\sum_k r_k \Delta t\right)
\]

and the probability of dying in way \( k \) is

\[
p_k = \frac{r_k}{\sum_j r_j}(1 - p_0).
\]

In this case, we say that

\[
(\Delta n_1, \ldots, \Delta n_K) \sim \text{Eulermultinom}(N, r, \Delta t),
\]

where \( r = (r_1, \ldots, r_K) \). Draw \( m \) random samples from this distribution by doing

\[
dn <- \text{reulermultinom}(n=m, size=N, rate=r, dt=dt),
\]

where \( r \) is the vector of rates. Evaluate the probability that \( x = (x_1, \ldots, x_K) \) are the numbers of individuals who have died in each of the \( K \) ways over the interval \( \Delta t = dt \), by doing

\[
deulermultinom(x=x, size=N, rate=r, dt=dt).
\]

Bretó & Ionides (2011) discuss how an infinitesimally overdispersed death process can be constructed by compounding a multinomial process with a Gamma white noise process. The Euler approximation of the resulting process can be obtained as follows. Let the increments of the equidispersed process be given by

\[
\text{reulermultinom(size=N, rate=r, dt=dt)}.
\]

In this expression, replace the rate \( r \) with \( r \Delta W/\Delta t \), where \( \Delta W \sim \Gamma(\Delta t/\sigma^2, \sigma^2) \) is the increment of an integrated Gamma white noise process with intensity \( \sigma \). That is, \( \Delta W \) has mean \( \Delta t \) and variance \( \sigma^2 \Delta t \). The resulting process is overdispersed and converges (as \( \Delta t \) goes to zero) to a well-defined process. The following lines of code accomplish this:

\[
dW <- \text{rgammawin}(sigma=sigma, dt=dt)
\]

\[
dn <- \text{reulermultinom(size=N, rate=r, dt=dW)}
\]

or

\[
dn <- \text{reulermultinom(size=N, rate=r*dW/dt, dt=dt)}.
\]

He et al. (2010) use such overdispersed death processes in modeling measles and the "Simulation-based Inference" course discusses the value of allowing for overdispersion more generally.

For all of the functions described here, access to the underlying C routines is available: see below.
Value

reulermultinom  Returns a length(rate) by n matrix. Each column is a different random draw. Each row contains the numbers of individuals that have succumbed to the corresponding process.

deulermultinom  Returns a vector (of length equal to the number of columns of x) containing the probabilities of observing each column of x given the specified parameters (size, rate, dt).

rgammawn  Returns a vector of length n containing random increments of the integrated Gamma white noise process with intensity sigma.

C API

An interface for C codes using these functions is provided by the package. Visit the package homepage to view the pomp C API document.

Author(s)

Aaron A. King

References


See Also

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, covariates, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification

Examples

```r
print(dn <- reulermultinom(5,size=100,rate=c(a=1,b=2,c=3),dt=0.1))
deulermultinom(x=dn,size=100,rate=c(1,2,3),dt=0.1)
## an Euler-multinomial with overdispersed transitions:
dt <- 0.1
dW <- rgammawn(sigma=0.1,dt=dt)
print(dn <- reulermultinom(5,size=100,rate=c(a=1,b=2,c=3),dt=dW))
```
**Description**

dmeasure evaluates the probability density of observations given states.

**Usage**

```r
## S4 method for signature 'pomp'
dmeasure(
  object,
  y = obs(object),
  x = states(object),
  times = time(object),
  params = coef(object),
  ..., log = FALSE
)
```

**Arguments**

- **object**: an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of pomp, simulate, or one of the pomp inference algorithms.
- **y**: a matrix containing observations. The dimensions of y are nobs x ntimes, where nobs is the number of observables and ntimes is the length of times.
- **x**: an array containing states of the unobserved process. The dimensions of x are nvars x nrep x ntimes, where nvars is the number of state variables, nrep is the number of replicates, and ntimes is the length of times. One can also pass x as a named numeric vector, which is equivalent to the nrep=1, ntimes=1 case.
- **times**: a numeric vector (length ntimes) containing times. These must be in non-decreasing order.
- **params**: a npar x nrep matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of x.
- **...**: additional arguments are ignored.
- **log**: if TRUE, log probabilities are returned.

**Value**

dmeasure returns a matrix of dimensions nreps x ntimes. If d is the returned matrix, d[j,k] is the likelihood (or log likelihood if log = TRUE) of the observation y[,k] at time times[k] given the state x[,j,k].
dmeasure specification

Description

Specification of the measurement model density function, dmeasure.

Details

The measurement model is the link between the data and the unobserved state process. It can be specified either by using one or both of the rmeasure and dmeasure arguments.

Suppose you have a procedure to compute the probability density of an observation given the value of the latent state variables. Then you can furnish

\[
dmeasure = f
\]

to pomp algorithms, where \( f \) is a C snippet or R function that implements your procedure.

Using a C snippet is much preferred, due to its much greater computational efficiency. See Csnippet for general rules on writing C snippets. The goal of a dmeasure C snippet is to fill the variable lik with the either the probability density or the log probability density, depending on the value of the variable give_log.

In writing a dmeasure C snippet, observe that:

1. In addition to the states, parameters, covariates (if any), and observables, the variable \( t \), containing the time of the observation will be defined in the context in which the snippet is executed.
2. Moreover, the Boolean variable give_log will be defined.
3. The goal of a dmeasure C snippet is to set the value of the lik variable to the likelihood of the data given the state, if give_log == 0. If give_log == 1, lik should be set to the log likelihood.

If dmeasure is to be provided instead as an R function, this is accomplished by supplying

\[
dmeasure = f
\]

to pomp, where \( f \) is a function. The arguments of \( f \) should be chosen from among the observables, state variables, parameters, covariates, and time. It must also have the arguments \ldots, and log. It can take additional arguments via the userdata facility. \( f \) must return a single numeric value, the probability density (or log probability density if log = TRUE) of \( y \) given \( x \) at time \( t \).
Important note

It is a common error to fail to account for both log = TRUE and log = FALSE when writing the dmeasure C snippet or function.

Default behavior

If dmeasure is left unspecified, calls to dmeasure will return missing values (NA).

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the cdir and cfile options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

See Also

dmeasure

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification

Examples

```r
## We start with the pre-built Ricker example:
  ricker() -> po

  ## To change the measurement model density, dmeasure,
  ## we use the 'dmeasure' argument in any 'pomp'
  ## elementary or estimation function.
  ## Here, we pass the dmeasure specification to 'pfilter'
  ## as an R function.

  po |>
     pfilter(
       dmeasure=function (y, N, phi, ..., log) {
         dpois(y,lambda=phi*N,log=log)
       },
       Np=100
     ) -> pf

  ## We can also pass it as a C snippet:

  po |>
     pfilter(
       dmeasure=Csnippet("lik = dpois(y,phi*N,give_log);")),
```

Description

Evaluates the prior probability density.

Usage

```r
## S4 method for signature 'pomp'
dprior(object, params = coef(object), ..., log = FALSE)
```

Arguments

- `object`: an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of pomp, simulate, or one of the pomp inference algorithms.
- `params`: a `npar x nrep` matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of `x`.
- `...`: additional arguments are ignored.
- `log`: if TRUE, log probabilities are returned.

Value

The required density (or log density), as a numeric vector.

See Also

Specification of the prior density evaluator: prior specification

More on pomp workhorse functions: dmeasure(), dprocess(), emeasure(), flow(), partrans(), pomp-package, rinit(), rmeasure(), rprior(), rprocess(), skeleton(), vmeasure(), workhorses

More on Bayesian methods: approximate Bayesian computation, bsmc2(), pmcmc(), prior specification, rprior()
Description

Evaluates the probability density of a sequence of consecutive state transitions.

Usage

```r
## S4 method for signature 'pomp'
dprocess(
  object,
  x = states(object),
  times = time(object),
  params = coef(object),
  ...
  log = FALSE
)
```

Arguments

- `object`: an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of `pomp`, `simulate`, or one of the `pomp` inference algorithms.
- `x`: an array containing states of the unobserved process. The dimensions of `x` are `nvars` x `nrep` x `ntimes`, where `nvars` is the number of state variables, `nrep` is the number of replicates, and `ntimes` is the length of `times`. One can also pass `x` as a named numeric vector, which is equivalent to the `nrep=1, ntimes=1` case.
- `times`: a numeric vector (length `ntimes`) containing times. These must be in non-decreasing order.
- `params`: a `npar` x `nrep` matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of `x`.
- `...`: additional arguments are ignored.
- `log`: if TRUE, log probabilities are returned.

Value

`dprocess` returns a matrix of dimensions `nrep` x `ntimes`-1. If `d` is the returned matrix, `d[j,k]` is the likelihood (or the log likelihood if `log=TRUE`) of the transition from state `x[,j,k-1]` at time `times[k-1]` to state `x[,j,k]` at time `times[k]`.

See Also

Specification of the process-model density evaluator: [dprocess specification](https://example.com/dprocess)

More on `pomp` workhorse functions: `dmeasure()`, `dprior()`, `emeasure()`, `flow()`, `partrans()`, `pomp-package`, `rinit()`, `rmeasure()`, `rprior()`, `rprocess()`, `skeleton()`, `vmeasure()`, `workhorses`
dprocess specification

The latent state process density

Description

Specification of the latent state process density function, dprocess.

Details

Suppose you have a procedure that allows you to compute the probability density of an arbitrary transition from state $x_1$ at time $t_1$ to state $x_2$ at time $t_2 > t_1$ under the assumption that the state remains unchanged between $t_1$ and $t_2$. Then you can furnish

$$
dprocess = f
$$

to pomp, where $f$ is a C snippet or R function that implements your procedure. Specifically, $f$ should compute the log probability density.

Using a C snippet is much preferred, due to its much greater computational efficiency. See Csnippet for general rules on writing C snippets. The goal of a dprocess C snippet is to fill the variable loglik with the log probability density. In the context of such a C snippet, the parameters, and covariates will be defined, as will the times $t_1$ and $t_2$. The state variables at time $t_1$ will have their usual name (see statenames) with a “_1” appended. Likewise, the state variables at time $t_2$ will have a “_2” appended.

If $f$ is given as an R function, it should take as arguments any or all of the state variables, parameter, covariates, and time. The state-variable and time arguments will have suffices “_1” and “_2” appended. Thus for example, if var is a state variable, when $f$ is called, var_1 will have value of state variable var at time $t_1$, var_2 will have the value of var at time $t_2$. $f$ should return the log likelihood of a transition from $x_1$ at time $t_1$ to $x_2$ at time $t_2$, assuming that no intervening transitions have occurred.

To see examples, consult the demos and the tutorials on the package website.

Note

It is not typically necessary (or even feasible) to define dprocess. In fact, no current pomp inference algorithm makes use of dprocess. This functionality is provided only to support future algorithm development.

Default behavior

By default, dprocess returns missing values (NA).
Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

See Also
dprocess

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, emeasure specification, parameter transformations, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification

ebola  


Description


Usage

```
ebolaModel(
  country = c("GIN", "LBR", "SLE"),
  data = NULL,
  timestep = 1/8,
  nstageE = 3L,
  R0 = 1.4,
  rho = 0.2,
  cfr = 0.7,
  k = 0,
  index_case = 10,
  incubation_period = 11.4,
  infectious_period = 7
)
```

Arguments

country  ISO symbol for the country (GIN=Guinea, LBR=Liberia, SLE=Sierra Leone).
data     if NULL, the situation report data (WHO Ebola Response Team 2014) for the appropriate country or region will be used. Providing a dataset here will override this behavior.
timestep  duration (in days) of Euler timestep for the simulations.
ebola

nstageE  integer; number of incubation stages.
R0  basic reproduction ratio
rho  case reporting efficiency
cfr  case fatality rate
k  dispersion parameter (negative binomial size parameter)
index_case  number of cases on day 0 (2014-04-01)
incubation_period, infectious_period  mean duration (in days) of the incubation and infectious periods.

Details
The data include monthly case counts and death reports derived from WHO situation reports, as reported by the U.S. CDC. The models are described in King et al. (2015).
The data-cleaning script is included in the R source code file ‘ebola.R’.

Model structure
The default incubation period is supposed to be Gamma distributed with shape parameter nstageE and mean 11.4 days and the case-fatality ratio (‘cfr’) is taken to be 0.7 (cf. WHO Ebola Response Team 2014). The discrete-time formula is used to calculate the corresponding alpha (cf. He et al. 2010).
The observation model is a hierarchical model for cases and deaths:

\[ p(R_t, D_t | C_t) = p(R_t | C_t) p(D_t | C_t, R_t). \]

Here, \( p(R_t | C_t) \) is negative binomial with mean \( \rho C_t \) and dispersion parameter \( 1/k \); \( p(D_t | C_t, R_t) \) is binomial with size \( R_t \) and probability equal to the case fatality rate cfr.

References

See Also
More data sets provided with pomp: blowflies, bsflu, childhood disease data, dacca(), parus
More examples provided with pomp: SIR models, blowflies, childhood disease data, dacca(), gompertz(), ou2(), pomp examples, ricker(), rw2(), verhulst()
eff_sample_size

Examples

# takes too long for R CMD check
if (require(ggplot2) && require(tidyverse)) {
  ebolaWA2014 |>
    pivot_longer(c(cases, deaths)) |>
    ggplot(aes(x=date, y=value, group=name, color=name)) +
    geom_line() +
    facet_grid(country ~ ., scales = "free_y") +
    theme_bw() +
    theme(axis.text = element_text(angle = -90))
}

plot(ebolaModel(country = "SLE"))
plot(ebolaModel(country = "GIN"))
plot(ebolaModel(country = "LBR"))

eff_sample_size   Effective sample size

Description

Estimate the effective sample size of a Monte Carlo computation.

Usage

## S4 method for signature 'bsmcd_pomp'

eff_sample_size(object, ..., format = c("numeric", "data.frame"))

## S4 method for signature 'pfilterd_pomp'

eff_sample_size(object, ..., format = c("numeric", "data.frame"))

## S4 method for signature 'wpfilterd_pomp'

eff_sample_size(object, ..., format = c("numeric", "data.frame"))

## S4 method for signature 'pfilterList'

eff_sample_size(object, ..., format = c("numeric", "data.frame"))

Arguments

- `object`: result of a filtering computation
- `...`: ignored
- `format`: format of the returned object
Details

Effective sample size is computed as
\[
\left( \sum_{i} w_{it}^2 \right)^{-1},
\]
where \( w_{it} \) is the normalized weight of particle \( i \) at time \( t \).

See Also

More on sequential Monte Carlo methods: bsmc2(), cond_logLik(), filter_mean(), filter_traj(), kalman.mif2(), pfilter(), pmcmc(), pred_mean(), pred_var(), saved_states(), wpfilter()

Other extraction methods: coef(), cond_logLik(), covmat(), filter_mean(), filter_traj(), forecast(), logLik, obs(), pred_mean(), pred_var(), saved_states(), spy(), states(), summary(), timezero(), time(), traces()

elementary algorithms  Elementary computations on POMP models.

Description

In pomp, elementary algorithms perform POMP model operations. These operations do not themselves estimate parameters, though they may be instrumental in inference methods.

Details

There are six elementary algorithms in pomp:

- **simulate** which simulates from the joint distribution of latent and observed variables,
- **pfilter**, which performs a simple particle filter operation,
- **wpfilter**, which performs a weighted particle filter operation,
- **probe**, which computes a suite of user-specified summary statistics to actual and simulated data,
- **spect**, which performs a power-spectral density function computation on actual and simulated data,
- **trajectory**, which iterates or integrates the deterministic skeleton (according to whether the latter is a (discrete-time) map or a (continuous-time) vectorfield.

Help pages detailing each elementary algorithm component are provided.

See Also

basic model components, workhorse functions, estimation algorithms.

More on pomp elementary algorithms: kalman, pfilter(), pomp-package, probe(), simulate(), spect(), trajectory(), wpfilter()
Description

Return the expected value of the observed variables, given values of the latent states and the parameters.

Usage

```r
## S4 method for signature 'pomp'
emeasure(
  object,
  x = states(object),
  times = time(object),
  params = coef(object),
  ...
)
```

Arguments

- **object**: an object of class `pomp`, or of a class that extends `pomp`. This will typically be the output of `pomp`, `simulate`, or one of the `pomp` inference algorithms.
- **x**: an array containing states of the unobserved process. The dimensions of `x` are `nvars x nrep x ntimes`, where `nvars` is the number of state variables, `nrep` is the number of replicates, and `ntimes` is the length of `times`. One can also pass `x` as a named numeric vector, which is equivalent to the `nrep=1, ntimes=1` case.
- **times**: a numeric vector (length `ntimes`) containing times. These must be in non-decreasing order.
- **params**: a `npar x nrep` matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of `x`.
- **...**: additional arguments are ignored.

Value

`emeasure` returns a rank-3 array of dimensions `nobs x nrep x ntimes`, where `nobs` is the number of observed variables.

See Also

Specification of the measurement-model expectation: `emeasure` specification

More on `pomp` workhorse functions: `dmeasure()`, `dprior()`, `dprocess()`, `flow()`, `partrans()`, `pomp-package`, `rinit()`, `rmeasure()`, `rprior()`, `rprocess()`, `skeleton()`, `vmeasure()`, `workhorses`
emeasure specification

*The expectation of the measurement model*

**Description**

Specification of the measurement-model conditional expectation, emeasure.

**Details**

The measurement model is the link between the data and the unobserved state process. Some algorithms require the conditional expectation of the measurement model, given the latent state and parameters. This is supplied using the emeasure argument.

Suppose you have a procedure to compute this conditional expectation, given the value of the latent state variables. Then you can furnish

\[
\text{emeasure} = f
\]

to pomp algorithms, where \( f \) is a C snippet or R function that implements your procedure.

Using a C snippet is much preferred, due to its much greater computational efficiency. See Csnippet for general rules on writing C snippets.

In writing an emeasure C snippet, bear in mind that:

1. The goal of such a snippet is to fill variables named \( E_y \) with the conditional expectations of observables \( y \). Accordingly, there should be one assignment of \( E_y \) for each observable \( y \).
2. In addition to the states, parameters, and covariates (if any), the variable \( t \), containing the time of the observation, will be defined in the context in which the snippet is executed.

The demos and the tutorials on the package website give examples.

It is also possible, though less efficient, to specify emeasure using an R function. In this case, specify the measurement model expectation by furnishing

\[
\text{emeasure} = f
\]

to pomp, where \( f \) is an R function. The arguments of \( f \) should be chosen from among the state variables, parameters, covariates, and time. It must also have the argument \( \ldots \). \( f \) must return a named numeric vector of length equal to the number of observable variables. The names should match those of the observable variables.

**Default behavior**

The default emeasure is undefined. It will yield missing values (NA).
estimation algorithms

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cf` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

See Also

emeasure

More on implementing POMP models: `Csnippet`, `accumulator variables`, `basic components`, `betabinomial`, `covariates`, `distributions`, `dmeasure specification`, `dprocess specification`, `parameter transformations`, `pomp-package`, `pomp`, `prior specification`, `rinit specification`, `rmeasure specification`, `rprocess specification`, `skeleton specification`, `transformations`, `userdata`, `vmeasure specification`

---

estimation algorithms Parameter estimation algorithms for POMP models.

Description

`pomp` currently implements the following algorithms for estimating model parameters:

- iterated filtering (IF2)
- particle Markov chain Monte Carlo (PMCMC)
- approximate Bayesian computation (ABC)
- probe-matching via synthetic likelihood
- nonlinear forecasting
- power-spectrum matching
- Liu-West Bayesian sequential Monte Carlo
- Ensemble and ensemble-adjusted Kalman filters

Details

Help pages detailing each estimation algorithm are provided.

See Also

`basic model components`, `workhorse functions`, `elementary algorithms`.

More on `pomp` estimation algorithms: `approximate Bayesian computation`, `bsmc2()`, `mif2()`, `nonlinear forecasting`, `pmcmc()`, `pomp-package`, `probe matching`, `spectrum matching`
filter_mean

Filtering mean

Description

The mean of the filtering distribution

Usage

## S4 method for signature 'kalmand_pomp'
filter_mean(object, vars, ..., format = c("array", "data.frame"))

## S4 method for signature 'pfilterd_pomp'
filter_mean(object, vars, ..., format = c("array", "data.frame"))

Arguments

- **object**: result of a filtering computation
- **vars**: optional character; names of variables
- **...**: ignored
- **format**: format of the returned object

Details

The filtering distribution is that of

\[
X(t_k) | Y(t_1) = y_1^*, \ldots, Y(t_k) = y_k^*,
\]

where \(X(t_k), Y(t_k)\) are the latent state and observable processes, respectively, and \(y_t^*\) is the data, at time \(t_k\).

The filtering mean is therefore the expectation of this distribution

\[
E[X(t_k) | Y(t_1) = y_1^*, \ldots, Y(t_k) = y_k^*].
\]

See Also

More on sequential Monte Carlo methods: bsmc2(), cond_logLik(), eff_sample_size(), filter_traj(), kalman, mif2(), pfilter(), pmcmc(), pred_mean(), pred_var(), saved_states(), wpfilter()

Other extraction methods: coef(), cond_logLik(), covmat(), eff_sample_size(), filter_traj(), forecast(), logLik, obs(), pred_mean(), pred_var(), saved_states(), spy(), states(), summary(), timezero(), time(), traces()
Description

Drawing from the smoothing distribution

Usage

```r
## S4 method for signature 'pfterror_pomp'
filter_traj(object, vars, ..., format = c("array", "data.frame"))

## S4 method for signature 'listie'
filter_traj(object, vars, ..., format = c("array", "data.frame"))

## S4 method for signature 'pmcmcd_pomp'
filter_traj(object, vars, ...)
```

Arguments

- `object` result of a filtering computation
- `vars` optional character; names of variables
- `...` ignored
- `format` format of the returned object

Details

The smoothing distribution is the distribution of

\[ X(t_k) | Y(t_1) = y_1^*, \ldots, Y(t_n) = y_n^* \]

where \( X(t_k) \) is the latent state process and \( Y(t_k) \) is the observable process at time \( t_k \), and \( n \) is the number of observations.

To draw samples from this distribution, one can run a number of independent particle filter (pferror) operations, sampling the full trajectory of one randomly-drawn particle from each one. One should view these as weighted samples from the smoothing distribution, where the weights are the likelihoods returned by each of the pferror computations.

One accomplishes this by setting `filter_traj = TRUE` in each pferror computation and extracting the trajectory using the `filter_traj` command.

In particle MCMC (pmcmc), the tracking of an individual trajectory is performed automatically.
Flow of a deterministic model

Compute the flow generated by a deterministic vectorfield or map.

Usage

```r
## S4 method for signature 'pomp'
flow(
  object,
  x0,
  t0 = timezero(object),
  times = time(object),
  params = coef(object),
  ...
)
```

Arguments

- `object`: an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of `pomp`, `simulate`, or one of the `pomp` inference algorithms.
- `x0`: an array with dimensions `nvar x nrep` giving the initial conditions of the trajectories to be computed.
- `t0`: the time at which the initial conditions are assumed to hold. By default, this is the zero-time (see `timezero`).
- `times`: a numeric vector (length `ntimes`) containing times at which the itineraries are desired. These must be in non-decreasing order with `times[1]>t0`. By default, this is the full set of observation times (see `time`).
- `params`: a `npar x nrep` matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of `x`.
- `...`: Additional arguments are passed to the ODE integrator (if the skeleton is a vectorfield) and are ignored if it is a map. See `ode` for a description of the additional arguments accepted by the ODE integrator. By default, this is the parameter vector stored in `object` (see `coef`).
- `verbose`: logical; if TRUE, diagnostic messages will be printed to the console.
Details

In the case of a discrete-time system (map), \texttt{flow} iterates the map to yield trajectories of the system. In the case of a continuous-time system (vectorfield), \texttt{flow} uses the numerical solvers in \texttt{deSolve} to integrate the vectorfield starting from given initial conditions.

Value

\texttt{flow} returns an array of dimensions \texttt{nvar x nrep x ntimes}. If \texttt{x} is the returned matrix, \texttt{x[i,j,k]} is the \texttt{i}-th component of the state vector at time \texttt{times[k]} given parameters \texttt{params[,j]}.

See Also

More on \texttt{pomp} workhorse functions: \texttt{dmeasure()}, \texttt{dprior()}, \texttt{dprocess()}, \texttt{emeasure()}, \texttt{partrans()}, \texttt{pomp-package}, \texttt{rinit()}, \texttt{rmeasure()}, \texttt{rprior()}, \texttt{rprocess()}, \texttt{skeleton()}, \texttt{vmeasure()}, \texttt{workhorses}

More on methods for deterministic process models: \texttt{skeleton specification}, \texttt{skeleton()}, \texttt{trajectory matching}, \texttt{trajectory()}

\begin{tabular}{ll}
\texttt{forecast} & \textit{Forecast mean} \\
\end{tabular}

Description

Mean of the one-step-ahead forecasting distribution.

Usage

\begin{verbatim}
forecast(object, ...)
## S4 method for signature 'kalmand_pomp'
forecast(object, vars, ..., format = c("array", "data.frame"))

## S4 method for signature 'pfilterd_pomp'
forecast(object, vars, ..., format = c("array", "data.frame"))
\end{verbatim}

Arguments

\begin{itemize}
\item \texttt{object} \hspace{1cm} result of a filtering computation
\item \texttt{...} \hspace{1cm} ignored
\item \texttt{vars} \hspace{1cm} optional character; names of variables
\item \texttt{format} \hspace{1cm} format of the returned object
\end{itemize}

See Also

Other extraction methods: \texttt{coef()}, \texttt{cond_logLik()}, \texttt{covmat()}, \texttt{eff_sample_size()}, \texttt{filter_mean()}, \texttt{filter_traj()}, \texttt{logLik.obs()}, \texttt{pred_mean()}, \texttt{pred_var()}, \texttt{saved_states()}, \texttt{spy()}, \texttt{states()}, \texttt{summary()}, \texttt{timezero()}, \texttt{time()}, \texttt{traces()}
Description

gompertz() constructs a ‘pomp’ object encoding a stochastic Gompertz population model with log-normal measurement error.

Usage

gompertz(
  K = 1,
  r = 0.1,
  sigma = 0.1,
  tau = 0.1,
  X_0 = 1,
  times = 1:100,
  t0 = 0
)

Arguments

K  carrying capacity
r  growth rate
sigma  process noise intensity
tau  measurement error s.d.
X_0  value of the latent state variable X at the zero time
times  observation times
t0  zero time

Details

The state process is

\[ X_{t+1} = K^{1-S} X_t^S \epsilon_t, \]

where \( S = e^{-r} \) and the \( \epsilon_t \) are i.i.d. lognormal random deviates with variance \( \sigma^2 \). The observed variables \( Y_t \) are distributed as

\[ Y_t \sim \text{Lognormal}(\log X_t, \tau). \]

Parameters include the per-capita growth rate \( r \), the carrying capacity \( K \), the process noise s.d. \( \sigma \), the measurement error s.d. \( \tau \), and the initial condition \( X_0 \). The ‘pomp’ object includes parameter transformations that log-transform the parameters for estimation purposes.

Value

A ‘pomp’ object with simulated data.
See Also

More examples provided with **pomp**: SIR models, blowflies, childhood disease data, dacca(), ebola, ou2(), pomp examples, ricker(), rw2(), verhulst()

Examples

```r
plot(gompertz())
plot(gompertz(K=2,r=0.01))
```

---

**hitch**

**Hitching C snippets and R functions to pomp_fun objects**

**Description**

The algorithms in **pomp** are formulated using R functions that access the basic model components (rprocess, dprocess, rmeasure, dmeasure, etc.). For short, we refer to these elementary functions as “workhorses”. In implementing a model, the user specifies basic model components using functions, procedures in dynamically-linked libraries, or C snippets. Each component is then packaged into a ‘pomp_fun’ objects, which gives a uniform interface. The construction of ‘pomp_fun’ objects is handled by the hitch function, which conceptually “hitches” the workhorses to the user-defined procedures.

**Usage**

```r
hitch(
    ..., 
    templates,
    obsnames,
    statenames,
    paramnames,
    covarnames,
    PACKAGE,
    globals,
    cfile,
    cdir =getOption("pomp_cdir", NULL),
    shlib.args,
    compile = TRUE,
    verbose =getOption("verbose", FALSE)
)
```

**Arguments**

... named arguments representing the user procedures to be hitched. These can be functions, character strings naming routines in external, dynamically-linked libraries, C snippets, or NULL. The first three are converted by hitch to ‘pomp_fun’
objects which perform the indicated computations. NULL arguments are translated to default ‘pomp_fun’ objects. If any of these procedures are already ‘pomp_fun’ objects, they are returned unchanged.

templates

named list of templates. Each workhorse must have a corresponding template. See pomp:::workhorse_templates for a list.

obsnames, statenames, paramnames, covarnames

character vectors specifying the names of observable variables, latent state variables, parameters, and covariates, respectively. These are only needed if one or more of the horses are furnished as C snippets.

PACKAGE

optional character; the name (without extension) of the external, dynamically loaded library in which any native routines are to be found. This is only useful if one or more of the model components has been specified using a precompiled dynamically loaded library; it is not used for any component specified using C snippets. PACKAGE can name at most one library.

globals

optional character; arbitrary C code that will be hard-coded into the shared-object library created when C snippets are provided. If no C snippets are used, globals has no effect.

cfile

optional character variable. cfile gives the name of the file (in directory cdir) into which C snippet codes will be written. By default, a random filename is used. If the chosen filename would result in over-writing an existing file, an error is generated.

cdir

optional character variable. cdir specifies the name of the directory within which C snippet code will be compiled. By default, this is in a temporary directory specific to the R session. One can also set this directory using the pomp_cdir global option.

shlib.args

optional character variables. Command-line arguments to the R CMD SHLIB call that compiles the C snippets. One can, for example, specify libraries against which the C snippets are to be linked. In doing so, take care to make sure the appropriate header files are available to the C snippets, e.g., using the globals argument. See Csnippet for more information.

compile

logical; if FALSE, compilation of the C snippets will be postponed until they are needed.

verbose

logical. Setting verbose=TRUE will cause additional information to be displayed.

Value

hitch returns a named list of length two. The element named “funs” is itself a named list of ‘pomp_fun’ objects, each of which corresponds to one of the horses passed in. The element named “lib” contains information on the shared-object library created using the C snippets (if any were passed to hitch). If no C snippets were passed to hitch, lib is NULL. Otherwise, it is a length-3 named list with the following elements:

name The name of the library created.

dir The directory in which the library was created. If this is NULL, the library was created in the session’s temporary directory.

src A character string with the full contents of the C snippet file.
## Description

The ensemble Kalman filter and ensemble adjustment Kalman filter.

### Usage

```r
## S4 method for signature 'data.frame'
enkf(
data, Np, params, rinit, rprocess, emeasure, vmeasure, ...
                , verbose = getOption("verbose", FALSE)
          )

## S4 method for signature 'pomp'
enkf(data, Np, ..., verbose = getOption("verbose", FALSE))

## S4 method for signature 'kalmand_pomp'
enkf(data, Np, ..., verbose = getOption("verbose", FALSE))

## S4 method for signature 'data.frame'
eakf(
data, Np, params, rinit, rprocess, emeasure, vmeasure, ...
                , verbose = getOption("verbose", FALSE)
          )
```
eakf(data, Np, ..., verbose = getOption("verbose", FALSE))

## Arguments

data:

either a data frame holding the time series data, or an object of class 'pomp',
i.e., the output of another pomp calculation. Internally, data will be internally
coerced to an array with storage-mode double.

Np:

integer; the number of particles to use, i.e., the size of the ensemble.

params:

optional; named numeric vector of parameters. This will be coerced internally
to storage mode double.

rinit:

simulator of the initial-state distribution. This can be furnished either as a C
snippet, an R function, or the name of a pre-compiled native routine available in
a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator
to its default. For more information, see rinit specification.

rprocess:

simulator of the latent state process, specified using one of the rprocess plugins.
Setting rprocess=NULL removes the latent-state simulator. For more informa-
tion, see rprocess specification for the documentation on these plugins.

emeasure:

the expectation of the measured variables, conditional on the latent state. This
can be specified as a C snippet, an R function, or the name of a pre-compiled
native routine available in a dynamically loaded library. Setting emeasure=NULL
removes the emeasure component. For more information, see emeasure specifi-
cation.

vmeasure:

the covariance of the measured variables, conditional on the latent state. This
can be specified as a C snippet, an R function, or the name of a pre-compiled
native routine available in a dynamically loaded library. Setting vmeasure=NULL
removes the vmeasure component. For more information, see vmeasure specifi-
cation.

...

additional arguments supply new or modify existing model characteristics or
components. See pomp for a full list of recognized arguments.

When named arguments not recognized by pomp are provided, these are made
available to all basic components via the so-called userdata facility. This al-

ows the user to pass information to the basic components outside of the usual
routes of covariates (covar) and model parameters (params). See userdata for
information on how to use this facility.

verbose:

logical; if TRUE, diagnostic messages will be printed to the console.

## Value

An object of class 'kalmand_pomp'.

## Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These ap-
pear to arise when the temporary files created during the C snippet compilation process are not
handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

**Author(s)**

Aaron A. King

**References**


**See Also**

kalmanFilter

More on sequential Monte Carlo methods: `bsmc2()`, `cond_logLik()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `mif2()`, `pfilter()`, `pmcmc()`, `pred_mean()`, `pred_var()`, `saved_states()`, `wpfilter()`

More on `pomp` elementary algorithms: `elementary_algorithms()`, `pfilter()`, `pomp-package`, `probe()`, `simulate()`, `spect()`, `trajectory()`, `wpfilter()`

---

**Kalman filter**

**Description**

The basic Kalman filter for multivariate, linear, Gaussian processes.

**Usage**

`kalmanFilter(object, X0 = rinit(object), A, Q, R, tol = 1e-06)`

**Arguments**

- `object`: a pomp object containing data;
- `X0`: length-m vector containing initial state. This is assumed known without uncertainty.
- `A`: $m \times m$ latent state-process transition matrix. $E[X_{t+1}|X_t] = A.X_t$.
- `Q`: $m \times m$ latent state-process covariance matrix. $Var[X_{t+1}|X_t] = Q$.
- `C`: $n \times m$ link matrix. $E[Y_t|X_t] = C.X_t$. 
R \[ n \times n \] observation process covariance matrix. \( \text{Var}[Y_t|X_t] = R \)

tol \quad \text{numeric; the tolerance to be used in computing matrix pseudoinverses via singular-
\quad \text{value decomposition. Singular values smaller than tol are set to zero.}

Details

If the latent state is \( X \), the observed variable is \( Y \), \( X_t \in \mathbb{R}^m \), \( Y_t \in \mathbb{R}^n \), and

\[
X_t \sim \text{MVN}(AX_{t-1}, Q)
\]

\[
Y_t \sim \text{MVN}(CX_t, R)
\]

where \( \text{MVN}(M, V) \) denotes the multivariate normal distribution with mean \( M \) and variance \( V \).

Then the Kalman filter computes the exact likelihood of \( Y \) given \( A, C, Q, \) and \( R \).

Value

A named list containing the following elements:

- **object** \quad \text{the ‘pomp’ object}
- **A, Q, C, R** \quad \text{as in the call}
- **filter.mean** \quad \text{\( E[X_t|y_t^*, \ldots, y_{t-1}^*] \)}
- **pred.mean** \quad \text{\( E[X_t|y_t^*, \ldots, y_{t-1}^*] \)}
- **forecast** \quad \text{\( E[Y_t|y_t^*, \ldots, y_{t-1}^*] \)}
- **cond.logLik** \quad \text{\( f(y_t^*|y_t^*, \ldots, y_{t-1}^*) \)}
- **logLik** \quad \text{\( f(y_t^*, \ldots, y_T^*) \)}

See Also

enkf, eakf

Examples

# takes too long for R CMD check

if (require(dplyr)) {

gompertz() -> po

po |>
  as.data.frame() |>
  mutate(
    logY=log(Y)
  ) |>
  select(time, logY) |>
  pomp(times="time", t0=0) |>
  kalmanFilter(
    X0=c(logX=0),
    A=matrix(exp(-0.1),1,1),
    Q=matrix(0.01,1,1),
}
```r
C=matrix(1,1,1),
R=matrix(0.01,1,1)
) -> kf

po |> 
pfilter(Np=1000) -> pf

kf$logLik
logLik(pf) + sum(log(obs(pf)))

logLik | Log likelihood

Description
Extract the estimated log likelihood (or related quantity) from a fitted model.

Usage
logLik(object, ...)

## S4 method for signature 'listie'
logLik(object, ...)

## S4 method for signature 'pfilterd_pomp'
logLik(object)

## S4 method for signature 'wpfilterd_pomp'
logLik(object)

## S4 method for signature 'probed_pomp'
logLik(object)

## S4 method for signature 'kalmand_pomp'
logLik(object)

## S4 method for signature 'pmcmcd_pomp'
logLik(object)

## S4 method for signature 'bsmcd_pomp'
logLik(object)

## S4 method for signature 'objfun'
logLik(object)
```
## S4 method for signature 'spect_match_objfun'
logLik(object)

## S4 method for signature 'nlf_objfun'
logLik(object, ...)

### Arguments

- **object**: fitted model object
- **...**: ignored

### Value

Numerical value of the log likelihood. Note that some methods compute not the log likelihood itself but instead a related quantity. To keep the code simple, the `logLik` function is nevertheless used to extract this quantity.

When `object` is of `pfilterd_pomp` class (i.e., the result of a `wpfilter` computation), `logLik` retrieves the estimated log likelihood.

When `object` is of `wpfilterd_pomp` class (i.e., the result of a `wpfilter` computation), `logLik` retrieves the estimated log likelihood.

When `object` is of `probed_pomp` class (i.e., the result of a `probe` computation), `logLik` retrieves the “synthetic likelihood”.

When `object` is of `kalmand_pomp` class (i.e., the result of an `eakf` or `enkf` computation), `logLik` retrieves the estimated log likelihood.

When `object` is of `pmcmcd_pomp` class (i.e., the result of a `pmcmc` computation), `logLik` retrieves the estimated log likelihood as of the last particle filter operation.

When `object` is of `bsmc2_pomp` class (i.e., the result of a `bsmc2` computation), `logLik` retrieves the “log evidence”.

When `object` is of `spect_match_objfun` class (i.e., an objective function constructed by `spect_objfun`), `logLik` retrieves minus the spectrum mismatch.

When `object` is an NLF objective function, i.e., the result of a call to `nlf_objfun`, `logLik` retrieves the "quasi log likelihood".

### See Also

Other extraction methods: `coef()`, `cond_logLik()`, `covmat()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `forecast()`, `obs()`, `pred_mean()`, `pred_var()`, `saved_states()`, `spy()`, `states()`, `summary()`, `timezero()`, `time()`, `traces()`
The log-mean-exp trick

Description

d\text{logmeanexp} computes

\[
\log \frac{1}{N} \sum_{n=1}^{N} e^x_i,
\]

avoiding over- and under-flow in doing so. It can optionally return an estimate of the standard error in this quantity.

Usage

\text{logmeanexp}(x, se = FALSE, ess = FALSE)

Arguments

\begin{itemize}
\item \textbf{x} numeric
\item \textbf{se} logical; give approximate standard error?
\item \textbf{ess} logical; give effective sample size?
\end{itemize}

Details

When \textbf{se} = TRUE, \text{logmeanexp} uses a jackknife estimate of the variance in \text{log}(x).

When \textbf{ess} = TRUE, \text{logmeanexp} returns an estimate of the effective sample size.

Value

\text{log(mean(exp(x)))} computed so as to avoid over- or underflow. If \textbf{se} = TRUE, the approximate standard error is returned as well. If \textbf{ess} = TRUE, the effective sample size is returned also.

Author(s)

Aaron A. King

Examples

\# takes too long for R CMD check
\#
\#
\#
\#
\#

\text{ricker()} |>
\text{pfilter(Np=1000)} |>
\text{logLik()} |>
\text{replicate(n=5) -> ll}
\text{logmeanexp(ll)}

\#
\#

\#
\#
\#

\# with standard error:
\text{logmeanexp(ll, se=TRUE)}

\# with effective sample size

mcap

logmeanexp(ll, ess=TRUE)

lookup

Description
Interpolate values from a lookup table

Usage
lookup(table, t)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>table</td>
<td>a 'covartable' object created by a call to covariate_table</td>
</tr>
<tr>
<td>t</td>
<td>numeric vector; times at which interpolated values of the covariates in table are required.</td>
</tr>
</tbody>
</table>

Details
A warning will be generated if extrapolation is performed.

Value
A numeric vector or matrix of the interpolated values.

See Also
More on interpolation: bsplines, covariates

mcap

Monte Carlo adjusted profile

Description
Given a collection of points maximizing the likelihood over a range of fixed values of a focal parameter, this function constructs a profile likelihood confidence interval accommodating both Monte Carlo error in the profile and statistical uncertainty present in the likelihood function.

Usage
mcap(logLik, parameter, level = 0.95, span = 0.75, Ngrid = 1000)
Arguments

- `logLik`: numeric; a vector of profile log likelihood evaluations.
- `parameter`: numeric; the corresponding values of the focal parameter.
- `level`: numeric; the confidence level required.
- `span`: numeric; the `loess` smoothing parameter.
- `Ngrid`: integer; the number of points to evaluate the smoothed profile.

Value

`mcap` returns a list including the `loess`-smoothed profile, a quadratic approximation, and the constructed confidence interval.

Author(s)

Edward L. Ionides

References


Description

An iterated filtering algorithm for estimating the parameters of a partially-observed Markov process. Running `mif2` causes the algorithm to perform a specified number of particle-filter iterations. At each iteration, the particle filter is performed on a perturbed version of the model, in which the parameters to be estimated are subjected to random perturbations at each observation. This extra variability effectively smooths the likelihood surface and combats particle depletion by introducing diversity into particle population. As the iterations progress, the magnitude of the perturbations is diminished according to a user-specified cooling schedule. The algorithm is presented and justified in Ionides et al. (2015).

Usage

```r
## S4 method for signature 'data.frame'
mif2(
data,
Nmif = 1,
rw.sd,
cooling.type = c("geometric", "hyperbolic"),
cooling.fraction.50,
Np,
```
params,
rinit,
rprocess,
dmeasure,
partrans,
...,
verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'
mif2(
data,
Nmif = 1,
rw.sd,
cooling.type = c("geometric", "hyperbolic"),
cooling.fraction.50,
Np,
...
verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pfiltrod_pomp'
mif2(data, Nmif = 1, Np, ..., verbose = getOption("verbose", FALSE))

## S4 method for signature 'mif2d_pomp'
mif2(
data,
Nmif,
rw.sd,
cooling.type,
cooling.fraction.50,
...
verbose = getOption("verbose", FALSE)
)

Arguments

data either a data frame holding the time series data, or an object of class 'pomp',
i.e., the output of another pomp calculation. Internally, data will be internally
coerced to an array with storage-mode double.

Nmif The number of filtering iterations to perform.

rw.sd specification of the magnitude of the random-walk perturbations that will be
applied to some or all model parameters. Parameters that are to be estimated
should have positive perturbations specified here. The specification is given
using the rw.sd function, which creates a list of unevaluated expressions. The
latter are evaluated in a context where the model time variable is defined (as
time). The expression ivp(s) can be used in this context as shorthand for
ifelse(time==time[1],s,0).
Likewise, ivp(s,lag) is equivalent to
ifelse(time==time[lag],s,0).

See below for some examples.

The perturbations that are applied are normally distributed with the specified s.d. If parameter transformations have been supplied, then the perturbations are applied on the transformed (estimation) scale.

cooling.type, cooling.fraction.50

specifications for the cooling schedule, i.e., the manner and rate with which the intensity of the parameter perturbations is reduced with successive filtering iterations. cooling.type specifies the nature of the cooling schedule. See below (under “Specifying the perturbations”) for more detail.

Np

the number of particles to use. This may be specified as a single positive integer, in which case the same number of particles will be used at each timestep. Alternatively, if one wishes the number of particles to vary across timesteps, one may specify Np either as a vector of positive integers of length

```
length(time(object,t0=TRUE))
```

or as a function taking a positive integer argument. In the latter case, Np(k) must be a single positive integer, representing the number of particles to be used at the k-th timestep: Np(0) is the number of particles to use going from timezero(object) to time(object)[1], Np(1), from timezero(object) to time(object)[1], and so on, while when T=length(time(object)), Np(T) is the number of particles to sample at the end of the time-series.

params

optional; named numeric vector of parameters. This will be coerced internally to storage mode double.

rinit

simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator to its default. For more information, see rinit specification.

rprocess

simulator of the latent state process, specified using one of the rprocess plugins. Setting rprocess=NULL removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

dmeasure

evaluator of the measurement model density, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting dmeasure=NULL removes the measurement density evaluator. For more information, see dmeasure specification.

partrans

optional parameter transformations, constructed using parameter_trans. Many algorithms for parameter estimation search an unconstrained space of parameters. When working with such an algorithm and a model for which the parameters are constrained, it can be useful to transform parameters. One should supply the partrans argument via a call to parameter_trans. For more information, see parameter_trans. Setting partrans=NULL removes the parameter transformations, i.e., sets them to the identity transformation.

... additional arguments supply new or modify existing model characteristics or components. See pomp for a full list of recognized arguments.
When named arguments not recognized by pomp are provided, these are made available to all basic components via the so-called userdata facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (covar) and model parameters (params). See userdata for information on how to use this facility.

Verbose
logical; if TRUE, diagnostic messages will be printed to the console.

Value
Upon successful completion, mif2 returns an object of class 'mif2d_pomp'.

Number of particles
If Np is anything other than a constant, the user must take care that the number of particles requested at the end of the time series matches that requested at the beginning. In particular, if T=length(time(object)), then one should have Np[1]==Np[T+1] when Np is furnished as an integer vector and Np(0)==Np(T) when Np is furnished as a function.

Methods
The following methods are available for such an object:

continue picks up where mif2 leaves off and performs more filtering iterations.

tomLogLik returns the so-called mif log likelihood which is the log likelihood of the perturbed model, not of the focal model itself. To obtain the latter, it is advisable to run several pfilter operations on the result of a mif2 computation.

tom extracts the point estimate
eff.sample.size extracts the effective sample size of the final filtering iteration

Various other methods can be applied, including all the methods applicable to a pfilterd_pomp object and all other pomp estimation algorithms and diagnostic methods.

Specifying the perturbations
The rw.sd function simply returns a list containing its arguments as unevaluated expressions. These are then evaluated in a context containing the model time variable. This allows for easy specification of the structure of the perturbations that are to be applied. For example,

\[
\text{rw_sd}(a=0.05, b=\text{ifelse}(\text{time}==\text{time}[1],0.2,0), \\
\quad c=\text{ivp}(0.2), d=\text{ifelse}(\text{time}==\text{time}[13],0.2,0), \\
\quad e=\text{ivp}(0.2,\text{lag}=13), f=\text{ifelse}(\text{time}<23,0.02,0))
\]

results in perturbations of parameter a with s.d. 0.05 at every time step, while parameters b and c both get perturbations of s.d. 0.2 only just before the first observation. Parameters d and e, by contrast, get perturbations of s.d. 0.2 only just before the thirteenth observation. Finally, parameter f gets a random perturbation of size 0.02 before every observation falling before \( t = 23 \).

On the \( m \)-th IF2 iteration, prior to time-point \( n \), the \( d \)-th parameter is given a random increment normally distributed with mean 0 and standard deviation \( c_{m,n} \sigma_{d,n} \), where \( c \) is the cooling schedule
and σ is specified using rw_sd, as described above. Let N be the length of the time series and α = cooling.fraction.50. Then, when cooling.type="geometric", we have
\[ c_{m,n} = \alpha^{n_0 + (m-1)N} \]
When cooling.type="hyperbolic", we have
\[ c_{m,n} = \frac{s + 1}{s + n + (m-1)N} \]
where s satisfies
\[ \frac{s + 1}{s + 50N} = \alpha. \]
Thus, in either case, the perturbations at the end of 50 IF2 iterations are a fraction α smaller than they are at first.

**Re-running IF2 iterations**

To re-run a sequence of IF2 iterations, one can use the mif2 method on a ‘mif2d_pomp’ object. By default, the same parameters used for the original IF2 run are re-used (except for verbose, the default of which is shown above). If one does specify additional arguments, these will override the defaults.

**Note for Windows users**

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the cdin and cfile options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

**Author(s)**

Aaron A. King, Edward L. Ionides, Dao Nguyen

**References**


**See Also**

More on full-information (i.e., likelihood-based) methods: bsmc2(), pfilter(), pmcmc(), wpfilter()
More on sequential Monte Carlo methods: bsmc2(), cond_logLik(), eff_sample_size(), filter_mean(), filter_traj(), kalman, pfilter(), pmcmc(), pred_mean(), pred_var(), saved_states(), wpfilter()
More on pomp estimation algorithms: approximate Bayesian computation, bsmc2(), estimation algorithms, nonlinear forecasting, pmcmc(), pomp-package, probe matching, spectrum matching
More on maximization-based estimation methods: nonlinear forecasting, probe matching, spectrum matching, trajectory matching
Description

Parameter estimation by maximum simulated quasi-likelihood.

Usage

```r
## S4 method for signature 'data.frame'
nlf_objfun(
  data,
  est = character(0),
  lags,
  nrbf = 4,
  ti,
  tf,
  seed = NULL,
  transform.data = identity,
  period = NA,
  tensor = TRUE,
  fail.value = NA_real_,
  params,
  rinit,
  rprocess,
  rmeasure,
  ..., 
  verbose = getOption("verbose")
)

## S4 method for signature 'pomp'
nlf_objfun(
  data,
  est = character(0),
  lags,
  nrbf = 4,
  ti,
  tf,
  seed = NULL,
  transform.data = identity,
  period = NA,
  tensor = TRUE,
  fail.value = NA,
  ..., 
  verbose = getOption("verbose")
)
```
nonlinear forecasting

## S4 method for signature 'nlf_objfun'
nlf_objfun(
  data,
  est,
  lags,
  nrbf,
  ti,
  tf,
  seed = NULL,
  period,
  tensor,
  transform.data,
  fail.value,
  ...
  verbose = getOption("verbose", FALSE)
)

Arguments

data either a data frame holding the time series data, or an object of class 'pomp', i.e., the output of another pomp calculation. Internally, data will be internally coerced to an array with storage-mode double.
est character vector; the names of parameters to be estimated.
lags A vector specifying the lags to use when constructing the nonlinear autoregressive prediction model. The first lag is the prediction interval.
numbf integer scalar; the number of radial basis functions to be used at each lag.
ti, tf required numeric values. NLF works by generating simulating long time series from the model. The simulated time series will be from ti to tf, with the same sampling frequency as the data. ti should be chosen large enough so that transient dynamics have died away. tf should be chosen large enough so that sufficiently many data points are available to estimate the nonlinear forecasting model well. An error will be generated unless the data-to-parameter ratio exceeds 10 and a warning will be given if the ratio is smaller than 30.
seed integer. When fitting, it is often best to fix the seed of the random-number generator (RNG). This is accomplished by setting seed to an integer. By default, seed = NULL, which does not alter the RNG state.
transform.data optional function. If specified, forecasting is performed using data and model simulations transformed by this function. By default, transform.data is the identity function, i.e., no transformation is performed. The main purpose of transform.data is to achieve approximately multivariate normal forecasting errors. If the data are univariate, transform.data should take a scalar and return a scalar. If the data are multivariate, transform.data should assume a vector input and return a vector of the same length.
period numeric; period=NA means the model is nonseasonal. period > 0 is the period of seasonal forcing. period <= 0 is equivalent to period = NA.
tensor logical; if FALSE, the fitted model is a generalized additive model with time mod period as one of the predictors, i.e., a gam with time-varying intercept. If
TRUE, the fitted model is a gam with lagged state variables as predictors and time-periodic coefficients, constructed using tensor products of basis functions of state variables with basis functions of time.

fail.value optional numeric scalar; if non-NA, this value is substituted for non-finite values of the objective function. It should be a large number (i.e., bigger than any legitimate values the objective function is likely to take).

params optional; named numeric vector of parameters. This will be coerced internally to storage mode double.

rinit simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator to its default. For more information, see rinit specification.

rprocess simulator of the latent state process, specified using one of the rprocess plugins. Setting rprocess=NULL removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

rmeasure simulator of the measurement model, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rmeasure=NULL removes the measurement model simulator. For more information, see rmeasure specification.

... additional arguments supply new or modify existing model characteristics or components. See pomp for a full list of recognized arguments.

When named arguments not recognized by pomp are provided, these are made available to all basic components via the so-called userdata facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (covar) and model parameters (params). See userdata for information on how to use this facility.

verbose logical; if TRUE, diagnostic messages will be printed to the console.

Details

Nonlinear forecasting (NLF) is an ‘indirect inference’ method. The NLF approximation to the log likelihood of the data series is computed by simulating data from a model, fitting a nonlinear autoregressive model to the simulated time series, and quantifying the ability of the resulting fitted model to predict the data time series. The nonlinear autoregressive model is implemented as a generalized additive model (GAM), conditional on lagged values, for each observation variable. The errors are assumed multivariate normal.

The NLF objective function constructed by nlf_objfun simulates long time series (nasymp is the number of observations in the simulated times series), perhaps after allowing for a transient period (ntransient steps). It then fits the GAM for the chosen lags to the simulated time series. Finally, it computes the quasi-likelihood of the data under the fitted GAM.

NLF assumes that the observation frequency (equivalently the time between successive observations) is uniform.

Value

nlf_objfun constructs a stateful objective function for NLF estimation. Specifically, nlf_objfun returns an object of class ‘nlf_objfun’, which is a function suitable for use in an optim-like opti-
mizer. In particular, this function takes a single numeric-vector argument that is assumed to contain the parameters named in `est`, in that order. When called, it will return the negative log quasilikelihood. It is a stateful function: Each time it is called, it will remember the values of the parameters and its estimate of the log quasilikelihood.

**Periodically-forced systems (seasonality)**

Unlike other `pomp` estimation methods, NLF cannot accommodate general time-dependence in the model via explicit time-dependence or dependence on time-varying covariates. However, NLF can accommodate periodic forcing. It does this by including forcing phase as a predictor in the nonlinear autoregressive model. To accomplish this, one sets `period` to the period of the forcing (a positive numerical value). In this case, if `tensor = FALSE`, the effect is to add a periodic intercept in the autoregressive model. If `tensor = TRUE`, by contrast, the fitted model includes time-periodic coefficients, constructed using tensor products of basis functions of observables with basis functions of time.

**Note for Windows users**

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

**Important Note**

Since `pomp` cannot guarantee that the final call an optimizer makes to the function is a call at the optimum, it cannot guarantee that the parameters stored in the function are the optimal ones. Therefore, it is a good idea to evaluate the function on the parameters returned by the optimization routine, which will ensure that these parameters are stored.

**Warning! Objective functions based on C snippets**

If you use C snippets (see `Csnippet`), a dynamically loadable library will be built. As a rule, `pomp` functions load this library as needed and unload it when it is no longer needed. The stateful objective functions are an exception to this rule. For efficiency, calls to the objective function do not execute `pompLoad` or `pompUnload`: rather, it is assumed that `pompLoad` has been called before any call to the objective function. When a stateful objective function using one or more C snippets is created, `pompLoad` is called internally to build and load the library; therefore, within a single R session, if one creates a stateful objective function, one can freely call that objective function and (more to the point) pass it to an optimizer that calls it freely, without needing to call `pompLoad`. On the other hand, if one retrieves a stored objective function from a file, or passes one to another R session, one must call `pompLoad` before using it. **Failure to do this will typically result in a segmentation fault (i.e., it will crash the R session).**

**Author(s)**

Stephen P. Ellner, Bruce E. Kendall, Aaron A. King
References


See Also

optim subplex nloptr

More on pomp estimation algorithms: approximate Bayesian computation, bsmc2(), estimation algorithms, mif2(), pmcmc(), pomp-package, probe matching, spectrum matching

More on methods based on summary statistics: approximate Bayesian computation, basic probes, probe matching, probe(), spectrum matching, spect()

More on maximization-based estimation methods: mif2(), probe matching, spectrum matching, trajectory matching

Examples

if (require(subplex)) {

ricker() |> nlf_objfun(est=c("r","sigma","N_0"), lags=c(4,6),
partrans=parameter_trans(log=c("r","sigma","N_0")),
paramnames=c("r","sigma","N_0"),
ti=100, tf=2000, seed=426094906L) -> m1

subplex(par=log(c(20,0.5,5)), fn=m1, control=list(reltol=1e-4)) -> out

m1(out$par)
coef(m1)
plot(simulate(m1))
}

nonlinear forecasting
Description

Extract the data array from a ‘pomp’ object.

Usage

## S4 method for signature 'pomp'
obs(object, vars, ..., format = c("array", "data.frame"))

## S4 method for signature 'listie'
obs(object, vars, ..., format = c("array", "data.frame"))

Arguments

object an object of class ‘pomp’, or of a class extending ‘pomp’
vars names of variables to retrieve
... ignored
format format of the returned object

See Also

Other extraction methods: coef(), cond_logLik(), covmat(), eff_sample_size(), filter_mean(),
filter_traj(), forecast(), logLik, pred_mean(), pred_var(), saved_states(), spy().states(),
summary(), timezero(), time(), traces()

ou2

Two-dimensional discrete-time Ornstein-Uhlenbeck process

Description

ou2() constructs a ‘pomp’ object encoding a bivariate discrete-time Ornstein-Uhlenbeck process
with noisy observations.

Usage

ou2(
  alpha_1 = 0.8,
  alpha_2 = -0.5,
  alpha_3 = 0.3,
  alpha_4 = 0.9,
  sigma_1 = 3,
  sigma_2 = -0.5,
\[
\begin{align*}
\sigma_3 &= 2, \\
tau &= 1, \\
x_{1,0} &= -3, \\
x_{2,0} &= 4, \\
times &= 1:100, \\
t0 &= 0
\end{align*}
\]

Arguments

- \textit{alpha_1, alpha_2, alpha_3, alpha_4} entries of the \(\alpha\) matrix, in column-major order. That is, \textit{alpha_2} is in the lower-left position.
- \textit{sigma_1, sigma_2, sigma_3} entries of the lower-triangular \(\sigma\) matrix. \textit{sigma_2} is the entry in the lower-left position.
- \textit{tau} measurement error s.d.
- \textit{x1_0, x2_0} latent variable values at time \(t_0\)
- \textit{times} vector of observation times
- \textit{t0} the zero time

Details

If the state process is \(X(t) = (X_1(t), X_2(t))\), then
\[
X(t + 1) = \alpha X(t) + \sigma \epsilon(t),
\]
where \(\alpha\) and \(\sigma\) are 2x2 matrices, \(\sigma\) is lower-triangular, and \(\epsilon(t)\) is standard bivariate normal. The observation process is \(Y(t) = (Y_1(t), Y_2(t))\), where \(Y_i(t) \sim \text{normal}(X_i(t), \tau)\).

Value

A 'pomp' object with simulated data.

See Also

More examples provided with \texttt{pomp}: \texttt{SIR models, blowflies, childhood disease data, dacca()}, \texttt{ebola, gompertz(), pomp examples, ricker(), rw2(), verhulst()}

Examples

```r
po <- ou2()
plot(po)
coef(po)
x <- simulate(po)
plot(x)
pf <- pfilter(po, Np=1000)
logLik(pf)
```
parameter transformations

Description

Equipping models with parameter transformations to ease searches in constrained parameter spaces.

Usage

```
parameter_trans(toEst, fromEst, ...)
```

## S4 method for signature '
NULL',
NULL'
```
parameter_trans(toEst, fromEst, ...)
```

## S4 method for signature 'pomp_fun,pomp_fun'
```
parameter_trans(toEst, fromEst, ...)
```

## S4 method for signature 'Csnippet,Csnippet'
```
parameter_trans(toEst, fromEst, ..., log, logit, barycentric)
```

## S4 method for signature 'character,character'
```
parameter_trans(toEst, fromEst, ...)
```

## S4 method for signature '
function',
function''
```
parameter_trans(toEst, fromEst, ...)
```

Arguments

- `toEst, fromEst` procedures that perform transformation of model parameters to and from the estimation scale, respectively. These can be furnished using C snippets, R functions, or via procedures in an external, dynamically loaded library.
- `...` ignored.
- `log` names of parameters to be log transformed.
- `logit` names of parameters to be logit transformed.
- `barycentric` names of parameters to be collectively transformed according to the log barycentric transformation. **Important note:** variables to be log-barycentrically transformed must be adjacent in the parameter vector.

Details

When parameter transformations are desired, they can be integrated into the `pomp` object via the `partrans` arguments using the `parameter_trans` function. As with the other basic model components, these should ordinarily be specified using C snippets. When doing so, note that:

1. The parameter transformation mapping a parameter vector from the scale used by the model codes to another scale, and the inverse transformation, are specified via a call to
parameter_trans(toEst, fromEst)

2. The goal of these snippets is the transformation of the parameters from the natural scale to the estimation scale, and vice-versa. If \( p \) is the name of a variable on the natural scale, its value on the estimation scale is \( T_p \). Thus the \( \text{toEst} \) snippet computes \( T_p \) given \( p \) whilst the \( \text{fromEst} \) snippet computes \( p \) given \( T_p \).

3. Time-, state-, and covariate-dependent transformations are not allowed. Therefore, neither the time, nor any state variables, nor any of the covariates will be available in the context within which a parameter transformation snippet is executed.

These transformations can also be specified using \( R \) functions with arguments chosen from among the parameters. Such an \( R \) function must also have the argument \( \ldots \). In this case, \( \text{toEst} \) should transform parameters from the scale that the basic components use internally to the scale used in estimation. \( \text{fromEst} \) should be the inverse of \( \text{toEst} \).

Note that it is the user’s responsibility to make sure that the transformations are mutually inverse. If \( \text{obj} \) is the constructed ‘pomp’ object, and \( \text{coef}(\text{obj}) \) is non-empty, a simple check of this property is

\[
\begin{align*}
  x &\leftarrow \text{coef}(\text{obj}, \text{transform} = \text{TRUE}) \\
  \text{obj1} &\leftarrow \text{obj} \\
  \text{identical}(\text{coef(}\text{obj1}, \text{transform} = \text{TRUE}) \leftarrow x \\
  \text{identical}(\text{coef(}\text{obj}), \text{coef(}\text{obj1})) \\
  \text{identical}(\text{coef(}\text{obj1}, \text{transform=TRUE}), x)
\end{align*}
\]

One can use the \( \log \) and \( \text{logit} \) arguments of \( \text{parameter_trans} \) to name variables that should be log-transformed or logit-transformed, respectively. The \( \text{barycentric} \) argument can name sets of parameters that should be log-barycentric transformed.

Note that using the \( \log \), \( \text{logit} \), or \( \text{barycentric} \) arguments causes \( C \) snippets to be generated. Therefore, you must make sure that variables named in any of these arguments are also mentioned in \( \text{paramnames} \) at the same time.

The logit transform is defined by

\[
\text{logit}(\theta) = \log \frac{\theta}{1-\theta}.
\]

The log barycentric transformation of variables \( \theta_1, \ldots, \theta_n \) is given by

\[
\text{logbarycentric}(\theta_1, \ldots, \theta_n) = \left( \log \frac{\theta_1}{\sum_i \theta_i}, \ldots, \log \frac{\theta_n}{\sum_i \theta_i} \right).
\]

Note for Windows users

Some Windows users report problems when using \( C \) snippets in parallel computations. These appear to arise when the temporary files created during the \( C \) snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the \( \text{cdir} \) and \( \text{cfile} \) options to cause the \( C \) snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.
parmat

See Also

partrans

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification

Description

parmat is a utility that makes a vector of parameters suitable for use in pomp functions.

Usage

parmat(params, ...)

## S4 method for signature 'numeric'
parmat(params, nrep = 1, ..., names = NULL)

## S4 method for signature 'array'
parmat(params, nrep = 1, ..., names = NULL)

## S4 method for signature 'data.frame'
parmat(params, nrep = 1, ...)

Arguments

params named numeric vector or matrix of parameters.
...
additional arguments, currently ignored.
nrep
number of replicates (columns) desired.
names optional character; column names.

Value

parmat returns a matrix consisting of nrep copies of params.

Author(s)

Aaron A. King
Examples

# takes too long for R CMD check
## generate a bifurcation diagram for the Ricker map
p <- parmat(coef(ricker()),nrep=500)
p["r",] <- exp(seq(from=1.5,to=4,length=500))
trajectory(
  ricker(),
  times=seq(from=1000,to=2000,by=1),
  params=p,
  format="array"
) -> x
matplot(p["r",],x["N",],pch=",",col='black',
  xlab=expression(log(r)),ylab="N",log='x')

Description

Performs parameter transformations.

Usage

## S4 method for signature 'pomp'
partrans(object, params, dir = c("fromEst", "toEst"), ...)

## S4 method for signature 'objfun'
partrans(object, ...)

Arguments

object an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of pomp, simulate, or one of the pomp inference algorithms.

params a npar x nrep matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of x.

dir the direction of the transformation to perform.

... additional arguments are ignored.

Value

If dir=fromEst, the parameters in params are assumed to be on the estimation scale and are transformed onto the natural scale. If dir=toEst, they are transformed onto the estimation scale. In both cases, the parameters are returned as a named numeric vector or an array with rownames, as appropriate.
### Description

Size of a population of great tits (*Parus major*) from Wytham Wood, near Oxford.

### Details


### References


### See Also

More data sets provided with *pomp*: blowflies, bsflu, childhood disease data, dacca(), ebola

### Examples

```r
# takes too long for R CMD check
defilter(Np=1000, times="year", t0=1960,  
params=c(K=190, r=2.7, sigma=0.2, theta=0.05, N.0=148),  
rprocess=discrete_time(  
  function (r, K, sigma, N, ...) {  
    e <- rnorm(n=1, mean=0, sd=sigma)  
    c(N = exp(log(N)+r*(1-N/K)+e))  
  },  
  delta.t=1  
),  
rmeasure=function (N, theta, ...) {  
  c(pop=rnbinom(n=1, size=1/theta, mu=N+1e-10))  
},  
dmeasure=function (pop, N, theta, ..., log) {  
  dbinom(x=pop, mu=N+1e-10, size=1/theta, log=log)  
}),
```
pf <- pfilter(
  data, 
  Np, 
  params, 
  rinit, 
  rprocess, 
  dmeasure, 
  pred.mean = FALSE, 
  pred.var = FALSE, 
  filter.mean = FALSE, 
  filter.traj = FALSE, 
  save.states = c("no", "weighted", "unweighted", "FALSE", "TRUE"), 
  ...,
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'

pf <- pfilter(
  data, 
  Np, 
  pred.mean = FALSE, 
  pred.var = FALSE, 
  filter.mean = FALSE, 
  filter.traj = FALSE, 
  save.states = c("no", "weighted", "unweighted", "FALSE", "TRUE"), 
  ...,
  verbose = getOption("verbose", FALSE)
)
## S4 method for signature 'pfILTER_d_pomp'
pFILTER(data, Np, ..., verbose = getOption("verbose", FALSE))

## S4 method for signature 'objfun'
pFILTER(data, ...)

**Arguments**

- **data**: either a data frame holding the time series data, or an object of class `pomp`, i.e., the output of another `pomp` calculation. Internally, data will be internally coerced to an array with storage-mode `double`.

- **Np**: the number of particles to use. This may be specified as a single positive integer, in which case the same number of particles will be used at each timestep. Alternatively, if one wishes the number of particles to vary across timesteps, one may specify `Np` either as a vector of positive integers of length

  \[
  \text{length}(\text{time}(\text{object}, t0=\text{TRUE}))
  \]

  or as a function taking a positive integer argument. In the latter case, `Np(k)` must be a single positive integer, representing the number of particles to be used at the `k`-th timestep: `Np(0)` is the number of particles to use going from `timezero(object)` to `time(object)[1]`, `Np(1)`, from `timezero(object)` to `time(object)[1]`, and so on, while when `T=\text{length}(\text{time}(\text{object}))`, `Np(T)` is the number of particles to sample at the end of the time-series.

- **params**: optional; named numeric vector of parameters. This will be coerced internally to storage mode `double`.

- **rinit**: simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting `rinit=NULL` sets the initial-state simulator to its default. For more information, see `rinit` specification.

- **rprocess**: simulator of the latent state process, specified using one of the `rprocess` plugins. Setting `rprocess=NULL` removes the latent-state simulator. For more information, see `rprocess` specification for the documentation on these plugins.

- **dmeasure**: evaluator of the measurement model density, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting `dmeasure=NULL` removes the measurement density evaluator. For more information, see `dmeasure` specification.

- **pred.mean**: logical; if `TRUE`, the prediction means are calculated for the state variables and parameters.

- **pred.var**: logical; if `TRUE`, the prediction variances are calculated for the state variables and parameters.

- **filter.mean**: logical; if `TRUE`, the filtering means are calculated for the state variables and parameters.

- **filter.traj**: logical; if `TRUE`, a filtered trajectory is returned for the state variables and parameters. See `filter_traj` for more information.
save.states character; If save.states="unweighted", the state-vector for each unweighted particle at each time is saved. If save.states="weighted", the state-vector for each weighted particle at each time is saved, along with the corresponding weight. If save.states="no", information on the latent states is not saved. "FALSE" is a synonym for "no" and "TRUE" is a synonym for "unweighted". To retrieve the saved states, applying saved.states to the result of the pfilter computation.

... additional arguments supply new or modify existing model characteristics or components. See pomp for a full list of recognized arguments.
When named arguments not recognized by pomp are provided, these are made available to all basic components via the so-called userdata facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (covar) and model parameters (params). See userdata for information on how to use this facility.

verbose logical; if TRUE, diagnostic messages will be printed to the console.

Value
An object of class ‘pfilterd_pomp’, which extends class ‘pomp’. Information can be extracted from this object using the methods documented below.

Methods

logLik the estimated log likelihood
cond_logLik the estimated conditional log likelihood
eff_sample_size the (time-dependent) estimated effective sample size
pred_mean, pred_var the mean and variance of the approximate prediction distribution
filter_mean the mean of the filtering distribution
filter_traj retrieve one particle trajectory. Useful for building up the smoothing distribution.
saved_states retrieve saved states
as.data.frame coerce to a data frame
plot diagnostic plots

Note for Windows users
Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the cdir and cfile options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Author(s)
Aaron A. King
References


See Also

More on *pomp* elementary algorithms: `elementary_algorithms`, `kalman`, `pomp-package`, `probe()`, `simulate()`, `spect()`, `trajectory()`, `wpfilter()`

More on sequential Monte Carlo methods: `bsmc2()`, `cond_logLik()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `kalman`, `mif2()`, `pmcmc()`, `pred_mean()`, `pred_var()`, `saved_states()`, `wpfilter()`

More on full-information (i.e., likelihood-based) methods: `bsmc2()`, `mif2()`, `pmcmc()`, `wpfilter()`

Examples

```r
pf <- pfilter(gompertz(), Np=1000)  # use 1000 particles
plot(pf)
logLik(pf)
cond_logLik(pf)  # conditional log-likelihoods
eff_sample_size(pf)  # effective sample size
logLik(pfilter(pf))  # run it again with 1000 particles

# run it again with 2000 particles
pf <- pfilter(pf, Np=2000, filter.mean=TRUE, filter.traj=TRUE, save.states="weighted")
fm <- filter_mean(pf)  # extract the filtering means
ft <- filter_traj(pf)  # one draw from the smoothing distribution
ss <- saved_states(pf, format="d")  # the latent-state portion of each particle

as(pf, "data.frame") |> head()
```

Description

Diagnostic plots.

Usage

```r
# S4 method for signature 'pomp_plottable'
plot(
  x,
  variables, # pomp plotting facilities
  panel = lines,
)```
nc = NULL,
yax.flip = FALSE,
mar = c(0, 5.1, 0, if (yax.flip) 5.1 else 2.1),
oma = c(6, 0, 5, 0),
axes = TRUE,
...)

## S4 method for signature 'Pmcmc'
plot(x, ..., pars)

## S4 method for signature 'Abc'
plot(x, ..., pars, scatter = FALSE)

## S4 method for signature 'Mif2'
plot(x, ..., pars, transform = FALSE)

## S4 method for signature 'probed_pomp'
plot(x, y, ...)

## S4 method for signature 'spectd_pomp'
plot(
  x,
  ...
  max.plots.per.page = 4,
  plot.data = TRUE,
  quantiles = c(0.025, 0.25, 0.5, 0.75, 0.975),
  quantile.styles = list(lwd = 1, lty = 1, col = "gray70"),
  data.styles = list(lwd = 2, lty = 2, col = "black")
)

## S4 method for signature 'bsmcd_pomp'
plot(x, pars, thin, ...)

## S4 method for signature 'probe_match_objfun'
plot(x, y, ...)

## S4 method for signature 'spect_match_objfun'
plot(x, y, ...)

Arguments

x the object to plot
variables optional character; names of variables to be displayed
panel function of the form panel(x, col, bg, pch, type, ...) which gives the action to be carried out in each panel of the display.
nc the number of columns to use. Defaults to 1 for up to 4 series, otherwise to 2.
The particle Markov chain Metropolis-Hastings algorithm

Description
The Particle MCMC algorithm for estimating the parameters of a partially-observed Markov process. Running pmcmc causes a particle random-walk Metropolis-Hastings Markov chain algorithm to run for the specified number of proposals.

Usage

```r
## S4 method for signature 'data.frame'
pmcmc(
  data,
  Nmcmc = 1,
  proposal,
  Np,
  params,
  rinit,
  rprocess,
  dmeasure,
  dprior,
  ...,
)```
verbose = getOption("verbose", FALSE)

## S4 method for signature 'pomp'
pmcmc(
  data,
  Nmcmc = 1,
  proposal,
  Np,
  ...
)

## S4 method for signature 'pfilterd_pomp'
pmcmc(
  data,
  Nmcmc = 1,
  proposal,
  Np,
  ...
)

## S4 method for signature 'pmcmcd_pomp'
pmcmc(data, Nmcmc, proposal, ..., verbose = getOption("verbose", FALSE))

Arguments

data either a data frame holding the time series data, or an object of class 'pomp', i.e., the output of another pomp calculation. Internally, data will be internally coerced to an array with storage-mode double.

Nmcmc The number of PMCMC iterations to perform.

proposal optional function that draws from the proposal distribution. Currently, the proposal distribution must be symmetric for proper inference: it is the user's responsibility to ensure that it is. Several functions that construct appropriate proposal function are provided: see MCMC proposals for more information.

Np the number of particles to use. This may be specified as a single positive integer, in which case the same number of particles will be used at each timestep. Alternatively, if one wishes the number of particles to vary across timesteps, one may specify Np either as a vector of positive integers of length length(time(object,t0=TRUE))
or as a function taking a positive integer argument. In the latter case, Np(k) must be a single positive integer, representing the number of particles to be used at the k-th timestep: Np(0) is the number of particles to use going from timezero(object) to time(object)[1], Np(1), from timezero(object) to time(object)[1], and so on, while when T=length(time(object)), Np(T) is the number of particles to sample at the end of the time-series.
params optional; named numeric vector of parameters. This will be coerced internally to storage mode double.

rinit simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator to its default. For more information, see rinit specification.

rprocess simulator of the latent state process, specified using one of the rprocess plugins. Setting rprocess=NULL removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

dmeasure evaluator of the measurement model density, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting dmeasure=NULL removes the measurement density evaluator. For more information, see dmeasure specification.

dprior optional; prior distribution density evaluator, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. For more information, see prior specification. Setting dprior=NULL resets the prior distribution to its default, which is a flat improper prior.

... additional arguments supply new or modify existing model characteristics or components. See pomp for a full list of recognized arguments. When named arguments not recognized by pomp are provided, these are made available to all basic components via the so-called userdata facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (covar) and model parameters (params). See userdata for information on how to use this facility.

verbose logical; if TRUE, diagnostic messages will be printed to the console.

Value

An object of class 'pmcmcd_pomp'.

Methods

The following can be applied to the output of a pmcmc operation:

pmcmc repeats the calculation, beginning with the last state
continue continues the pmcmc calculation
plot produces a series of diagnostic plots
filter_traj extracts a random sample from the smoothing distribution
traces produces an mcmc object, to which the various coda convergence diagnostics can be applied

Re-running PMCMC Iterations

To re-run a sequence of PMCMC iterations, one can use the pmcmc method on a ‘pmcmc’ object. By default, the same parameters used for the original PMCMC run are re-used (except for verbose, the default of which is shown above). If one does specify additional arguments, these will override the defaults.
Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Author(s)

Edward L. Ionides, Aaron A. King, Sebastian Funk

References


See Also

More on pomp estimation algorithms: approximate Bayesian computation, `bsmc2()`, estimation algorithms, `mif2()`, nonlinear forecasting, pomp-package, probe matching, spectrum matching

More on sequential Monte Carlo methods: `bsmc2()`, `cond_logLik()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `kalman`, `mif2()`, `pfilter()`, `pred_mean()`, `pred_var()`, `saved_states()`, `wpfilter()`

More on full-information (i.e., likelihood-based) methods: `bsmc2()`, `mif2()`, `pfilter()`, `wpfilter()`

More on Markov chain Monte Carlo methods: approximate Bayesian computation, proposals

More on Bayesian methods: approximate Bayesian computation, `bsmc2()`, `dprior()`, prior specification, `rprior()`

---

**pomp**

*Constructor of the basic pomp object*

**Description**

This function constructs a `pomp` object, encoding a partially-observed Markov process (POMP) model together with a uni- or multi-variate time series. As such, it is central to all the package’s functionality. One implements the POMP model by specifying some or all of its `basic components`. These comprise:

- `rinit`, which samples from the distribution of the state process at the zero-time;
- `rprocess`, the simulator of the unobserved Markov state process;
- `dprocess`, the evaluator of the probability density function for transitions of the unobserved Markov state process;
- `rmeasure`, the simulator of the observed process, conditional on the unobserved state;
- `dmeasure`, the evaluator of the measurement model probability density function;
- `emeasure`, the expectation of the measurements, conditional on the latent state;
vmeasure, the covariance matrix of the measurements, conditional on the latent state;

rprior, which samples from a prior probability distribution on the parameters;

dprior, which evaluates the prior probability density function;

skeleton, which computes the deterministic skeleton of the unobserved state process;

partrans, which performs parameter transformations.

The basic structure and its rationale are described in the *Journal of Statistical Software* paper, an updated version of which is to be found on the package website.

Usage

```r
pomp(
data,
times,
t0,
..., 
rinit, 
rprocess, 
dprocess, 
rmeasure, 
dmeasure, 
emeasure, 
vmeasure, 
skeleton, 
rprior, 
dprior, 
partrans, 
covar, 
params, 
accumvars, 
obsnames, 
statenames, 
paramnames, 
covarnames, 
PACKAGE, 
globals, 
cdir =getOption("pomp_cdir", NULL), 
cfile, 
shlib.args, 
compile = TRUE, 
verbose =getOption("verbose", FALSE)
)
```

Arguments

data either a data frame holding the time series data, or an object of class ‘pomp’, i.e., the output of another pomp calculation. Internally, data will be internally coerced to an array with storage-mode double.
times

the sequence of observation times. times must indicate the column of observation times by name or index. The time vector must be numeric and non-decreasing.

t0

The zero-time, i.e., the time of the initial state. This must be no later than the time of the first observation, i.e., t0 <= times[1].

... additional arguments supply new or modify existing model characteristics or components. See pomp for a full list of recognized arguments. When named arguments not recognized by pomp are provided, these are made available to all basic components via the so-called userdata facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (covar) and model parameters (params). See userdata for information on how to use this facility.

rinit

simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=Null sets the initial-state simulator to its default. For more information, see rinit specification.

rprocess

simulator of the latent state process, specified using one of the rprocess plugins. Setting rprocess=Null removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

dprocess

optional; specification of the probability density evaluation function of the unobserved state process. Setting dprocess=Null removes the latent-state density evaluator. For more information, see dprocess specification.

rmeasure

simulator of the measurement model, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rmeasure=Null removes the measurement model simulator. For more information, see rmeasure specification.

dmeasure

evaluator of the measurement model density, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting dmeasure=Null removes the measurement density evaluator. For more information, see dmeasure specification.

emeasure

the expectation of the measured variables, conditional on the latent state. This can be specified as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting emeasure=Null removes the emeasure component. For more information, see emeasure specification.

vmeasure

the covariance of the measured variables, conditional on the latent state. This can be specified as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting vmeasure=Null removes the vmeasure component. For more information, see vmeasure specification.

skeleton

optional; the deterministic skeleton of the unobserved state process. Depending on whether the model operates in continuous or discrete time, this is either a vectorfield or a map. Accordingly, this is supplied using either the vectorfield or map functions. For more information, see skeleton specification. Setting skeleton=Null removes the deterministic skeleton.
rprior optional; prior distribution sampler, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. For more information, see prior specification. Setting rprior=NULL removes the prior distribution sampler.

dprior optional; prior distribution density evaluator, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. For more information, see prior specification. Setting dprior=NULL resets the prior distribution to its default, which is a flat improper prior.

partrans optional parameter transformations, constructed using parameter_trans. Many algorithms for parameter estimation search an unconstrained space of parameters. When working with such an algorithm and a model for which the parameters are constrained, it can be useful to transform parameters. One should supply the partrans argument via a call to parameter_trans. For more information, see parameter_trans. Setting partrans=NULL removes the parameter transformations, i.e., sets them to the identity transformation.

covar optional covariate table, constructed using covariate_table. If a covariate table is supplied, then the value of each of the covariates is interpolated as needed. The resulting interpolated values are made available to the appropriate basic components. See the documentation for covariate_table for details.

params optional; named numeric vector of parameters. This will be coerced internally to storage mode double.

accumvars optional character vector; contains the names of accumulator variables. See accumulators for a definition and discussion of accumulator variables.

obsnames optional character vector; names of the observables. It is not usually necessary to specify obsnames since, by default, these are read from the names of the data variables.

statenames optional character vector; names of the latent state variables. It is typically only necessary to supply statenames when C snippets are in use.

paramnames optional character vector; names of model parameters. It is typically only necessary to supply paramnames when C snippets are in use.

covarnames optional character vector; names of the covariates. It is not usually necessary to specify covarnames since, by default, these are read from the names of the covariates.

PACKAGE optional character; the name (without extension) of the external, dynamically loaded library in which any native routines are to be found. This is only useful if one or more of the model components has been specified using a precompiled dynamically loaded library; it is not used for any component specified using C snippets. PACKAGE can name at most one library.

globals optional character; arbitrary C code that will be hard-coded into the shared-object library created when C snippets are provided. If no C snippets are used, globals has no effect.

cdir optional character variable. cdir specifies the name of the directory within which C snippet code will be compiled. By default, this is in a temporary
directory specific to the R session. One can also set this directory using the pomp_cdir global option.

cfile
optional character variable. cfile gives the name of the file (in directory cdir) into which C snippet codes will be written. By default, a random filename is used. If the chosen filename would result in over-writing an existing file, an error is generated.

shlib.args
optional character variables. Command-line arguments to the R CMD SHLIB call that compiles the C snippets. One can, for example, specify libraries against which the C snippets are to be linked. In doing so, take care to make sure the appropriate header files are available to the C snippets, e.g., using the globals argument. See Csnippet for more information.

compile
logical; if FALSE, compilation of the C snippets will be postponed until they are needed.

verbose
logical; if TRUE, diagnostic messages will be printed to the console.

Details
Each basic component is supplied via an argument of the same name. These can be given in the call to pomp, or to many of the package’s other functions. In any case, the effect is the same: to add, remove, or modify the basic component.

Each basic component can be furnished using C snippets, R functions, or pre-compiled native routine available in user-provided dynamically loaded libraries.

Value
The pomp constructor function returns an object, call it P, of class ‘pomp’. P contains, in addition to the data, any elements of the model that have been specified as arguments to the pomp constructor function. One can add or modify elements of P by means of further calls to pomp, using P as the first argument in such calls. One can pass P to most of the pomp package methods via their data argument.

Note
It is not typically necessary (or indeed feasible) to define all of the basic components for any given purpose. However, each pomp algorithm makes use of only a subset of these components. When an algorithm requires a basic component that has not been furnished, an error is generated to let you know that you must provide the needed component to use the algorithm.

Note for Windows users
Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the cdir and cfile options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Author(s)
Aaron A. King
### References


### See Also

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification.

---

### pomp examples  

#### Description

Pre-built POMP examples

#### Details

**pomp** includes a number of pre-built examples of pomp objects and data that can be analyzed using **pomp** methods. These include:

- **blowflies** Data from Nicholson’s experiments with sheep blowfly populations
- **blowflies1** A pomp object with some of the blowfly data together with a discrete delay equation model.
- **blowflies2** A variant of **blowflies1**.
- **bsflu** Data from an outbreak of influenza in a boarding school.
- **dacca** Fifty years of census and cholera mortality data, together with a stochastic differential equation transmission model (King et al. 2008).
- **ebolaModel** Data from the 2014 West Africa outbreak of Ebola virus disease, together with simple transmission models (King et al. 2015).
- **gompertz** The Gompertz population dynamics model, with simulated data.
- **LondonYorke** Data on incidence of several childhood diseases (London and Yorke 1973)
- **ewmeas** Measles incidence data from England and Wales
- **ewcitmeas** Measles incidence data from 7 English cities
- **ou2** A 2-D Ornstein-Uhlenbeck process with simulated data
- **ricker** The Ricker population dynamics model, with simulated data
- **rw2** A 2-D Brownian motion model, with simulated data.
sir() A simple continuous-time Markov chain SIR model, coded using Euler-multinomial steps, with simulated data.
sir2() A simple continuous-time Markov chain SIR model, coded using Gillespie’s algorithm, with simulated data.
verhulst() The Verhulst-Pearl (logistic) model, a continuous-time model of population dynamics, with simulated data.

See also the tutorials on the package website for more examples.

References

See Also
More examples provided with pomp: SIR models, blowflies, childhood disease data, dacca(), ebola, gompertz(), ou2(), ricker(), rw2(), verhulst().

| pred_mean | Prediction mean |

Description
The mean of the prediction distribution

Usage
```r
## S4 method for signature 'kalmand_pomp'
pred_mean(object, vars, ..., format = c("array", "data.frame"))
```
```r
## S4 method for signature 'pfilterd_pomp'
pred_mean(object, vars, ..., format = c("array", "data.frame"))
```
Arguments

object result of a filtering computation
vars optional character; names of variables
... ignored
format format of the returned object

Details

The prediction distribution is that of

\[ X(t_k)|Y(t_1) = y_1^*, \ldots, Y(t_{k-1}) = y_{k-1}^* \]

where \( X(t_k), Y(t_k) \) are the latent state and observable processes, respectively, and \( y_k^* \) is the data, at time \( t_k \).

The prediction mean is therefore the expectation of this distribution

\[ E[X(t_k)|Y(t_1) = y_1^*, \ldots, Y(t_{k-1}) = y_{k-1}^*]. \]

See Also

More on sequential Monte Carlo methods: bsmc2(), cond_logLik(), eff_sample_size(), filter_mean(), filter_traj(), kalman, mif2(), pfilter(), pmcmc(), pred_var(), saved_states(), wpfilter()

Other extraction methods: coef(), cond_logLik(), covmat(), eff_sample_size(), filter_mean(), filter_traj(), forecast(), logLik, obs(), pred_var(), saved_states(), spy(), states(), summary(), timezero(), time(), traces()

Description

The variance of the prediction distribution

Usage

```r
## S4 method for signature 'pfilterd_pomp'
pred_var(object, vars, ..., format = c("array", "data.frame"))
```

Arguments

object result of a filtering computation
vars optional character; names of variables
... ignored
format format of the returned object
Details

The prediction distribution is that of
\[ X(t_k) | Y(t_1) = y^*_1, \ldots, Y(t_{k-1}) = y^*_{k-1}, \]
where \( X(t_k), Y(t_k) \) are the latent state and observable processes, respectively, and \( y^*_k \) is the data, at time \( t_k \).

The prediction variance is therefore the variance of this distribution
\[ \text{Var}[X(t_k) | Y(t_1) = y^*_1, \ldots, Y(t_{k-1}) = y^*_{k-1}] \].

See Also

More on sequential Monte Carlo methods: bsmc2(), cond_logLik(), eff_sample_size(), filter_mean(), filter_traj(), kalman, mif2(), pfiltet(), pmcmc(), pred_mean(), saved_states(), wpfilter()

Other extraction methods: coef(), cond_logLik(), covmat(), eff_sample_size(), filter_mean(), filter_traj(), forecast(), logLik, obs(), pred_mean(), saved_states(), spy(), states(), summary(), timezero(), time(), traces()

Description

Specification of prior distributions.

Details

A prior distribution on parameters is specified by means of the rprior and/or dprior arguments to pomp. As with the other basic model components, it is preferable to specify these using C snippets. In writing a C snippet for the prior sampler (rprior), keep in mind that:

1. Within the context in which the snippet will be evaluated, only the parameters will be defined.
2. The goal of such a snippet is the replacement of parameters with values drawn from the prior distribution.
3. Hyperparameters can be included in the ordinary parameter list. Obviously, hyperparameters should not be replaced with random draws.

In writing a C snippet for the prior density function (dprior), observe that:

1. Within the context in which the snippet will be evaluated, only the parameters and give_log will be defined.
2. The goal of such a snippet is computation of the prior probability density, or the log of same, at a given point in parameter space. This scalar value should be returned in the variable lik. When give_log == 1, lik should contain the log of the prior probability density.
3. Hyperparameters can be included in the ordinary parameter list.
General rules for writing C snippets can be found here.

Alternatively, one can furnish R functions for one or both of these arguments. In this case, \texttt{rprior} must be a function that makes a draw from the prior distribution of the parameters and returns a named vector containing all the parameters. The only required argument of this function is \ldots.

Similarly, the \texttt{dprior} function must evaluate the prior probability density (or log density if \texttt{log} == \texttt{TRUE}) and return that single scalar value. The only required arguments of this function are \ldots and \texttt{log}.

Default behavior

By default, the prior is assumed flat and improper. In particular, \texttt{dprior} returns 1 (0 if \texttt{log} = \texttt{TRUE}) for every parameter set. Since it is impossible to simulate from a flat improper prior, \texttt{rprocess} returns missing values (NAs).

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the \texttt{cdir} and \texttt{cfile} options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

See Also

\texttt{dprior \texttt{rprior}}

More on implementing POMP models: \texttt{Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification}

More on Bayesian methods: \texttt{approximate Bayesian computation, bsmc2(), dprior(), pmcmc(), rprior()}

Examples

```
# takes too long for R CMD check
## Starting with an existing pomp object:
verhulst() |> window(end=30) -> po

## We add or change prior distributions using the two
## arguments 'rprior' and 'dprior'. Here, we introduce
## a Gamma prior on the 'r' parameter.
## We construct 'rprior' and 'dprior' using R functions.

po |> bsmc2(
    rprior=function (n_0, K0, K1, sigma, tau, r0, r1, \ldots) {
        c(
            n_0 = n_0,
```
K = rgamma(n=1, shape=K0, scale=K1),
r = rgamma(n=1, shape=r0, scale=r1),
 sigma = sigma,
tau = tau
)

},
dprior=function(K, K0, K1, r, r0, r1, ..., log) {
p <- dgamma(x=c(K,r), shape=c(K0,r0), scale=c(K1,r1), log=log)
if (log) sum(p) else prod(p)
},
params=c(n_0=10000, K=10000, K0=10, K1=1000,
r=0.9, r0=0.9, r1=1, sigma=0.5, tau=0.3),
 Np=1000
) -> B

## We can also pass them as C snippets:

po |> bsmc2{
  rprior=Csnippet("K = rgamma(K0,K1);
r = rgamma(r0,r1);"
),
dprior=Csnippet("double lik1 = dgamma(K,K0,K1,give_log);
double lik2 = dgamma(r,r0,r1,give_log);
lik = (give_log) ? lik1+lik2 : lik1*lik2;"
),
paramnames=c("K", "K0", "K1", "r", "r0", "r1"),
params=c(n_0=10000, K=10000, K0=10, K1=1000,
r=0.9, r0=0.9, r1=1, sigma=0.5, tau=0.3),
 Np=10000
) -> B

## The prior is plotted in grey; the posterior, in blue.
plot(B)

B |> pmcmc(Nmcmc=100, Np=1000, proposal=mvn_diag_rw(c(r=0.01, K=10))) -> Bb
plot(Bb, pars=c("loglik", "log.prior", "r", "K"))

---

**Probes (AKA summary statistics)**

**Description**

Probe a partially-observed Markov process by computing summary statistics and the synthetic likelihood.
Usage

```r
## S4 method for signature 'data.frame'
probe(
  data,
  probes,
  nsim,
  seed = NULL,
  params,
  rinit,
  rprocess,
  rmeasure,
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'
probe(
  data,
  probes,
  nsim,
  seed = NULL,
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'probed_pomp'
probe(
  data,
  probes,
  nsim,
  seed = NULL,
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'probe_match_objfun'
probe(data, seed, ..., verbose = getOption("verbose", FALSE))

## S4 method for signature 'objfun'
probe(data, seed = NULL, ...)
```

Arguments

- **data**: either a data frame holding the time series data, or an object of class 'pomp', i.e., the output of another pomp calculation. Internally, data will be internally coerced to an array with storage-mode double.
- **probes**: a single probe or a list of one or more probes. A probe is simply a scalar- or vector-valued function of one argument that can be applied to the data array of
a ‘pomp’. A vector-valued probe must always return a vector of the same size. A number of useful probes are provided with the package: see basic probes.

**nsim**
the number of model simulations to be computed.

**seed**
optional integer; if non-NULL, the random number generator will be initialized with this seed for simulations. See simulate.

**params**
optional; named numeric vector of parameters. This will be coerced internally to storage mode double.

**rinit**
simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator to its default. For more information, see rinit specification.

**rprocess**
simulator of the latent state process, specified using one of the rprocess plugins. Setting rprocess=NULL removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

**rmeasure**
simulator of the measurement model, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rmeasure=NULL removes the measurement model simulator. For more information, see rmeasure specification.

... additional arguments supply new or modify existing model characteristics or components. See pomp for a full list of recognized arguments.

When named arguments not recognized by pomp are provided, these are made available to all basic components via the so-called userdata facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (covar) and model parameters (params). See userdata for information on how to use this facility.

**verbose**
logical; if TRUE, diagnostic messages will be printed to the console.

**Details**

probe applies one or more “probes” to time series data and model simulations and compares the results. It can be used to diagnose goodness of fit and/or as the basis for “probe-matching”, a generalized method-of-moments approach to parameter estimation.

A call to probe results in the evaluation of the probe(s) in probes on the data. Additionally, nsim simulated data sets are generated (via a call to simulate) and the probe(s) are applied to each of these. The results of the probe computations on real and simulated data are stored in an object of class ‘probed_pomp’.

When probe operates on a probe-matching objective function (a ‘probe_match_objfun’ object), by default, the random-number generator seed is fixed at the value given when the objective function was constructed. Specifying NULL or an integer for seed overrides this behavior.

**Value**

probe returns an object of class ‘probed_pomp’, which contains the data and the model, together with the results of the probe calculation.
Methods

The following methods are available.

plot  displays diagnostic plots.

summary  displays summary information. The summary includes quantiles (fractions of simulations with probe values less than those realized on the data) and the corresponding two-sided p-values. In addition, the “synthetic likelihood” (Wood 2010) is computed, under the assumption that the probe values are multivariate-normally distributed.

logLik  returns the synthetic likelihood for the probes. NB: in general, this is not the same as the likelihood.

as.data.frame  coerces a ‘probed_pomp’ to a ‘data.frame’. The latter contains the realized values of the probes on the data and on the simulations. The variable .id indicates whether the probes are from the data or simulations.

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the cdir and cfile options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Author(s)

Daniel C. Reuman, Aaron A. King

References


See Also

More on pomp elementary algorithms: elementary algorithms, kalman, pfilter(), pomp-package, simulate(), spect(), trajectory(), wpfilter()

More on methods based on summary statistics: approximate Bayesian computation, basic probes, nonlinear forecasting, probe matching, spectrum matching, spect()
**Description**

Estimation of parameters by maximum synthetic likelihood

**Usage**

```r
## S4 method for signature 'data.frame'
probe_objfun(
  data,
  est = character(0),
  fail.value = NA,
  probes,
  nsim,
  seed = NULL,
  params,
  rinit,
  rprocess,
  rmeasure,
  partrans,
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'
probe_objfun(
  data,
  est = character(0),
  fail.value = NA,
  probes,
  nsim,
  seed = NULL,
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'probed_pomp'
probe_objfun(
  data,
  est = character(0),
  fail.value = NA,
  probes,
  nsim,
  seed = NULL,
  ...
)```

verbose =getOption("verbose", FALSE)
)

## S4 method for signature 'probe_match_objfun'
probe_objfun(
  data,
  est,
  fail.value,
  seed = NULL,
  ...
  verbose =getOption("verbose", FALSE)
)

Arguments

data 	either a data frame holding the time series data, or an object of class 'pomp',
i.e., the output of another pomp calculation. Internally, data will be internally
coerced to an array with storage-mode double.
est 	character vector; the names of parameters to be estimated.
fail.value 	optional numeric scalar; if non-NA, this value is substituted for non-finite values
of the objective function. It should be a large number (i.e., bigger than any
legitimate values the objective function is likely to take).
probes 
a single probe or a list of one or more probes. A probe is simply a scalar- or
vector-valued function of one argument that can be applied to the data array of
a 'pomp'. A vector-valued probe must always return a vector of the same size.
A number of useful probes are provided with the package: see basic probes.
nsim 	the number of model simulations to be computed.
seed 	integer. When fitting, it is often best to fix the seed of the random-number
generator (RNG). This is accomplished by setting seed to an integer. By default,
seed = NULL, which does not alter the RNG state.
params 	optional; named numeric vector of parameters. This will be coerced internally
to storage mode double.
rinit 	simulator of the initial-state distribution. This can be furnished either as a C
snippet, an R function, or the name of a pre-compiled native routine available in
a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator
to its default. For more information, see rinit specification.
rprocess 	simulator of the latent state process, specified using one of the rprocess plugins.
Setting rprocess=NULL removes the latent-state simulator. For more informa-
tion, see rprocess specification for the documentation on these plugins.
rmeasure 	simulator of the measurement model, specified either as a C snippet, an R func-
tion, or the name of a pre-compiled native routine available in a dynamically
loaded library. Setting rmeasure=NULL removes the measurement model simu-
lator. For more information, see rmeasure specification.
partrans 	ontional parameter transformations, constructed using parameter_trans.
Many algorithms for parameter estimation search an unconstrained space of parameters. When working with such an algorithm and a model for which the parameters are constrained, it can be useful to transform parameters. One should supply the partrans argument via a call to `parameter_trans`. For more information, see `parameter_trans`. Setting partrans=NULL removes the parameter transformations, i.e., sets them to the identity transformation.

... additional arguments supply new or modify existing model characteristics or components. See `pomp` for a full list of recognized arguments.

When named arguments not recognized by `pomp` are provided, these are made available to all basic components via the so-called `userdata` facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (`covar`) and model parameters (`params`). See `userdata` for information on how to use this facility.

verbose logical; if TRUE, diagnostic messages will be printed to the console.

Details

In probe-matching, one attempts to minimize the discrepancy between simulated and actual data, as measured by a set of summary statistics called probes. In `pomp`, this discrepancy is measured using the “synthetic likelihood” as defined by Wood (2010).

Value

`probe_objfun` constructs a stateful objective function for probe matching. Specifically, `probe_objfun` returns an object of class ‘probe_match_objfun’, which is a function suitable for use in an optim-like optimizer. In particular, this function takes a single numeric-vector argument that is assumed to contain the parameters named in `est`, in that order. When called, it will return the negative synthetic log likelihood for the probes specified. It is a stateful function: Each time it is called, it will remember the values of the parameters and its estimate of the synthetic likelihood.

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Important Note

Since `pomp` cannot guarantee that the final call an optimizer makes to the function is a call at the optimum, it cannot guarantee that the parameters stored in the function are the optimal ones. Therefore, it is a good idea to evaluate the function on the parameters returned by the optimization routine, which will ensure that these parameters are stored.

Warning! Objective functions based on C snippets

If you use C snippets (see `Csnippet`), a dynamically loadable library will be built. As a rule, `pomp` functions load this library as needed and unload it when it is no longer needed. The stateful objective
functions are an exception to this rule. For efficiency, calls to the objective function do not execute `pompLoad` or `pompUnload`: rather, it is assumed that `pompLoad` has been called before any call to the objective function. When a stateful objective function using one or more C snippets is created, `pompLoad` is called internally to build and load the library: therefore, within a single R session, if one creates a stateful objective function, one can freely call that objective function and (more to the point) pass it to an optimizer that calls it freely, without needing to call `pompLoad`. On the other hand, if one retrieves a stored objective function from a file, or passes one to another R session, one must call `pompLoad` before using it. Failure to do this will typically result in a segmentation fault (i.e., it will crash the R session).

### Author(s)

Aaron A. King

### See Also

- `optim`, `subplex`, `nloptr`
- More on methods based on summary statistics: `approximate Bayesian computation`, `basic probes`, `nonlinear forecasting`, `probe()`, `spectrum matching`, `spect()`
- More on `pomp` estimation algorithms: `approximate Bayesian computation`, `bsmc2()`, `estimation algorithms`, `mif2()`, `nonlinear forecasting`, `pmcmc()`, `pomp-package`, `spectrum matching`
- More on maximization-based estimation methods: `mif2()`, `nonlinear forecasting`, `spectrum matching`, `trajectory matching`

### Examples

```r
# A list of probes:
plist <- list(
  mean=probe_mean("Y",trim=0.1,transform=sqrt),
  sd=probe_sd("Y",transform=sqrt),
  probe_marginal("Y",ref=obs(po)),
  probe_acf("Y",lags=c(1,3,5),type="correlation",transform=sqrt),
  probe_quantile("Y",prob=c(0.25,0.75),na.rm=TRUE)
)

# Construct the probe-matching objective function.
# Here, we just want to estimate 'K'.
po |> 
  probe_objfun(probes=plist,nsim=100,seed=5069977,
    est="K") -> f

# Any numerical optimizer can be used to minimize 'f'.
if (require(subplex)) {
  subplex(fn=f,par=0.4,control=list(reltol=1e-5)) -> out
} else {
```
proposals

MCMC proposal distributions

Description

Functions to construct proposal distributions for use with MCMC methods.

Usage

mvn.diag_rw(rw.sd)

mvn_rw(rw.var)

mvn_rw_adaptive(
  rw.sd,
  rw.var,
  scale.start = NA,
  scale.cooling = 0.999,
  shape.start = NA,
  target = 0.234,
  max.scaling = 50
)
Arguments

rw.sd  named numeric vector; random-walk SDs for a multivariate normal random-walk proposal with diagonal variance-covariance matrix.

rw.var  square numeric matrix with row- and column-names. Specifies the variance-covariance matrix for a multivariate normal random-walk proposal distribution.

scale.start, scale.cooling, shape.start, target, max.scaling  parameters to control the proposal adaptation algorithm. Beginning with MCMC iteration scale.start, the scale of the proposal covariance matrix will be adjusted in an effort to match the target acceptance ratio. This initial scale adjustment is “cooled”, i.e., the adjustment diminishes as the chain moves along. The parameter scale.cooling specifies the cooling schedule: at n iterations after scale.start, the current scaling factor is multiplied with scale.cooling^n. The maximum scaling factor allowed at any one iteration is max.scaling. After shape.start accepted proposals have accumulated, a scaled empirical covariance matrix will be used for the proposals, following Roberts and Rosenthal (2009).

Value

Each of these calls constructs a function suitable for use as the proposal argument of pmcmc or abc. Given a parameter vector, each such function returns a single draw from the corresponding proposal distribution.

Author(s)

Aaron A. King, Sebastian Funk

References


See Also

More on Markov chain Monte Carlo methods: approximate Bayesian computation, pmcmc()
Usage

bake(
  file,
  expr,
  seed = NULL,
  kind = NULL,
  normal.kind = NULL,
  dependson = NULL,
  info = FALSE,
  timing = TRUE,
  dir = getOption("pomp_archive_dir", getwd())
)

stew(
  file,
  expr,
  seed = NULL,
  kind = NULL,
  normal.kind = NULL,
  dependson = NULL,
  info = FALSE,
  dir = getOption("pomp_archive_dir", getwd())
)

freeze(
  expr,
  seed = NULL,
  kind = NULL,
  normal.kind = NULL,
  envir = parent.frame(),
  enclos = if (is.list(envir) || is.pairlist(envir)) parent.frame() else baseenv()
)

Arguments

file Name of the archive file in which the result will be stored or retrieved, as appropriate. For bake, this will contain a single object and hence be an RDS file (extension ‘rds’); for stew, this will contain one or more named objects and hence be an RDA file (extension ‘rda’).

expr Expression to be evaluated.

seed, kind, normal.kind optional. To set the state and of the RNG. The default, seed = NULL, will not change the RNG state. seed should be a single integer. See set.seed for more information.

dependson arbitrary R object (optional). Variables on which the computation in expr depends. A hash of these objects will be archived in file, along with the results of evaluation expr. When bake or stew are called and file exists, the hash
of these objects will be compared against the archived hash; recomputation is forced when these do not match. The dependencies should be specified as unquoted symbols: use a list if there are multiple dependencies. See the note below about avoiding using 'pomp' objects as dependencies.

info

logical. If TRUE, the “ingredients” of the calculation are returned as a list. In the case of bake, this list is the “ingredients” attribute of the returned object. In the case of stew, this list is a hidden object named “.ingredients”, located in the environment within which stew was called.

timing

logical. If TRUE, the time required for the computation is returned. This is returned as the “system.time” attribute of the returned object.

dir

Directory holding archive files; by default, this is the current working directory. This can also be set using the global option pomp_archive_dir. If it does not exist, this directory will be created (with a message).

envir

the environment in which expr is to be evaluated. May also be NULL, a list, a data frame, a pairlist or an integer as specified to sys.call.

enclos

Relevant when envir is a (pair)list or a data frame. Specifies the enclosure, i.e., where R looks for objects not found in envir. This can be NULL (interpreted as the base package environment, baseenv()) or an environment.

Details

On cooking shows, recipes requiring lengthy baking or stewing are prepared beforehand. The bake and stew functions perform analogously: an computation is performed and archived in a named file. If the function is called again and the file is present, the computation is not executed. Instead, the results are loaded from the archive. Moreover, via their optional seed argument, bake and stew can control the pseudorandom-number generator (RNG) for greater reproducibility. After the computation is finished, these functions restore the pre-existing RNG state to avoid side effects.

The freeze function doesn’t save results, but does set the RNG state to the specified value and restore it after the computation is complete.

Both bake and stew first test to see whether file exists. If it does, bake reads it using readRDS and returns the resulting object. By contrast, stew loads the file using load and copies the objects it contains into the user’s workspace (or the environment of the call to stew).

If file does not exist, then both bake and stew evaluate the expression expr; they differ in the results that they save. bake saves the value of the evaluated expression to file as a single object. The name of that object is not saved. By contrast, stew creates a local environment within which expr is evaluated; all objects in that environment are saved (by name) in file. bake and stew also store information about the code executed, the dependencies, and the state of the random-number generator (if the latter is controlled) in the archive file. Re-computation is triggered if any of these things change.

Value

bake returns the value of the evaluated expression expr. Other objects created in the evaluation of expr are discarded along with the temporary, local environment created for the evaluation.

The latter behavior differs from that of stew, which returns the names of the objects created during the evaluation of expr. After stew completes, these objects are copied into the environment in which stew was called.
freeze returns the value of evaluated expression expr. However, freeze evaluates expr within the parent environment, so other objects created in the evaluation of expr will therefore exist after freeze completes.

bake and stew store information about the code executed, the dependencies, and the state of the random-number generator in the archive file. In the case of bake, this is recorded in the “ingredients” attribute (attr(.,”ingredients”)); in the stew case, this is recorded in an object, “.ingredients”, in the archive. This information is returned only if info=TRUE.

The time required for execution is also recorded. bake stores this in the “system.time” attribute of the archived R object; stew does so in a hidden variable named .system.time. The timing is obtained using system.time.

Avoid using ‘pomp’ objects as dependencies

Note that when a ‘pomp’ object is built with one or more C snippets, the resulting code is “salted” with a random element to prevent collisions in parallel computations. As a result, two such ‘pomp’ objects will never match perfectly, even if the codes and data used to construct them are identical. Therefore, avoid using ‘pomp’ objects as dependencies in bake and stew.

Compatibility with older versions

With pomp version 3.4.4.2, the behavior of bake and stew changed. In particular, older versions did no dependency checking, and did not check to see whether expr had changed. Accordingly, the archive files written by older versions have a format that is not compatible with the newer ones. When an archive file in the old format is encountered, it will be updated to the new format, with a warning message. Note that this will overwrite existing archive files! However, there will be no loss of information.

Author(s)

Aaron A. King

Examples

## Not run:
bake(file="example1.rds",{
  x <- runif(1000)
  mean(x)
})
bake(file="example1.rds",{
  x <- runif(1000)
  mean(x)
})
bake(file="example1.rds",{
  a <- 3
  x <- runif(1000)
  mean(x)
})
a <- 5
b <- 2

stew(file="example2.rda",
dependson=list(a,b),{
  x <- runif(10)
y <- rnorm(n=10,mean=a*x+b,sd=2)
})

plot(x,y)

set.seed(11)
runif(2)
freeze(runif(3),seed=5886730)
runif(2)
freeze(runif(3),seed=5886730)
runif(2)

set.seed(11)
runif(2)
runif(2)
runif(2)

## End(Not run)

---

**ricker**

*Ricker model with Poisson observations.*

**Description**

*ricker* is a ‘pomp’ object encoding a stochastic Ricker model with Poisson measurement error.

**Usage**

```r
ricker(r = exp(3.8), sigma = 0.3, phi = 10, c = 1, N_0 = 7)
```

**Arguments**

- **r** intrinsic growth rate
- **sigma** environmental process noise s.d.
- **phi** sampling rate
- **c** density dependence parameter
- **N_0** initial condition

**Details**

The state process is \( N_{t+1} = r N_t \exp(-c N_t + e_t) \), where the \( e_t \) are i.i.d. normal random deviates with zero mean and variance \( \sigma^2 \). The observed variables \( y_t \) are distributed as \( \text{Poisson}(\phi N_t) \).
Value

A ‘pomp’ object containing the Ricker model and simulated data.

See Also

More examples provided with pomp: SIR models, blowflies, childhood disease data, dacca(), ebola, gompertz(), ou2(), pomp examples, rw2(), verhulst()

Examples

```r
po <- ricker()
plot(po)
coef(po)
simulate(po) |> plot()
# takes too long for R CMD check
## generate a bifurcation diagram for the Ricker map
p <- parmat(coef(ricker()),nrep=500)
p["r",] <- exp(seq(from=1.5,to=4,length=500))
trajectory(
  ricker(),
  times=seq(from=1000,to=2000,by=1),
  params=p,
  format="array"
) -> x
matplot(p["r",],x["N",],pch=`,.`,col=`,black`,
  xlab=expression(log(r)),ylab="N",log=`,x`
)
```

Description

Samples from the initial-state distribution.

Usage

```r
## S4 method for signature 'pomp'
rintit(object, params = coef(object), t0 = timezero(object), nsim = 1, ...)
```

Arguments

- **object**: an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of pomp, simulate, or one of the pomp inference algorithms.
- **params**: a npar x nrep matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of x.
- **t0**: the initial time, i.e., the time corresponding to the initial-state distribution.
- **nsim**: optional integer; the number of initial states to simulate per column of params.
- **...**: additional arguments are ignored.
Value

\texttt{rinit} returns an \texttt{nvar x nsim x ncol(params)} matrix of state-process initial conditions when given an \texttt{npar x nsim} matrix of parameters, \texttt{params}, and an initial time \texttt{t0}. By default, \texttt{t0} is the initial time defined when the ‘pomp’ object was constructed.

See Also

Specification of the initial-state distribution: \texttt{rinit specification}

More on \texttt{pomp} workhorse functions: \texttt{dmeasure(), dprior(), dprocess(), emeasure(), flow(), partrans(), pomp-package, rmeasure(), rprior(), rprocess(), skeleton(), vmeasure(), workhorses}

\begin{verbatim}

rinit specification The initial-state distribution

Description
Specification of the initial-state distribution simulator, rinit.

Details
To fully specify the unobserved Markov state process, one must give its distribution at the zero-time (t0). One does this by furnishing a value for the \texttt{rinit} argument. As usual, this can be provided either as a C snippet or as an R function. In the former case, bear in mind that:

1. The goal of a this snippet is the construction of a state vector, i.e., the setting of the dynamical states at time t0.
2. In addition to the parameters and covariates (if any), the variable \texttt{t}, containing the zero-time, will be defined in the context in which the snippet is executed.
3. \textbf{NB:} The \texttt{statenames} argument plays a particularly important role when the \texttt{rinit} is specified using a C snippet. In particular, every state variable must be named in \texttt{statenames}. Failure to follow this rule will result in undefined behavior.

General rules for writing C snippets can be found here.

If an R function is to be used, pass

\begin{verbatim}
rinit = f
\end{verbatim}

to \texttt{pomp}, where \texttt{f} is a function with arguments that can include the initial time \texttt{t0}, any of the model parameters, and any covariates. As usual, \texttt{f} may take additional arguments, provided these are passed along with it in the call to \texttt{pomp}. \texttt{f} must return a named numeric vector of initial states. It is of course important that the names of the states match the expectations of the other basic components.

Note that the state-process \texttt{rinit} can be either deterministic (as in the default) or stochastic. In the latter case, it samples from the distribution of the state process at the zero-time, \texttt{t0}.
**Default behavior**

By default, pomp assumes that the initial distribution is concentrated on a single point. In particular, any parameters in `params`, the names of which end in "\_0" or "\_0.0", are assumed to be initial values of states. When the state process is initialized, these are simply copied over as initial conditions. The names of the resulting state variables are obtained by dropping the suffix.

**Note for Windows users**

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

**See Also**

- `rinit`
- More on implementing POMP models: `Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp.prior specification, rmeasure specification, rprocess specification, skeleton specification, transformations, userdata, vmeasure specification`

**Examples**

```r
## Starting with an existing pomp object

verhulst() -> po

## we add or change the initial-state simulator, `rinit`, using the 'rinit' argument in any 'pomp' or elementary or estimation function (or in the 'pomp' constructor itself).
## Here, we pass the rinit specification to 'simulate' as an R function.

po |> simulate(
     rinit=function (n_0, ...) {
       c(n=rpois(n=1,lambda=n_0))
     } |
   ) -> sim

## We can also pass it as a C snippet:

po |> simulate(
     rinit=Csnippet("n = rpois(n_0);") |
   paramnames="n_0",
```
Description

Sample from the measurement model distribution, given values of the latent states and the parameters.

Usage

```r
## S4 method for signature 'pomp'
rmeasure(
  object,
  x = states(object),
  times = time(object),
  params = coef(object),
  ...
)
```

Arguments

- **object**: an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of `pomp`, `simulate`, or one of the `pomp` inference algorithms.
- **x**: an array containing states of the unobserved process. The dimensions of x are `nvars x nrep x ntimes`, where `nvars` is the number of state variables, `nrep` is the number of replicates, and `ntimes` is the length of `times`. One can also pass `x` as a named numeric vector, which is equivalent to the `nrep=1, ntimes=1` case.
- **times**: a numeric vector (length `ntimes`) containing times. These must be in non-decreasing order.
- **params**: a `npar x nrep` matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of `x`.
- **...**: additional arguments are ignored.

Value

`rmeasure` returns a rank-3 array of dimensions `nobs x nrep x ntimes`, where `nobs` is the number of observed variables.

See Also

Specification of the measurement-model simulator: `rmeasure specification`

More on `pomp` workhorse functions: `dmeasure()`, `dprior()`, `dprocess()`, `emeasure()`, `flow()`, `partrans()`, `pomp-package`, `rinit()`, `rprior()`, `rprocess()`, `skeleton()`, `vmeasure()`, `workhorses`
The measurement-model simulator

Description
Specification of the measurement-model simulator, rmeasure.

Details
The measurement model is the link between the data and the unobserved state process. It can be specified either by using one or both of the rmeasure and dmeasure arguments.

Suppose you have a procedure to simulate observations given the value of the latent state variables. Then you can furnish

\[ rmeasure = f \]

to pomp algorithms, where \( f \) is a C snippet or R function that implements your procedure.

Using a C snippet is much preferred, due to its much greater computational efficiency. See Csnippet for general rules on writing C snippets.

In writing an rmeasure C snippet, bear in mind that:

1. The goal of such a snippet is to fill the observables with random values drawn from the measurement model distribution. Accordingly, each observable should be assigned a new value.
2. In addition to the states, parameters, and covariates (if any), the variable \( t \), containing the time of the observation, will be defined in the context in which the snippet is executed.

The demos and the tutorials on the package website give examples.

It is also possible, though far less efficient, to specify rmeasure using an R function. In this case, specify the measurement model simulator by furnishing

\[ rmeasure = f \]

to pomp, where \( f \) is an R function. The arguments of \( f \) should be chosen from among the state variables, parameters, covariates, and time. It must also have the argument \( \ldots \ f \) must return a named numeric vector of length equal to the number of observable variables.

Default behavior
The default rmeasure is undefined. It will yield missing values (NA).

Note for Windows users
Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the cdir and cfile options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.
### Examples

```r
## We start with the pre-built Ricker example:

ricker() -> po

## To change the measurement model simulator, rmeasure, we use the 'rmeasure' argument in any 'pomp' elementary or estimation function. Here, we pass the rmeasure specification to 'simulate' as an R function.

po |> simulate(
    rmeasure=function (N, phi, ...) {
        c(y=rpois(n=1,lambda=phi*N))
    }
) -> sim

## We can also pass it as a C snippet:

po |> simulate(
    rmeasure=Csnippet("y = rpois(phi*N);"),
    paramnames="phi",
    statenames="N"
) -> sim
```

### Description

Sample from the prior probability distribution.

### Usage

```r
## S4 method for signature 'pomp'
rprior(object, params = coef(object), ...)
```
Arguments

object  an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of pomp, simulate, or one of the pomp inference algorithms.

params a \( npar \times nrep \) matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of \( x \).

... additional arguments are ignored.

Value

A numeric matrix containing the required samples.

See Also

Specification of the prior distribution simulator: prior specification

More on pomp workhorse functions: dmeasure(), dprior(), dprocess(), emeasure(), flow(), partrans(), pomp-package, rinit(), rmeasure(), rprocess(), skeleton(), vmeasure(), workhorses

More on Bayesian methods: approximate Bayesian computation, bsmc2(), dprior(), pmcmc(), prior specification

rprocess  

Description

rprocess simulates the process-model portion of partially-observed Markov process.

Usage

## S4 method for signature 'pomp'
rprocess(
  object,
  x0 = rinit(object),
  t0 = timezero(object),
  times = time(object),
  params = coef(object),
  ...
)

Arguments

object  an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of pomp, simulate, or one of the pomp inference algorithms.

x0  an \( nvar \times nrep \) matrix containing the starting state of the system. Columns of \( x0 \) correspond to states; rows to components of the state vector. One independent simulation will be performed for each column. Note that in this case, params must also have \( nrep \) columns.
rprocess specification

The latent state process simulator

Description

Specification of the latent state process simulator, rprocess.

Usage

onestep(step.fun)

discrete_time(step.fun, delta.t = 1)

euler(step.fun, delta.t)

gillespie(rate.fun, v, hmax = Inf)

gillespie_hl(..., .pre = "", .post = "", hmax = Inf)
Arguments

step.fun  
a C snippet, an R function, or the name of a native routine in a shared-object library. This gives a procedure by which one simulates a single step of the latent state process.

delta.t  
positive numerical value; for euler and discrete_time, the size of the step to take

rate.fun  
a C snippet, an R function, or the name of a native routine in a shared-object library. This gives a procedure by which one computes the event-rate of the elementary events in the continuous-time latent Markov chain.

v  
integer matrix; giving the stoichiometry of the continuous-time latent Markov process. It should have dimensions nvar x nevent, where nvar is the number of state variables and nevent is the number of elementary events. v describes the changes that occur in each elementary event: it will usually comprise the values 1, -1, and 0 according to whether a state variable is incremented, decremented, or unchanged in an elementary event. The rows of v may be unnamed or named. If the rows are unnamed, they are assumed to be in the same order as the vector of state variables returned by rinit. If the rows are named, the names of the state variables returned by rinit will be matched to the rows of v to ensure a correct mapping. If any of the row names of v cannot be found among the state variables or if any row names of v are duplicated, an error will occur.

hmax  
maximum time step allowed (see below)

...  
individual C snippets corresponding to elementary events

.pre, .post  
C snippets (see Details)

Discrete-time processes

If the state process evolves in discrete time, specify rprocess using the discrete_time plug-in. Specifically, provide

\[
\text{rprocess} = \text{discrete_time}(\text{step.fun} = f, \text{delta.t}),
\]

where f is a C snippet or R function that simulates one step of the state process. The former is the preferred option, due to its much greater computational efficiency. The goal of such a C snippet is to replace the state variables with their new random values at the end of the time interval. Accordingly, each state variable should be overwritten with its new value. In addition to the states, parameters, covariates (if any), and observables, the variables t and dt, containing respectively the time at the beginning of the step and the step’s duration, will be defined in the context in which the C snippet is executed. See Csnippet for general rules on writing C snippets. Examples are to be found in the tutorials on the package website.

If f is given as an R function, its arguments should come from the state variables, parameters, covariates, and time. It may also take the argument ‘delta.t’; when called, the latter will be the timestep. It must also have the argument ‘...’. It should return a named vector of length equal to the number of state variables, representing a draw from the distribution of the state process at time t+delta.t conditional on its value at time t.
### Continuous-time processes

If the state process evolves in continuous time, but you can use an Euler approximation, implement `rprocess` using the `euler` plug-in. Specify

```
rprocess = euler(step.fun = f, delta.t)
```

in this case. As before, `f` can be provided either as a C snippet or as an R function, the former resulting in much quicker computations. The form of `f` will be the same as above (in the discrete-time case).

If you have a procedure that allows you, given the value of the state process at any time, to simulate it at an arbitrary time in the future, use the `onestep` plug-in. To do so, specify

```
rprocess = onestep(step.fun = f).
```

Again, `f` can be provided either as a C snippet or as an R function, the former resulting in much quicker computations. The form of `f` should be as above (in the discrete-time or Euler cases).

### Size of time step

The simulator plug-ins `discrete_time`, `euler`, and `onestep` all work by taking discrete time steps. They differ as to how this is done. Specifically,

1. `onestep` takes a single step to go from any given time `t1` to any later time `t2` (`t1 < t2`). Thus, this plug-in is designed for use in situations where a closed-form solution to the process exists.
2. To go from `t1` to `t2`, `euler` takes `n` steps of equal size, where
   ```
   n = ceiling((t2-t1)/delta.t).
   ```
3. `discrete_time` assumes that the process evolves in discrete time, where the interval between successive times is `delta.t`. Thus, to go from `t1` to `t2`, `discrete_time` takes `n` steps of size exactly `delta.t`, where
   ```
   n = floor((t2-t1)/delta.t).
   ```

### Exact (event-driven) simulations

If you desire exact simulation of certain continuous-time Markov chains, an implementation of Gillespie’s algorithm (Gillespie 1977) is available, via the `gillespie` and `gillespie_hl` plug-ins.

The former allows for the rate function to be provided as an R function or a single C snippet, while the latter provides a means of specifying the elementary events via a list of C snippets.

A high-level interface to the simulator is provided by `gillespie_hl`. To use it, supply

```
rprocess = gillespie_hl(..., .pre = "", .post = "", hmax = Inf)
```
to `pomp`. Each argument in `...` corresponds to a single elementary event and should be a list containing two elements. The first should be a string or C snippet; the second should be a named integer vector. The variable `rate` will exist in the context of the C snippet, as will the parameter, state variables, covariates, and the time `t`. The C snippet should assign to the variable `rate` the corresponding elementary event rate.
The named integer vector specifies the changes to the state variables corresponding to the elementary event. There should be a named value for each of the state variables returned by \texttt{rinit}. The arguments \texttt{.pre} and \texttt{.post} can be used to provide C code that will run respectively before and after the elementary-event snippets. These hooks can be useful for avoiding duplication of code that performs calculations needed to obtain several of the different event rates.

Here's how a simple birth-death model might be specified:

\begin{verbatim}
gillespie_hl(
    birth=list("rate = b*N;",c(N=1)),
    death=list("rate = m*N;",c(N=-1))
)
\end{verbatim}

In the above, the state variable \texttt{N} represents the population size and parameters \texttt{b}, \texttt{m} are the birth and death rates, respectively.

To use the lower-level \texttt{gillespie} interface, furnish

\begin{verbatim}
rprocess = gillespie(rate.fun = f, v, hmax = Inf)
\end{verbatim}

to \texttt{pomp}, where \texttt{f} gives the rates of the elementary events. Here, \texttt{f} may be an R function of the form

\begin{verbatim}
f(j, x, t, params, ...)
\end{verbatim}

When \texttt{f} is called, the integer \texttt{j} will be the number of the elementary event (corresponding to the column the matrix \texttt{v}, see below). \texttt{x} will be a named numeric vector containing the value of the state process at time \texttt{t} and \texttt{params} is a named numeric vector containing parameters. \texttt{f} should return a single numerical value, representing the rate of that elementary event at that point in state space and time.

Here, the stoichiometric matrix \texttt{v} specifies the continuous-time Markov process in terms of its elementary events. It should have dimensions \texttt{nvar x nevent}, where \texttt{nvar} is the number of state variables and \texttt{nevent} is the number of elementary events. \texttt{v} describes the changes that occur in each elementary event: it will usually comprise the values 1, -1, and 0 according to whether a state variable is incremented, decremented, or unchanged in an elementary event. The rows of \texttt{v} should have names corresponding to the state variables. If any of the row names of \texttt{v} cannot be found among the state variables or if any row names of \texttt{v} are duplicated, an error will occur.

It is also possible to provide a C snippet via the \texttt{rate.fun} argument to \texttt{gillespie}. Such a snippet should assign the correct value to a rate variable depending on the value of \texttt{j}. The same variables will be available as for the C code provided to \texttt{gillespie_hl}. This lower-level interface may be preferable if it is easier to write code that calculates the correct rate based on \texttt{j} rather than to write a snippet for each possible value of \texttt{j}. For example, if the number of possible values of \texttt{j} is large and the rates vary according to a few simple rules, the lower-level interface may provide the easier way of specifying the model.

When the process is non-autonomous (i.e., the event rates depend explicitly on time), it can be useful to set \texttt{hmax} to the maximum step that will be taken. By default, the elementary event rates will be recomputed at least once per observation interval.

**Default behavior**

The default \texttt{rprocess} is undefined. It will yield missing values (\texttt{NA}) for all state variables.
Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the cdir and cfile options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

See Also

rprocess

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, skeleton specification, transformations, userdata, vmeasure specification

---

**rw2**

*Two-dimensional random-walk process*

**Description**

rw2 constructs a 'pomp' object encoding a 2-D Gaussian random walk.

**Usage**

rw2(x1_0 = 0, x2_0 = 0, s1 = 1, s2 = 3, tau = 1, times = 1:100, t0 = 0)

**Arguments**

- x1_0, x2_0: initial conditions (i.e., latent state variable values at the zero time t0)
- s1, s2: random walk intensities
- tau: observation error s.d.
- times: observation times
- t0: zero time

**Details**

The random-walk process is fully but noisily observed.

**Value**

A ‘pomp’ object containing simulated data.

**See Also**

More examples provided with pomp: SIR models, blowflies, childhood disease data, dacca(), ebola, gompertz(), ou2(), pomp examples, ricker(), verhulst()
Examples

```r
if (require(ggplot2)) {
  rw2() |> plot()
  rw2(s1=1,s2=1,tau=0.1) |> 
    simulate(nsim=10,format="d") |> 
    ggplot(aes(x=y1,y=y2,group=.id,color=.id))+ 
    geom_path()+ 
    guides(color="none")+ 
    theme_bw()
}
```

Description

Specifying random-walk intensities.

Usage

```r
rw_sd(...)
```

Arguments

```r
...
```

Specification of the random-walk intensities (as standard deviations).

Details

See `mif2` for details.

See Also

`mif2`
Simulated annealing with box constraints.

Description
A straightforward implementation of simulated annealing with box constraints.

Usage
\[
sannbox(par, fn, control = list(), \ldots)
\]

Arguments
- **par**: Initial values for the parameters to be optimized over.
- **fn**: A function to be minimized, with first argument the vector of parameters over which minimization is to take place. It should return a scalar result.
- **control**: A named list of control parameters. See ‘Details’.
- **\ldots**: ignored.

Details
The control argument is a list that can supply any of the following components:

- **trace**: Non-negative integer. If positive, tracing information on the progress of the optimization is produced. Higher values may produce more tracing information.
- **fnscale**: An overall scaling to be applied to the value of \( fn \) during optimization. If negative, turns the problem into a maximization problem. Optimization is performed on \( fn(par)/fnscale \).
- **parscale**: A vector of scaling values for the parameters. Optimization is performed on \( par/parscale \) and these should be comparable in the sense that a unit change in any element produces about a unit change in the scaled value.
- **maxit**: The total number of function evaluations: there is no other stopping criterion. Defaults to 10000.
- **temp**: starting temperature for the cooling schedule. Defaults to 1.
- **tmax**: number of function evaluations at each temperature. Defaults to 10.
- **candidate.dist**: function to randomly select a new candidate parameter vector. This should be a function with three arguments, the first being the current parameter vector, the second the temperature, and the third the parameter scaling. By default, candidate.dist is
  \[
  \text{function}(par, temp, scale) \\
  \quad \text{rnorm}(n=length(par), mean=par, sd=scale*temp).
  \]
- **sched**: cooling schedule. A function of a three arguments giving the temperature as a function of iteration number and the control parameters temp and tmax. By default, sched is
  \[
  \text{function}(k, temp, tmax) \quad \text{temp/log(((k-1)%/%tmax)*tmax+exp(1))}.
  \]
Alternatively, one can supply a numeric vector of temperatures. This must be of length at least maxit.

lower, upper optional numeric vectors. These describe the lower and upper box constraints, respectively. Each can be specified either as a single scalar (common to all parameters) or as a vector of the same length as par. By default, lower = -Inf and upper = Inf, i.e., there are no constraints.

Value

sannbox returns a list with components:

counts two-element integer vector. The first number gives the number of calls made to fn. The second number is provided for compatibility with optim and will always be NA.

convergence provided for compatibility with optim; will always be 0.

final.params last tried value of par.

final.value value of fn corresponding to final.params.

par best tried value of par.

value value of fn corresponding to par.

Author(s)

Daniel Reuman, Aaron A. King

See Also

trajectory matching, probe matching, spectrum matching, nonlinear forecasting.

===

saved_states

Saved states

Description

Retrieve latent state trajectories from a particle filter calculation.

Usage

## S4 method for signature 'pfilterd_pomp'
saved_states(object, ..., format = c("list", "data.frame"))

## S4 method for signature 'pfilterList'
saved_states(object, ..., format = c("list", "data.frame"))

Arguments

object result of a filtering computation

... ignored

format character; format of the returned object (see below).
Details

When one calls `pfilter` with `save.states=TRUE`, the latent state vector associated with each particle is saved. This can be extracted by calling `saved_states` on the 'pfilterd.pomp' object. These are the *unweighted* particles, saved after resampling.

Value

According to the `format` argument, the saved states are returned either as a list or a data frame.

If `format="data.frame"`, then the returned data frame holds the state variables and (optionally) the unnormalized log weight of each particle at each observation time. The `.id` variable distinguishes particles.

If `format="list"` and `pfilter` was called with `save.states="unweighted"` or `save.states="TRUE"`, the returned list contains one element per observation time. Each element consists of a matrix, with one row for each state variable and one column for each particle. If `pfilter` was called with `save.states="weighted"`, the list itself contains two lists: the first holds the particles as above, the second holds the corresponding unnormalized log weights. In particular, it has one element per observation time; each element is the vector of per-particle log weights.

See Also

More on sequential Monte Carlo methods: `bsmc2`, `cond_logLik`, `eff_sample_size`, `filter_mean`, `filter_traj`, `kalman`, `mif2`, `pfilter`, `pmcmc`, `pred_mean`, `pred_var`, `wpfilter`

Other extraction methods: `coef`, `cond_logLik`, `covmat`, `eff_sample_size`, `filter_mean`, `filter_traj`, `forecast`, `logLik.obs`, `pred_mean`, `pred_var`, `spy`, `states`, `summary`, `timezero`, `time`, `traces`

simulate Simulations of a partially-observed Markov process

Description

`simulate` generates simulations of the state and measurement processes.

Usage

```r
## S4 method for signature 'missing'
simulate(
  nsim = 1,
  seed = NULL,
  times,
  t0,
  params,
  rinit,
  rprocess,
  rmeasure,
  format = c("pomps", "arrays", "data.frame"),
)```
include.data = FALSE,
..., verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'data.frame'
simulate(
  object,
  nsim = 1,
  seed = NULL,
  times,
  t0,
  params,
  rinit,
  rprocess,
  rmeasure,
  format = c("pomps", "arrays", "data.frame"),
  include.data = FALSE,
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'
simulate(
  object,
  nsim = 1,
  seed = NULL,
  format = c("pomps", "arrays", "data.frame"),
  include.data = FALSE,
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'objfun'
simulate(object, nsim = 1, seed = NULL, ...)

Arguments

nsim The number of simulations to perform. Note that the number of replicates will be nsim times ncol(params).

seed optional; if set, the pseudorandom number generator (RNG) will be initialized with seed. The random seed to use. The RNG will be restored to its original state afterward.

times the sequence of observation times. times must indicate the column of observation times by name or index. The time vector must be numeric and non-decreasing.

t0 The zero-time, i.e., the time of the initial state. This must be no later than the time of the first observation, i.e., t0 <= times[1].
params: a named numeric vector or a matrix with rownames containing the parameters at which the simulations are to be performed.

rinit: simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator to its default. For more information, see rinit specification.

rprocess: simulator of the latent-state process, specified using one of the rprocess plugins. Setting rprocess=NULL removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

rmeasure: simulator of the measurement model, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rmeasure=NULL removes the measurement model simulator. For more information, see rmeasure specification.

format: the format in which to return the results.
- format = "pomp" causes the results to be returned as a single “pomp” object, identical to object except for the latent states and observations, which have been replaced by the simulated values.
- format = "arrays" causes the results to be returned as a list of two arrays. The “states” element will contain the simulated state trajectories in a rank-3 array with dimensions nvar x (ncol(params)*nsim) x ntimes. Here, nvar is the number of state variables and ntimes the length of the argument times. The “obs” element will contain the simulated data, returned as a rank-3 array with dimensions nobs x (ncol(params)*nsim) x ntimes. Here, nobs is the number of observables.
- format = "data.frame" causes the results to be returned as a single data frame containing the time, states, and observations. An ordered factor variable, ‘.id’, distinguishes one simulation from another.

include.data: if TRUE, the original data and covariates (if any) are included (with .id = "data"). This option is ignored unless format = "data.frame".

verbose: logical; if TRUE, diagnostic messages will be printed to the console.

object: optional; if present, it should be a data frame or a ‘pomp’ object.

Value
A single “pomp” object, a “pompList” object, a named list of two arrays, or a data frame, according to the format option.

If params is a matrix, each column is treated as a distinct parameter set. In this case, if nsim=1, then simulate will return one simulation for each parameter set. If nsim>1, then simulate
SIR models

will yield \texttt{nsim} simulations for each parameter set. These will be ordered such that the first \texttt{ncol(params)} simulations represent one simulation from each of the distinct parameter sets, the second \texttt{ncol(params)} simulations represent a second simulation from each, and so on.

Adding column names to \texttt{params} can be helpful.

**Note for Windows users**

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the \texttt{cdir} and \texttt{cfile} options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

**Author(s)**

Aaron A. King

**See Also**

More on \texttt{pomp} elementary algorithms: \texttt{elementary
d algorithms}, \texttt{kalman}, \texttt{pfilter()}, \texttt{pomp-package}, \texttt{probe()}, \texttt{spect()}, \texttt{trajectory()}, \texttt{wpfilter()}

---

**SIR models**

---

**Compartmental epidemiological models**

---

**Description**

Simple SIR-type models implemented in various ways.

**Usage**

```R
sir(
  gamma = 26,
  mu = 0.02,
  iota = 0.01,
  beta1 = 400,
  beta2 = 480,
  beta3 = 320,
  beta_sd = 0.001,
  rho = 0.6,
  k = 0.1,
  pop = 2100000,
  S_0 = 26/400,
  I_0 = 0.001,
  R_0 = 1 - S_0 - I_0,
  t0 = 0,
  times = seq(from = t0 + 1/52, to = t0 + 4, by = 1/52),
)```
SIR models

seed = 329343545,
delta.t = 1/52/20
)
sir2(
  gamma = 24,
  mu = 1/70,
  iota = 0.1,
  beta1 = 330,
  beta2 = 410,
  beta3 = 490,
  rho = 0.1,
  k = 0.1,
  pop = 1e+06,
  S_0 = 0.05,
  I_0 = 1e-04,
  R_0 = 1 - S_0 - I_0,
  t0 = 0,
  times = seq(from = t0 + 1/12, to = t0 + 10, by = 1/12),
  seed = 1772464524
)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>gamma</td>
<td>recovery rate</td>
</tr>
<tr>
<td>mu</td>
<td>death rate (assumed equal to the birth rate)</td>
</tr>
<tr>
<td>iota</td>
<td>infection import rate</td>
</tr>
<tr>
<td>beta1, beta2, beta3</td>
<td>seasonal contact rates</td>
</tr>
<tr>
<td>beta_sd</td>
<td>environmental noise intensity</td>
</tr>
<tr>
<td>rho</td>
<td>reporting efficiency</td>
</tr>
<tr>
<td>k</td>
<td>reporting overdispersion parameter (reciprocal of the negative-binomial size parameter)</td>
</tr>
<tr>
<td>pop</td>
<td>overall host population size</td>
</tr>
<tr>
<td>S_0, I_0, R_0</td>
<td>the fractions of the host population that are susceptible, infectious, and recovered, respectively, at time zero.</td>
</tr>
<tr>
<td>t0</td>
<td>zero time</td>
</tr>
<tr>
<td>times</td>
<td>observation times</td>
</tr>
<tr>
<td>seed</td>
<td>seed of the random number generator</td>
</tr>
<tr>
<td>delta.t</td>
<td>Euler step size</td>
</tr>
</tbody>
</table>

Details

sir() produces a ‘pomp’ object encoding a simple seasonal SIR model with simulated data. Simulation is performed using an Euler multinomial approximation.
sir2() has the same model implemented using Gillespie’s algorithm.
In both cases the measurement model is negative binomial: reports is distributed as a negative
binomial random variable with mean equal to rho\times cases and size equal to 1/k.
This and similar examples are discussed and constructed in tutorials available on the package website.

Value

These functions return ‘pomp’ objects containing simulated data.

See Also

More examples provided with pomp: blowflies, childhood disease data, dacca(), ebola,
gompertz(), ou2(), pomp examples, ricker(), rw2(), verhulst()

Examples

```r
po <- sir()
plot(po)
coef(po)

po <- sir2()
plot(po)
plot(simulate(window(po,end=3)))
coef(po)

po |> as.data.frame() |> head()
```

Description

Evaluates the deterministic skeleton at a point or points in state space, given parameters. In the
case of a discrete-time system, the skeleton is a map. In the case of a continuous-time system, the
skeleton is a vectorfield. NB: skeleton just evaluates the deterministic skeleton; it does not iterate
or integrate (see trajectory for this).

Usage

```r
## S4 method for signature 'pomp'
skeleton(
  object,
  x = states(object),
  times = time(object),
  params = coef(object),
  ...
)
```
**Arguments**

- **object** an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of `pomp`, `simulate`, or one of the `pomp` inference algorithms.
- **x** an array containing states of the unobserved process. The dimensions of `x` are `nvars x nrep x ntimes`, where `nvars` is the number of state variables, `nrep` is the number of replicates, and `ntimes` is the length of `times`. One can also pass `x` as a named numeric vector, which is equivalent to the `nrep=1, ntimes=1` case.
- **times** a numeric vector (length `ntimes`) containing times. These must be in non-decreasing order.
- **params** a `npar x nrep` matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of `x`.
- **...** additional arguments are ignored.

**Value**

`skeleton` returns an array of dimensions `nvar x nrep x ntimes`. If `f` is the returned matrix, `f[i,j,k]` is the i-th component of the deterministic skeleton at time `times[k]` given the state `x[,j,k]` and parameters `params[,j]`.

**See Also**

Specification of the deterministic skeleton: `skeleton specification`

More on `pomp` workhorse functions: `dmeasure()`, `dprior()`, `dprocess()`, `emeasure()`, `flow()`, `partrans()`, `pomp-package`, `rinit()`, `rmeasure()`, `rprior()`, `rprocess()`, `vmeasure()`, `workhorses`

More on methods for deterministic process models: `flow()`, `skeleton specification`, `trajectory matching`, `trajectory()`

---

**skeleton specification**

The deterministic skeleton of a model

---

**Description**

Specification of the deterministic skeleton.

**Usage**

```r
vectorfield(f)
map(f, delta.t = 1)
```

**Arguments**

- **f** procedure for evaluating the deterministic skeleton. This can be a C snippet, an R function, or the name of a native routine in a dynamically linked library.
- **delta.t** positive numerical value; the size of the discrete time step corresponding to an application of the map
skeleton specification

Details

The skeleton is a dynamical system that expresses the central tendency of the unobserved Markov state process. As such, it is not uniquely defined, but can be both interesting in itself and useful in practice. In pomp, the skeleton is used by trajectory and traj_objfun.

If the state process is a discrete-time stochastic process, then the skeleton is a discrete-time map. To specify it, provide

\[ \text{skeleton} = \text{map}(f, \Delta t) \]

to pomp, where \( f \) implements the map and \( \Delta t \) is the size of the timestep covered at one map iteration.

If the state process is a continuous-time stochastic process, then the skeleton is a vectorfield (i.e., a system of ordinary differential equations). To specify it, supply

\[ \text{skeleton} = \text{vectorfield}(f) \]

to pomp, where \( f \) implements the vectorfield, i.e., the right-hand-size of the differential equations.

In either case, \( f \) can be furnished either as a C snippet (the preferred choice), or an R function. General rules for writing C snippets can be found here. In writing a skeleton C snippet, be aware that:

1. For each state variable, there is a corresponding component of the deterministic skeleton. The goal of such a snippet is to compute all the components.
2. When the skeleton is a map, the component corresponding to state variable \( x \) is named \( D_x \) and is the new value of \( x \) after one iteration of the map.
3. When the skeleton is a vectorfield, the component corresponding to state variable \( x \) is named \( D_x \) and is the value of \( dx/dt \).
4. As with the other C snippets, all states, parameters and covariates, as well as the current time, \( t \), will be defined in the context within which the snippet is executed.
5. NB: When the skeleton is a map, the duration of the timestep will not be defined in the context within which the snippet is executed. When the skeleton is a vectorfield, of course, no timestep is defined. In this regard, C snippets for the skeleton and rprocess components differ.

The tutorials on the package website give some examples.

If \( f \) is an R function, its arguments should be taken from among the state variables, parameters, covariates, and time. It must also take the argument ‘...’. As with the other basic components, \( f \) may take additional arguments, provided these are passed along with it in the call to pomp. The function \( f \) must return a numeric vector of the same length as the number of state variables, which contains the value of the map or vectorfield at the required point and time.

Masking of map

Other packages (most notably the tidyverse package purrr) have functions named ‘map’. Beware that, if you load one of these packages after you load pomp, the pomp function map described here will be masked. You can always access the pomp function by calling pomp::map.
Default behavior

The default skeleton is undefined. It will yield missing values (NA) for all state variables.

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

See Also

`skeleton`

More on implementing POMP models: `Csnippet`, `accumulator variables`, `basic components`, `betabinomial`, `covariates`, `distributions`, `dmeasure specification`, `dprocess specification`, `emeasure specification`, `parameter transformations`, `pomp-package`, `pomp.prior specification`, `rinit specification`, `rmeasure specification`, `rprocess specification`, `transformations`, `userdata`, `vmeasure specification`

More on methods for deterministic process models: `flow()`, `skeleton()`, `trajectory matching`, `trajectory()`

Examples

```r
## Starting with an existing pomp object, 
## e.g., the continuous-time Verhulst-Pearl model,

verhulst() -> po

## we add or change the deterministic skeleton 
## using the 'skeleton' argument in any 'pomp' 
## elementary or estimation function 
## (or in the 'pomp' constructor itself).
## Here, we pass the skeleton specification 
## to 'trajectory' as an R function. 
## Since this is a continuous-time POMP, the 
## skeleton is a vectorfield.

po |>
  trajectory(
    skeleton=vectorfield(
      function(r, K, n, ...) {
        c(n=r*n*(1-n/K))
      }
    ),
    format="data.frame"
  ) -> traj

## We can also pass it as a C snippet:
```
### For a discrete-time POMP, the deterministic skeleton is a map. For example,

```
gompertz() -> po
```

```
po |> traj_objfun(
  skeleton=vectorfield(Csnippet("Dn=r*n*(1-n/K);")),
  paramnames=c("r","K"),
  statenames="n"
) -> ofun

ofun()
```

```
## For a discrete-time POMP, the deterministic skeleton is a map. For example,

gompertz() -> po
```

```
po |> traj_objfun(
  skeleton=map(
    Csnippet("
      double dt = 1.0;
      double s = exp(-r*dt);
      DX = pow(K,(1-s))*pow(X,s);
      ), delta.t=1
    ),
    paramnames=c("r","K"),
    statenames=c("X")
) -> ofun

ofun()
```

---

**spect**

---

### Description

Power spectrum computation and spectrum-matching for partially-observed Markov processes.

### Usage

```
## S4 method for signature 'data.frame'
spect(
  data,
  vars,
  kernel.width,
  nsim,
  seed = NULL,
  transform.data = identity,
  detrend = c("none", "mean", "linear", "quadratic"),
```

params,
  rinit,
  rprocess,
  rmeasure,
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'
spect(  
data,
  vars,
  kernel.width,
  nsim,
  seed = NULL,
  transform.data = identity,
  detrend = c("none", "mean", "linear", "quadratic"),
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'spectd_pomp'
spect(  
data,
  vars,
  kernel.width,
  nsim,
  seed = NULL,
  transform.data,
  detrend,
  ...
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'spect_match_objfun'
spect(data, seed, ..., verbose = getOption("verbose", FALSE))

## S4 method for signature 'objfun'
spect(data, seed = NULL, ...)

Arguments

data either a data frame holding the time series data, or an object of class 'pomp', i.e., the output of another pomp calculation. Internally, data will be internally coerced to an array with storage-mode double.

vars optional; names of observed variables for which the power spectrum will be computed. By default, the spectrum will be computed for all observables.

kernel.width width parameter for the smoothing kernel used for calculating the estimate of
the spectrum.

nsim  
number of model simulations to be computed.

seed  
optional; if non-NULL, the random number generator will be initialized with this seed for simulations. See simulate.

transform.data  
function; this transformation will be applied to the observables prior to estimation of the spectrum, and prior to any detrending.

detrend  
de-trending operation to perform. Options include no detrending, and subtraction of constant, linear, and quadratic trends from the data. Detrending is applied to each data series and to each model simulation independently.

params  
optional; named numeric vector of parameters. This will be coerced internally to storage mode double.

rinit  
simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator to its default. For more information, see rinit specification.

rprocess  
simulator of the latent state process, specified using one of the rprocess plugins. Setting rprocess=NULL removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

rmeasure  
simulator of the measurement model, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rmeasure=NULL removes the measurement model simulator. For more information, see rmeasure specification.

...  
additional arguments supply new or modify existing model characteristics or components. See pomp for a full list of recognized arguments.

When named arguments not recognized by pomp are provided, these are made available to all basic components via the so-called userdata facility. This allows the user to pass information to the basic components outside of the usual routes of covariates (covar) and model parameters (params). See userdata for information on how to use this facility.

verbose  
logical; if TRUE, diagnostic messages will be printed to the console.

Details

spect estimates the power spectrum of time series data and model simulations and compares the results. It can be used to diagnose goodness of fit and/or as the basis for frequency-domain parameter estimation (spect.match).

A call to spect results in the estimation of the power spectrum for the (transformed, detrended) data and nsim model simulations. The results of these computations are stored in an object of class 'spectd_pomp'.

When spect operates on a spectrum-matching objective function (a 'spect_match_objfun' object), by default, the random-number generator seed is fixed at the value given when the objective function was constructed. Specifying NULL or an integer for seed overrides this behavior.
Value

An object of class `spectd_pomp`, which contains the model, the data, and the results of the spectrum computation. The following methods are available:

- **plot** produces some diagnostic plots
- **summary** displays a summary
- **logLik** gives a measure of the agreement of the power spectra

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Author(s)

Daniel C. Reuman, Cai GoGwilt, Aaron A. King

References


See Also

More on methods based on summary statistics: approximate Bayesian computation, basic probes, nonlinear forecasting, probe matching, probe(), spectrum matching

More on pomp elementary algorithms: elementary algorithms, kalman, pfilter(), pomp-package, probe(), simulate(), trajectory(), wpfilter()
spectrum matching

Usage

```r
## S4 method for signature 'data.frame'
spect_objfun(
  data,
  est = character(0),
  weights = 1,
  fail.value = NA,
  vars,
  kernel.width,
  nsim,
  seed = NULL,
  transform.data = identity,
  detrend = c("none", "mean", "linear", "quadratic"),
  params,
  rinit,
  rprocess,
  rmeasure,
  partrans,
  ...
)

## S4 method for signature 'pomp'
spect_objfun(
  data,
  est = character(0),
  weights = 1,
  fail.value = NA,
  vars,
  kernel.width,
  nsim,
  seed = NULL,
  transform.data = identity,
  detrend = c("none", "mean", "linear", "quadratic"),
  ...
)

## S4 method for signature 'spectd_pomp'
spect_objfun(
  data,
  est = character(0),
  weights = 1,
  fail.value = NA,
  vars,
  kernel.width,
  nsim,
  seed = NULL,
  ```
transform.data = identity,
    detrend,
    ...
    verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'spect_match_objfun'
spect_objfun(
    data,
    est,
    weights,
    fail.value,
    seed = NULL,
    ...
    verbose = getOption("verbose", FALSE)
)

### Arguments

- **data**: either a data frame holding the time series data, or an object of class `pomp`, i.e., the output of another `pomp` calculation. Internally, data will be internally coerced to an array with storage-mode double.
- **est**: character vector; the names of parameters to be estimated.
- **weights**: optional numeric or function. The mismatch between model and data is measured by a weighted average of mismatch at each frequency. By default, all frequencies are weighted equally. weights can be specified either as a vector (which must have length equal to the number of frequencies) or as a function of frequency. If the latter, weights(freq) must return a nonnegative weight for each frequency.
- **fail.value**: optional numeric scalar; if non-NA, this value is substituted for non-finite values of the objective function. It should be a large number (i.e., bigger than any legitimate values the objective function is likely to take).
- **vars**: optional; names of observed variables for which the power spectrum will be computed. By default, the spectrum will be computed for all observables.
- **kernel.width**: width parameter for the smoothing kernel used for calculating the estimate of the spectrum.
- **nsim**: the number of model simulations to be computed.
- **seed**: integer. When fitting, it is often best to fix the seed of the random-number generator (RNG). This is accomplished by setting seed to an integer. By default, seed = NULL, which does not alter the RNG state.
- **transform.data**: function; this transformation will be applied to the observables prior to estimation of the spectrum, and prior to any detrending.
- **detrend**: de-trending operation to perform. Options include no detrending, and subtraction of constant, linear, and quadratic trends from the data. Detrending is applied to each data series and to each model simulation independently.
**params**
optional; named numeric vector of parameters. This will be coerced internally to storage mode `double`.

**rinit**
simulator of the initial-state distribution. This can be furnished either as a C snippet, an `R` function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting `rinit=NULL` sets the initial-state simulator to its default. For more information, see `rinit specification`.

**rprocess**
simulator of the latent state process, specified using one of the `rprocess plugins`. Setting `rprocess=NULL` removes the latent-state simulator. For more information, see `rprocess specification for the documentation on these plugins`.

**rmeasure**
simulator of the measurement model, specified either as a C snippet, an `R` function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting `rmeasure=NULL` removes the measurement model simulator. For more information, see `rmeasure specification`.

**partrans**
optional parameter transformations, constructed using `parameter_trans`. Many algorithms for parameter estimation search an unconstrained space of parameters. When working with such an algorithm and a model for which the parameters are constrained, it can be useful to transform parameters. One should supply the `partrans` argument via a call to `parameter_trans`. For more information, see `parameter_trans`. Setting `partrans=NULL` removes the parameter transformations, i.e., sets them to the identity transformation.

**verbose**
logical; if `TRUE`, diagnostic messages will be printed to the console.

**Details**

In spectrum matching, one attempts to minimize the discrepancy between a POMP model’s predictions and data, as measured in the frequency domain by the power spectrum.

`spect_objfun` constructs an objective function that measures the discrepancy. It can be passed to any one of a variety of numerical optimization routines, which will adjust model parameters to minimize the discrepancies between the power spectrum of model simulations and that of the data.

**Value**

`spect_objfun` constructs a stateful objective function for spectrum matching. Specifically, `spect_objfun` returns an object of class ‘spect_match_objfun’, which is a function suitable for use in an `optim`-like optimizer. This function takes a single numeric-vector argument that is assumed to contain the parameters named in `est`, in that order. When called, it will return the (optionally weighted) $L^2$ distance between the data spectrum and simulated spectra. It is a stateful function: Each time it is called, it will remember the values of the parameters and the discrepancy measure.
Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Important Note

Since `pomp` cannot guarantee that the final call an optimizer makes to the function is a call at the optimum, it cannot guarantee that the parameters stored in the function are the optimal ones. Therefore, it is a good idea to evaluate the function on the parameters returned by the optimization routine, which will ensure that these parameters are stored.

Warning! Objective functions based on C snippets

If you use C snippets (see `Csnippet`), a dynamically loadable library will be built. As a rule, `pomp` functions load this library as needed and unload it when it is no longer needed. The stateful objective functions are an exception to this rule. For efficiency, calls to the objective function do not execute `pompLoad` or `pompUnload`: rather, it is assumed that `pompLoad` has been called before any call to the objective function. When a stateful objective function using one or more C snippets is created, `pompLoad` is called internally to build and load the library: therefore, within a single R session, if one creates a stateful objective function, one can freely call that objective function and (more to the point) pass it to an optimizer that calls it freely, without needing to call `pompLoad`. On the other hand, if one retrieves a stored objective function from a file, or passes one to another R session, one must call `pompLoad` before using it. Failure to do this will typically result in a segmentation fault (i.e., it will crash the R session).

See Also

`spect`, `optim`, `subplex`, `nloptr`

More on `pomp` estimation algorithms: `approximate Bayesian computation`, `bsmc2()`, `estimation algorithms`, `mif2()`, `nonlinear forecasting`, `pmcmc()`, `pomp-package`, `probe matching`

More on methods based on summary statistics: `approximate Bayesian computation`, `basic probes`, `nonlinear forecasting`, `probe matching`, `probe()` , `spect()` 

More on maximization-based estimation methods: `mif2()`, `nonlinear forecasting`, `probe matching`, `trajectory matching`

Examples

```r
ricker() %>%
spect_objfun(
est=c("r","sigma","N_0"),
partrans=parameter_trans(log=c("r","sigma","N_0")),
paramnames=c("r","sigma","N_0"),
kernwidth=3,
nsim=100,
```
spy

### Description

Peek into the inside of one of pomp's objects.

### Usage

```r
## S4 method for signature 'pomp'
spy(object)
```

### Arguments

- **object**
  - the object whose structure we wish to examine

### See Also

Csnippet

Other extraction methods: `coef()`, `cond_logLik()`, `covmat()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `forecast()`, `logLik.obs()`, `pred_mean()`, `pred_var()`, `saved_states()`, `states()`, `summary()`, `timezero()`, `time()`, `traces()`
states

Latent states

Description
Extract the latent states from a 'pomp' object.

Usage
```r
## S4 method for signature 'pomp'
states(object, vars, ..., format = c("array", "data.frame"))
```

```r
## S4 method for signature 'listie'
states(object, vars, ..., format = c("array", "data.frame"))
```

Arguments
- `object`: an object of class 'pomp', or of a class extending 'pomp'
- `vars`: names of variables to retrieve
- `...`: ignored
- `format`: format of the returned object

See Also
Other extraction methods: `coef()`, `cond_logLik()`, `covmat()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `forecast()`, `logLik.obs()`, `pred_mean()`, `pred_var()`, `saved_states()`, `spy()`, `summary()`, `timezero()`, `time()`, `traces()`

summary

Summary methods

Description
Display a summary of a fitted model object.

Usage
```r
## S4 method for signature 'probed_pomp'
summary(object, ...)
```

```r
## S4 method for signature 'spectd_pomp'
summary(object, ...)
```

```r
## S4 method for signature 'objfun'
summary(object, ...)
```
Arguments

object  a fitted model object
...   ignored or passed to the more primitive function

See Also

Other extraction methods: coef(), cond_logLik(), covmat(), eff_sample_size(), filter_mean(), filter_traj(), forecast(), logLik.obs(), pred_mean(), pred_var(), saved_states(), spy(), states(), timezero(), time(), traces()

time  

Methods to extract and manipulate the observation times

description

Get and set the vector of observation times.

Usage

## S4 method for signature 'pomp'

```
time(x, t0 = FALSE, ...)
```

## S4 replacement method for signature 'pomp'

```
time(object, t0 = FALSE, ...) <- value
```

## S4 method for signature 'listie'

```
time(x, t0 = FALSE, ...)
```

Arguments

x  a 'pomp' object
t0  logical; should the zero time be included?
...   ignored or passed to the more primitive function
object  a 'pomp' object
value  numeric vector; the new vector of times

details

time(object) returns the vector of observation times. time(object, t0=TRUE) returns the vector of observation times with the zero-time t0 prepended.
time(object) <- value replaces the observation times slot(times) of object with value. time(object, t0=TRUE) <- value has the same effect, but the first element in value is taken to be the initial time. The second and subsequent elements of value are taken to be the observation times. Those data and states (if they exist) corresponding to the new times are retained.
### timezero

**Description**

Get and set the zero-time.

**Usage**

```r
## S4 method for signature 'pomp'
timezero(object, ...)

## S4 replacement method for signature 'pomp'
timezero(object, ...) <- value
```

**Arguments**

- `object` an object of class ‘pomp’, or of a class that extends ‘pomp’
- `...` ignored or passed to the more primitive function
- `value` numeric; the new zero-time value

**Value**

the value of the zero time

**See Also**

Other extraction methods: `coef()`, `cond_logLik()`, `covmat()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `forecast()`, `logLik.obs()`, `pred_mean()`, `pred_var()`, `saved_states()`, `spy()`, `states()`, `summary()`, `timezero()`, `traces()`
Description

Retrieve the history of an iterative calculation.

Usage

## S4 method for signature 'mif2d_pomp'
traces(object, pars, transform = FALSE, ...)

## S4 method for signature 'mif2List'
traces(object, pars, ...)

## S4 method for signature 'abcd_pomp'
traces(object, pars, ...)

## S4 method for signature 'abcList'
traces(object, pars, ...)

## S4 method for signature 'pmcmcd_pomp'
traces(object, pars, ...)

## S4 method for signature 'pmcmcList'
traces(object, pars, ...)

Arguments

object an object of class extending ‘pomp’, the result of the application of a parameter estimation algorithm
pars names of parameters
transform logical; should the traces be transformed back onto the natural scale?
... ignored or passed to the more primitive function

Details

Note that pmcmc does not currently support parameter transformations.

Value

When object is the result of a mif2 calculation, traces(object, pars) returns the traces of the parameters named in pars. By default, the traces of all parameters are returned. If transform=TRUE, the parameters are transformed from the natural scale to the estimation scale.

When object is a ‘abcd_pomp’, traces(object) extracts the traces as a coda::mcmc.
When object is a ‘abcList’, traces(object) extracts the traces as a coda::mcmc.list.
When object is a 'pmmc_pomp', traces(object) extracts the traces as a coda::mcmc.
When object is a 'pmmcList', traces(object) extracts the traces as a coda::mcmc.list.

See Also
Other extraction methods: coef(), cond_logLik(), covmat(), eff_sample_size(), filter_mean(), filter_traj(), forecast(), logLik.obs(), pred_mean(), pred_var(), saved_states(), spy(), states(), summary(), timezero(), time()

trajectory  Trajectory of a deterministic model

Description
Compute trajectories of the deterministic skeleton of a Markov process.

Usage
## S4 method for signature 'missing'
trajectory(
t0, times, params, skeleton, rinit, ..., ode_control = list(), format = c("pomps", "array", "data.frame"), verbose =getOption("verbose", FALSE)
)

## S4 method for signature 'data.frame'
trajectory(
object, ..., t0, times, params, skeleton, rinit, ode_control = list(), format = c("pomps", "array", "data.frame"), verbose =getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'
trajectory(
object,  
params,  
...,  
skeleton,  
rinit,  
ode_control = list(),  
format = c("pomps", "array", "data.frame"),  
verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'traj_match_objfun'
trajectory(object, ..., verbose = getOption("verbose", FALSE))

Arguments

t0  The zero-time, i.e., the time of the initial state. This must be no later than the
time of the first observation, i.e., t0 <= times[1].
times  the sequence of observation times. times must indicate the column of obser-
vation times by name or index. The time vector must be numeric and non-
decreasing.
params  optional; named numeric vector of parameters. This will be coerced internally
to storage mode double.
skeleton  optional; the deterministic skeleton of the unobserved state process. Depend-
ing on whether the model operates in continuous or discrete time, this is either a
vectorfield or a map. Accordingly, this is supplied using either the vectorfield
or map functions. For more information, see skeleton specification. Setting
skeleton=NULL removes the deterministic skeleton.
rinit  simulator of the initial-state distribution. This can be furnished either as a C
snippet, an R function, or the name of a pre-compiled native routine available in
dynamically loaded library. Setting rinit=NULL sets the initial-state simulator
to its default. For more information, see rinit specification.
...
additional arguments supply new or modify existing model characteristics or
components. See pomp for a full list of recognized arguments.

When named arguments not recognized by pomp are provided, these are made
available to all basic components via the so-called userdata facility. This al-

ows the user to pass information to the basic components outside of the usual
routes of covariates (covar) and model parameters (params). See userdata for
information on how to use this facility.

ode_control  optional list; the elements of this list will be passed to ode if the skeleton is a
vectorfield, and ignored if it is a map.
format  the format in which to return the results.
format = "pomps" causes the trajectories to be returned as a single ‘pomp’ ob-
ject (if a single parameter vector have been furnished to trajectory) or as
a ‘pompList’ object (if multiple parameters have been furnished). In each of
these, the states slot will have been replaced by the computed trajectory. Use
states to view these.
format = "array" causes the trajectories to be returned in a rank-3 array with dimensions nvar x ncol(params) x ntimes. Here, nvar is the number of state variables and ntimes the length of the argument times. Thus if x is the returned array, x[i,j,k] is the i-th component of the state vector at time times[k] given parameters params[,j].

format = "data.frame" causes the results to be returned as a single data frame containing the time and states. An ordered factor variable, '.id', distinguishes the trajectories from one another.

verbose logical; if TRUE, diagnostic messages will be printed to the console.

object optional; if present, it should be a data frame or a ‘pomp’ object.

Details

In the case of a discrete-time system, the deterministic skeleton is a map and a trajectory is obtained by iterating the map. In the case of a continuous-time system, the deterministic skeleton is a vectorfield; trajectory uses the numerical solvers in deSolve to integrate the vectorfield.

Value

The format option controls the nature of the return value of trajectory. See above for details.

See Also

More on pomp elementary algorithms: elementary algorithms, kalman, pfilter(), pomp-package, probe(), simulate(), spect(), wpfilter()

More on methods for deterministic process models: flow(), skeleton specification, skeleton(), trajectory matching

Examples

```r
## The basic components needed to compute trajectories
## of a deterministic dynamical system are
## rinit and skeleton.

## The following specifies these for a simple continuous-time
## model: dx/dt = r (1+e cos(t)) x

trajectory(
  t0 = 0, times = seq(1,30,by=0.1),
  rinit = function (x0, ...) {
    c(x = x0)
  },
  skeleton = vectorfield(
    function (r, e, t, x, ...) {
      c(x=r*(1+e*cos(t))*x)
    }
  ),
  params = c(r=1,e=3,x0=1)
) -> po
```
## In the case of a discrete-time skeleton, we use the 'map' function. For example, the following computes a trajectory from the dynamical system with skeleton $x \rightarrow x \exp(r \sin(\omega t))$.

```r
trajectory(
  t0 = 0, times=seq(1,100),
  rinit = function (x0, ...) {
    c(x = x0)
  },
  skeleton = map(
    function (r, t, x, omega, ...) {
      c(x=x*exp(r*sin(omega*t)))
    },
    delta.t=1
  ),
  params = c(r=1,x0=1,omega=4)
) -> po
plot(po)
```

## generate a bifurcation diagram for the Ricker map
```r
p <- parmat(coef(ricker()),nrep=500)
p["r",] <- exp(seq(from=1.5,to=4,length=500))
trajectory(
  ricker(),
  times=seq(from=1000,to=2000,by=1),
  params=p,
  format="array"
) -> x
matplot(p["r",],x["N",],pch='.',col='black',
       xlab=expression(log(r)),ylab="N",log='x')
```

---

### trajectory matching

**Description**

Estimation of parameters for deterministic POMP models via trajectory matching.

**Usage**

```r
## S4 method for signature 'data.frame'
```
trajectory matching

```r
traj_objfun(
  data,
  est = character(0),
  fail.value = NA,
  ode_control = list(),
  params,
  rinit,
  skeleton,
  dmeasure,
  partrans,
  ...
  verbose = getOption("verbose", FALSE)
)
```

```r
## S4 method for signature 'pomp'
traj_objfun(
  data,
  est = character(0),
  fail.value = NA,
  ode_control = list(),
  ...
  verbose = getOption("verbose", FALSE)
)
```

```r
## S4 method for signature 'traj_match_objfun'
traj_objfun(
  data,
  est,
  fail.value,
  ode_control,
  ...
  verbose = getOption("verbose", FALSE)
)
```

### Arguments

- **data**: either a data frame holding the time series data, or an object of class `pomp`, i.e., the output of another `pomp` calculation. Internally, data will be internally coerced to an array with storage-mode `double`.

- **est**: character vector; the names of parameters to be estimated.

- **fail.value**: optional numeric scalar; if non-NA, this value is substituted for non-finite values of the objective function. It should be a large number (i.e., bigger than any legitimate values the objective function is likely to take).

- **ode_control**: optional list; the elements of this list will be passed to `ode` if the skeleton is a `vectorfield`, and ignored if it is a `map`.

- **params**: optional; named numeric vector of parameters. This will be coerced internally to storage mode `double`.
trajectory matching

**rinit** simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting `rinit=NULL` sets the initial-state simulator to its default. For more information, see *rinit specification*.

**skeleton** optional; the deterministic skeleton of the unobserved state process. Depending on whether the model operates in continuous or discrete time, this is either a vectorfield or a map. Accordingly, this is supplied using either the `vectorfield` or `map` functions. For more information, see *skeleton specification*. Setting `skeleton=NULL` removes the deterministic skeleton.

**dmeasure** evaluator of the measurement model density, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting `dmeasure=NULL` removes the measurement density evaluator. For more information, see *dmeasure specification*.

**partrans** optional parameter transformations, constructed using `parameter_trans`. Many algorithms for parameter estimation search an unconstrained space of parameters. When working with such an algorithm and a model for which the parameters are constrained, it can be useful to transform parameters. One should supply the `partrans` argument via a call to `parameter_trans`. For more information, see *parameter_trans*. Setting `partrans=NULL` removes the parameter transformations, i.e., sets them to the identity transformation.

... additional arguments will modify the model structure

**verbose** logical; if TRUE, diagnostic messages will be printed to the console.

**Details**

In trajectory matching, one attempts to minimize the discrepancy between a POMP model’s predictions and data under the assumption that the latent state process is deterministic and all discrepancies between model and data are due to measurement error. The measurement model likelihood (dmeasure), or rather its negative, is the natural measure of the discrepancy.

Trajectory matching is a generalization of the traditional nonlinear least squares approach. In particular, if, on some scale, measurement errors are normal with constant variance, then trajectory matching is equivalent to least squares on that particular scale.

traj_objfun constructs an objective function that evaluates the likelihood function. It can be passed to any one of a variety of numerical optimization routines, which will adjust model parameters to minimize the discrepancies between the power spectrum of model simulations and that of the data.

**Value**

traj_objfun constructs a stateful objective function for spectrum matching. Specifically, traj_objfun returns an object of class ‘traj_match_objfun’, which is a function suitable for use in an *optim*-like optimizer. In particular, this function takes a single numeric-vector argument that is assumed to contain the parameters named in est, in that order. When called, it will return the negative log likelihood. It is a stateful function: Each time it is called, it will remember the values of the parameters and its estimate of the log likelihood.
Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

Important Note

Since `pomp` cannot guarantee that the final call an optimizer makes to the function is a call at the optimum, it cannot guarantee that the parameters stored in the function are the optimal ones. Therefore, it is a good idea to evaluate the function on the parameters returned by the optimization routine, which will ensure that these parameters are stored.

Warning! Objective functions based on C snippets

If you use C snippets (see `Csnippet`), a dynamically loadable library will be built. As a rule, `pomp` functions load this library as needed and unload it when it is no longer needed. The stateful objective functions are an exception to this rule. For efficiency, calls to the objective function do not execute `pompLoad` or `pompUnload`: rather, it is assumed that `pompLoad` has been called before any call to the objective function. When a stateful objective function using one or more C snippets is created, `pompLoad` is called internally to build and load the library: therefore, within a single R session, if one creates a stateful objective function, one can freely call that objective function and (more to the point) pass it to an optimizer that calls it freely, without needing to call `pompLoad`. On the other hand, if one retrieves a stored objective function from a file, or passes one to another R session, one must call `pompLoad` before using it. Failure to do this will typically result in a segmentation fault (i.e., it will crash the R session).

See Also

`optim`, `subplex`, `nloptr`

More on methods for deterministic process models: `flow()`, `skeleton specification`, `skeleton()`, `trajectory()`

More on maximization-based estimation methods: `mif2()`, `nonlinear forecasting`, `probe matching`, `spectrum matching`

Examples

```r
ricker() |> 
traj_objfun(
  est=c("r","sigma","N_0"),
  partrans=parameter_trans(log=c("r","sigma","N_0")),
  paramnames=c("r","sigma","N_0"),
) -> f

f(log(c(20,0.3,10)))
```
if (require(subplex)) {
  subplex(fn=f,par=log(c(20,0.3,10)),control=list(reltol=1e-5)) -> out
} else {
  optim(fn=f,par=log(c(20,0.3,10)),control=list(reltol=1e-5)) -> out
}

f(out$par)

if (require(ggplot2)) {
  f |> trajectory(format="data.frame") |> 
  ggplot(aes(x=time,y=N))+geom_line()+theme_bw()
}

---

## Transformations

### Description

Some useful parameter transformations.

### Usage

- `logit(p)`
- `expit(x)`
- `log_barycentric(X)`
- `inv_log_barycentric(Y)`

### Arguments

- `p`: numeric; a quantity in [0,1].
- `x`: numeric; the log odds ratio.
- `X`: numeric; a vector containing the quantities to be transformed according to the log-barycentric transformation.
- `Y`: numeric; a vector containing the log fractions.
Details

Parameter transformations can be used in many cases to recast constrained optimization problems as unconstrained problems. Although there are no limits to the transformations one can implement using the `parameter_trans` facility, `pomp` provides a few ready-built functions to implement some very commonly useful ones.

The logit transformation takes a probability $p$ to its log odds, $\log \frac{p}{1-p}$. It maps the unit interval $[0, 1]$ into the extended real line $[-\infty, \infty]$.

The inverse of the logit transformation is the expit transformation.

The log-barycentric transformation takes a vector $X_i, i = 1, \ldots, n$, to a vector $Y_i$, where

$$ Y_i = \log \frac{X_i}{\sum_j X_j}. $$

If $X$ is an $n$-vector, it takes every simplex defined by $\sum_i X_i = c, c$ constant, to $n$-dimensional Euclidean space $\mathbb{R}^n$.

The inverse of the log-barycentric transformation is implemented as `inv_log_barycentric`. Note that it is not a true inverse, in the sense that it takes $\mathbb{R}^n$ to the unit simplex, $\sum_i X_i = 1$. Thus,

$$ \log\text{barycentric}(\text{inv_log\text{barycentric}}(Y)) == Y, $$

but

$$ \text{inv_log\text{barycentric}}(\log\text{barycentric}(X)) == X $$

only if $\text{sum}(X) == 1$.

See Also

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, userdata, vmeasure specification

**userdata**

Facilities for making additional information to basic components

Description

When POMP basic components need information they can’t get from parameters or covariates.
Details

It can happen that one desires to pass information to one of the POMP model basic components (see here for a definition of this term) outside of the standard routes (i.e., via model parameters or covariates). pomp provides facilities for this purpose. We refer to the objects one wishes to pass in this way as user data.

The following will apply to every basic model component. For the sake of definiteness, however, we'll use the rmeasure component as an example. To be even more specific, the measurement model we wish to implement is

\[
y_1 \sim \text{Poisson}(x_1+\theta), \quad y_2 \sim \text{Poisson}(x_2+\theta),\]

where \( \theta \) is a parameter. Although it would be very easy (and indeed far preferable) to include \( \theta \) among the ordinary parameters (by including it in \texttt{params}), we will assume here that we have some reason for not wanting to do so.

Now, we have the choice of providing \texttt{rmeasure} in one of three ways:

1. as an \texttt{R} function,
2. as a C snippet, or
3. as a procedure in an external, dynamically loaded library.

We'll deal with these three cases in turn.

**When the basic component is specified as an \texttt{R} function**

We can implement a simulator for the aforementioned measurement model so:

```r
f <- function (t, x, params, theta, ...) {
    y <- rpois(n=2,x[c("x1","x2")]+theta)
    setNames(y,c("y1","y2"))
}
```

So far, so good, but how do we get \( \theta \) to this function? We simply provide an additional argument to whichever pomp algorithm we are employing (e.g., \texttt{simulate}, \texttt{pfilter}, \texttt{mif2}, \texttt{abc}, etc.). For example:

\[
\text{simulate(..., rmeasure = f, theta = 42, ...)}
\]

where the \( ... \) represent the other simulate arguments we might want to supply. When we do so, a message will be generated, informing us that \( \theta \) is available for use by the POMP basic components. This warning helps forestall accidental triggering of this facility due to typographical error.

**When the basic component is specified via a C snippet**

A C snippet implementation of the aforementioned measurement model is:

```c
f <- Csnippet("
    double theta = *(get_userdata_double("\theta"));
    y1 = rpois(x1+theta); y2 = rpois(x2+theta);
")
```
Here, the call to get_userdata_double retrieves a pointer to the stored value of theta. Note the need to escape the quotes in the C snippet text.

It is possible to store and retrieve integer objects also, using get_userdata_int.

One must take care that one stores the user data with the appropriate storage type. For example, it is wise to wrap floating point scalars and vectors with as.double and integers with as.integer. In the present example, our call to simulate might look like

```c
simulate(..., rmeasure = f, theta = as.double(42), ...)
```

Since the two functions get_userdata_double and get_userdata_int return pointers, it is trivial to pass vectors of double-precision and integers.

A simpler and more elegant approach is afforded by the globals argument (see below).

**When the basic component is specified via an external library**

The rules are essentially the same as for C snippets. typedef declarations for the get_userdata_double and get_userdata_int are given in the 'pomp.h' header file and these two routines are registered so that they can be retrieved via a call to R_GetCCallable. See the Writing R extensions manual for more information.

**Setting globals**

The use of the userdata facilities incurs a run-time cost. It is faster and more elegant, when using C snippets, to put the needed objects directly into the C snippet library. The globals argument does this. See the example below.

**See Also**

More on implementing POMP models: Csnippet, accumulator variables, basic components, betabinomial, covariates, distributions, dmeasure specification, dprocess specification, emeasure specification, parameter transformations, pomp-package, pomp, prior specification, rinit specification, rmeasure specification, rprocess specification, skeleton specification, transformations, vmeasure specification

**Examples**

```r
## The familiar Ricker example
## For some bizarre reason, we wish to pass 'phi'
## via the userdata facility.

## C snippet approach:

 simulate(times=1:100,t0=0,
 phi=as.double(100),
 params=c(r=3.8,sigma=0.3,N.0=7),
 rprocess=discrete_time(
   step.fun=Csnippet("
   double e = (sigma > 0.0) ? rnorm(0,sigma) : 0.0;
   N = r*N*exp(-N+e);
   ")
  ));
```
## The same problem solved using 'globals':
```
simulate(times=1:100,t0=0,
globals=Csnippet("static double phi = 100;"),
params=c(r=3.8,sigma=0.3,N.0=7),
rprocess=discrete_time(
    step.fun=Csnippet("
        double e = (sigma > 0.0) ? rnorm(0,sigma) : 0.0;
        N = r*N*exp(-N+e);
    "),
    delta.t=1
  ),
  rmeasure=Csnippet("y = rpois(phi*N);"),
  paramnames=c("r","sigma"),
  statenames="N",
  obsnames="y"
) -> rick2
```
## Finally, the R function approach:
```
simulate(times=1:100,t0=0,
  phi=100,
  params=c(r=3.8,sigma=0.3,N.0=7),
  rprocess=discrete_time(
    step.fun=function (r, N, sigma, ...) {
      e <- rnorm(n=1,mean=0,sd=sigma)
      c(N=r*N*exp(-N+e))
    },
    delta.t=1
  ),
  rmeasure=function(phi, N, ...) {
    c(y=rpois(n=1,lambda=phi*N))
  }
) -> rick3
```
Description

The Verhulst-Pearl (logistic) model of population growth.

Usage

verhulst(n_0 = 10000, K = 10000, r = 0.9, sigma = 0.4, tau = 0.1, dt = 0.01)

Arguments

n_0  initial condition
K    carrying capacity
r    intrinsic growth rate
sigma environmental process noise s.d.
tau  measurement error s.d.
dt    Euler timestep

Details

A stochastic version of the Verhulst-Pearl logistic model. This evolves in continuous time, according to the stochastic differential equation

\[ dN_t = r N_t \left(1 - \frac{N_t}{K}\right) dt + \sigma N_t dW_t. \]

Numerically, we simulate the stochastic dynamics using an Euler approximation.

The measurements are assumed to be log-normally distributed:

\[ N_t \sim \text{Lognormal} (\log N_t, \tau). \]

Value

A ‘pomp’ object containing the model and simulated data. The following basic components are included in the ‘pomp’ object: ‘rinit’, ‘rprocess’, ‘rmeasure’, ‘dmeasure’, and ‘skeleton’.

See Also

More examples provided with pomp: SIR models, blowflies, childhood disease data, dacca(), ebola, gompertz(), ou2(), pomp examples, ricker(), rw2()

Examples

# takes too long for R CMD check
verhulst() -> po
plot(po)
plot(simulate(po))
pfilter(po, Np=1000) -> pf
logLik(pf)
spy(po)
Description

Return the covariance matrix of the observed variables, given values of the latent states and the parameters.

Usage

```r
## S4 method for signature 'pomp'
vmeasure(
  object,
  x = states(object),
  times = time(object),
  params = coef(object),
  ...
)
```

Arguments

- `object`: an object of class ‘pomp’, or of a class that extends ‘pomp’. This will typically be the output of `pomp`, `simulate`, or one of the `pomp` inference algorithms.
- `x`: an array containing states of the unobserved process. The dimensions of `x` are `nvars x nrep x ntimes`, where `nvars` is the number of state variables, `nrep` is the number of replicates, and `ntimes` is the length of `times`. One can also pass `x` as a named numeric vector, which is equivalent to the `nrep=1, ntimes=1` case.
- `times`: a numeric vector (length `ntimes`) containing times. These must be in non-decreasing order.
- `params`: a `npar x nrep` matrix of parameters. Each column is treated as an independent parameter set, in correspondence with the corresponding column of `x`.
- `...`: additional arguments are ignored.

Value

`vmeasure` returns a rank-4 array of dimensions `nobs x nobs x nrep x ntimes`, where `nobs` is the number of observed variables. If `v` is the returned array, `v[,]j,k` contains the covariance matrix at time `times[k]` given the state `x[,]j,k`.

See Also

- Specification of the measurement-model covariance matrix: `vmeasure specification`
- More on `pomp` workhorse functions: `dmeasure()`, `dprior()`, `dprocess()`, `emeasure()`, `flow()`, `partrans()`, `pomp-package`, `rinit()`, `rmeasure()`, `rprior()`, `rprocess()`, `skeleton()`, `workhorses`
vmeasure specification

The variance of the measurement model

Description

Specification of the measurement-model covariance matrix, vmeasure.

Details

The measurement model is the link between the data and the unobserved state process. Some algorithms require the conditional covariance of the measurement model, given the latent state and parameters. This is supplied using the vmeasure argument.

Suppose you have a procedure to compute this conditional covariance matrix, given the value of the latent state variables. Then you can furnish

$vmeasure = f$

to pomp algorithms, where $f$ is a C snippet or R function that implements your procedure.

Using a C snippet is much preferred, due to its much greater computational efficiency. See Csnippet for general rules on writing C snippets.

In writing a vmeasure C snippet, bear in mind that:

1. The goal of such a snippet is to fill variables named $V_{y,z}$ with the conditional covariances of observables $y$, $z$. Accordingly, there should be one assignment of $V_{y,z}$ and one assignment of $V_{z,y}$ for each pair of observables $y$ and $z$.

2. In addition to the states, parameters, and covariates (if any), the variable $t$, containing the time of the observation, will be defined in the context in which the snippet is executed.

The demos and the tutorials on the package website give examples.

It is also possible, though less efficient, to specify vmeasure using an R function. In this case, specify it by furnishing

$vmeasure = f$

to pomp, where $f$ is an R function. The arguments of $f$ should be chosen from among the state variables, parameters, covariates, and time. It must also have the argument $...$. $f$ must return a square matrix of dimension equal to the number of observable variables. The row- and column-names of this matrix should match the names of the observable variables. The matrix should of course be symmetric.

Default behavior

The default vmeasure is undefined. It will yield missing values (NA).
Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These appear to arise when the temporary files created during the C snippet compilation process are not handled properly by the operating system. To circumvent this problem, use the `cdir` and `cfile` options to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary files altogether.

See Also

`vmeasure`

More on implementing POMP models: `Csnippet`, `accumulator variables`, `basic components`, `betabinomial`, `covariates`, `distributions`, `dmeasure specification`, `dprocess specification`, `emeasure specification`, `parameter transformations`, `pomp-package`, `pomp.prior specification`, `rinit specification`, `rmeasure specification`, `rprocess specification`, `skeleton specification`, `transformations`, `userdata`

---

### window

**Description**

Restrict to a portion of a time series.

**Usage**

```r
## S4 method for signature 'pomp'
window(x, start, end, ...)
```

**Arguments**

- `x`: a `pomp` object or object of class extending `pomp`
- `start`, `end`: the left and right ends of the window, in units of time
- `...`: ignored

**Description**

These functions mediate the interface between the user’s model and the package algorithms. They are low-level functions that do the work needed by the package’s inference methods.
Details

They include

- `dmeasure` which evaluates the measurement model density,
- `rmeasure` which samples from the measurement model distribution,
- `emeasure` which computes the expectation of the observed variables conditional on the latent state,
- `vmeasure` which computes the covariance matrix of the observed variables conditional on the latent state,
- `dprocess` which evaluates the process model density,
- `rprocess` which samples from the process model distribution,
- `dprior` which evaluates the prior probability density,
- `rprior` which samples from the prior distribution,
- `skeleton` which evaluates the model's deterministic skeleton,
- `flow` which iterates or integrates the deterministic skeleton to yield trajectories,
- `partrans` which performs parameter transformations associated with the model.

Author(s)

Aaron A. King

See Also

- `basic model components`, `elementary algorithms`, `estimation algorithms`

More on `pomp` workhorse functions: `dmeasure()`, `dprior()`, `dprocess()`, `emeasure()`, `flow()`, `partrans()`, `pomp-package`, `rinit()`, `rmeasure()`, `rprior()`, `rprocess()`, `skeleton()`, `vmeasure()`

---

**wpfilter**

*Weighted particle filter*

**Description**

A sequential importance sampling (particle filter) algorithm. Unlike in `pfilter`, resampling is performed only when triggered by deficiency in the effective sample size.

**Usage**

```r
## S4 method for signature 'data.frame'
wpfilter(
  data,
  Np,
  params,
  rinit,
  rprocess,
  dmeasure,
```
trigger = 1,
target = 0.5,
...,  
verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'pomp'
wpfilter(
  data,
  Np,
  trigger = 1,
  target = 0.5,
  ..., 
  verbose = getOption("verbose", FALSE)
)

## S4 method for signature 'wpfilterd_pomp'
wpfilter(data, Np, trigger, target, ..., verbose = getOption("verbose", FALSE))

Arguments

data either a data frame holding the time series data, or an object of class ‘pomp’, i.e., the output of another pomp calculation. Internally, data will be internally coerced to an array with storage-mode double.

Np the number of particles to use. This may be specified as a single positive integer, in which case the same number of particles will be used at each timestep. Alternatively, if one wishes the number of particles to vary across timesteps, one may specify Np either as a vector of positive integers of length

\[ \text{length}(\text{time}(\text{object}, t0=\text{TRUE})) \]

or as a function taking a positive integer argument. In the latter case, \( Np(k) \) must be a single positive integer, representing the number of particles to be used at the \( k \)-th timestep: \( Np(0) \) is the number of particles to use going from \( \text{timezero}(\text{object}) \) to \( \text{time}(\text{object})[1] \), \( Np(1) \), from \( \text{timezero}(\text{object}) \) to \( \text{time}(\text{object})[1] \), and so on, while when \( T=\text{length}(\text{time}(\text{object})) \), \( Np(T) \) is the number of particles to sample at the end of the time-series.

params optional; named numeric vector of parameters. This will be coerced internally to storage mode double.

rinit simulator of the initial-state distribution. This can be furnished either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynamically loaded library. Setting rinit=NULL sets the initial-state simulator to its default. For more information, see rinit specification.

rprocess simulator of the latent state process, specified using one of the rprocess plugins. Setting rprocess=NULL removes the latent-state simulator. For more information, see rprocess specification for the documentation on these plugins.

dmeasure evaluator of the measurement model density, specified either as a C snippet, an R function, or the name of a pre-compiled native routine available in a dynami-
wpfilter
cally loaded library. Setting dmeasure=NULL removes the measurement density
evaluator. For more information, see dmeasure specification.

trigger numeric; if the effective sample size becomes smaller than trigger * Np, re-
sampling is triggered.

target numeric; target power.

... additional arguments supply new or modify existing model characteristics or
components. See pomp for a full list of recognized arguments.

When named arguments not recognized by pomp are provided, these are made
available to all basic components via the so-called userdata facility. This al-
allows the user to pass information to the basic components outside of the usual
routes of covariates (covar) and model parameters (params). See userdata for
information on how to use this facility.

verbose logical; if TRUE, diagnostic messages will be printed to the console.

Details

This function is experimental and should be considered in alpha stage. Both interface and
underlying algorithms may change without warning at any time. Please explore the function
and give feedback via the pomp Issues page.

Value

An object of class ‘wpfilterd_pomp’, which extends class ‘pomp’. Information can be extracted
from this object using the methods documented below.

Methods

logLik the estimated log likelihood
cond_logLik the estimated conditional log likelihood
eff_sample_size the (time-dependent) estimated effective sample size
as.data.frame coerce to a data frame
plot diagnostic plots

Note for Windows users

Some Windows users report problems when using C snippets in parallel computations. These ap-
pear to arise when the temporary files created during the C snippet compilation process are not
handled properly by the operating system. To circumvent this problem, use the cdir and cfile op-
tions to cause the C snippets to be written to a file of your choice, thus avoiding the use of temporary
files altogether.

Author(s)

Aaron A. King
References


See Also

More on `pomp` elementary algorithms: `elementary_algorithms`, `kalman`, `pfilter()`, `pomp-package`, `probe()`, `simulate()`, `spect()`, `trajectory()`

More on sequential Monte Carlo methods: `bsmc2()`, `cond_logLik()`, `eff_sample_size()`, `filter_mean()`, `filter_traj()`, `kalman`, `mif2()`, `pfilter()`, `pmcmc()`, `pred_mean()`, `pred_var()`, `saved_states()`

More on full-information (i.e., likelihood-based) methods: `bsmc2()`, `mif2()`, `pfilter()`, `pmcmc()`

---

**wquant**

*Weighted quantile function*

Description

Estimate weighted quantiles.

Usage

```r
wquant(
  x,
  weights = rep(1, length(x)),
  probs = c(`0%` = 0, `25%` = 0.25, `50%` = 0.5, `75%` = 0.75, `100%` = 1)
)
```

Arguments

- `x` numeric; a vector of data.
- `weights` numeric; vector of weights.
- `probs` numeric; desired quantiles.

Details

`wquant` estimates quantiles of weighted data using the estimator of Harrell & Davis (1982), with improvements recommended by Andrey Akinshin.

Value

`wquant` returns a vector containing the estimated quantiles. If `probs` has names, these are inherited.

Author(s)

Aaron A. King
References


Examples

```r
x <- c(1,1,1,2,2,3,3,3,3,4,5,5,6,6,6)
quantile(x)
wquant(x)
wquant(c(1,2,3,4,5),weights=c(3,2,4,1,2,3))
wquant(c(1,2,3,4,5),c(1,0,0,1,1))
```
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