

# Package ‘stochvol’

March 3, 2024

**Encoding** UTF-8

**Type** Package

**Title** Efficient Bayesian Inference for Stochastic Volatility (SV) Models

**Version** 3.2.4

**Description** Efficient algorithms for fully Bayesian estimation of stochastic volatility (SV) models with and without asymmetry (leverage) via Markov chain Monte Carlo (MCMC) methods. Methodological details are given in Kastner and Frühwirth-Schnatter (2014) <[doi:10.1016/j.csda.2013.01.002](https://doi.org/10.1016/j.csda.2013.01.002)> and Hosszejni and Kastner (2019) <[doi:10.1007/978-3-030-30611-3\\_8](https://doi.org/10.1007/978-3-030-30611-3_8)>; the most common use cases are described in Hosszejni and Kastner (2021) <[doi:10.18637/jss.v100.i12](https://doi.org/10.18637/jss.v100.i12)> and Kastner (2016) <[doi:10.18637/jss.v069.i05](https://doi.org/10.18637/jss.v069.i05)> and the package examples.

**License** GPL (>= 2)

**Depends** R (>= 3.5)

**Imports** Rcpp (>= 1.0), coda (>= 0.19), graphics, stats, utils, grDevices

**Suggests** testthat (>= 2.3.2), mvtnorm, knitr

**LinkingTo** Rcpp, RcppArmadillo (>= 0.9.900)

**RoxygenNote** 7.2.3

**BuildResaveData** best

**VignetteBuilder** knitr

**BugReports** <https://github.com/gregorkastner/stochvol/issues>

**URL** <https://gregorkastner.github.io/stochvol/>

**NeedsCompilation** yes

**Author** Darjus Hosszejni [aut, cre] (<<https://orcid.org/0000-0002-3803-691X>>),  
Gregor Kastner [aut] (<<https://orcid.org/0000-0002-8237-8271>>)

**Maintainer** Darjus Hosszejni <[darjus.hosszejni@icloud.com](mailto:darjus.hosszejni@icloud.com)>

**Repository** CRAN

**Date/Publication** 2024-03-03 12:10:03 UTC

**R topics documented:**

stochvol-package	2
extrates	4
extractors	4
get_default_fast_sv	7
logret	8
paradensplot	8
paratraceplot	10
paratraceplot.svdraws	10
plot.svdraws	11
plot.svpredict	14
predict.svdraws	15
specify_priors	17
svlm	18
svsample	21
svsample_fast_cpp	31
svsample_roll	34
svsim	39
sv_constant	41
updatesummary	42
update_fast_sv	44
update_general_sv	45
update_regressors	46
update_t_error	46
validate_and_process_expert	47
volplot	48
<b>Index</b>	<b>51</b>

stochvol-package

*Efficient Bayesian Inference for Stochastic Volatility (SV) Models***Description**

This package provides an efficient algorithm for fully Bayesian estimation of stochastic volatility (SV) models via Markov chain Monte Carlo (MCMC) methods. Methodological details are given in Kastner and Frühwirth-Schnatter (2014); the most common use cases are described in Kastner (2016). Recently, the package has been extended to allow for the leverage effect.

**Details**

Bayesian inference for stochastic volatility models using MCMC methods highly depends on actual parameter values in terms of sampling efficiency. While draws from the posterior utilizing the standard centered parameterization break down when the volatility of volatility parameter in the latent state equation is small, non-centered versions of the model show deficiencies for highly persistent latent variable series. The novel approach of ancillarity-sufficiency interweaving (Yu and Meng, 2011) has recently been shown to aid in overcoming these issues for a broad class of multilevel

models. This package provides software for “combining best of different worlds” which allows for inference for parameter constellations that have previously been infeasible to estimate without the need to select a particular parameterization beforehand.

### Note

This package is currently in active development. Your comments, suggestions and requests are warmly welcome!

### Author(s)

Gregor Kastner <gregor.kastner@wu.ac.at>, Darjus Hosszejni <darjus.hosszejni@wu.ac.at>

### References

Kastner, G. and Frühwirth-Schnatter, S. (2014). Ancillarity-Sufficiency Interweaving Strategy (ASIS) for Boosting MCMC Estimation of Stochastic Volatility Models. *Computational Statistics & Data Analysis*, **76**, 408–423, doi:10.1016/j.csda.2013.01.002.

Kastner, G. (2016). Dealing with Stochastic Volatility in Time Series Using the R Package stochvol. *Journal of Statistical Software*, **69**(5), 1–30, doi:10.18637/jss.v069.i05.

Yu, Y. and Meng, X.-L. (2011). To Center or Not to Center: That is Not the Question—An Ancillarity-Sufficiency Interweaving Strategy (ASIS) for Boosting MCMC Efficiency. *Journal of Computational and Graphical Statistics*, **20**(3), 531–570, doi:10.1198/jcgs.2011.203main.

### Examples

```
## Simulate a highly persistent SV process
sim <- svsim(500, mu = -10, phi = 0.99, sigma = 0.2)

## Obtain 4000 draws from the sampler (that's too few!)
draws <- svsample(sim$y, draws = 4000, burnin = 100, priormu = c(-10, 1),
                 priorphi = c(20, 1.2), priorsigma = 0.2)

## Predict 20 days ahead
fore <- predict(draws, 20)

## plot the results
plot(draws, forecast = fore)

## Not run:
## Simulate an SV process with leverage
sim <- svsim(500, mu = -10, phi = 0.95, sigma = 0.2, rho=-0.5)

## Obtain 8000 draws from the sampler (that's too little!)
draws <- svsample(sim$y, draws = 4000, burnin = 3000, priormu = c(-10, 1),
                 priorphi = c(20, 1.2), priorsigma = 0.2,
                 priorrho = c(1, 1))

## Predict 20 days ahead
fore <- predict(draws, 20)
```

```
## plot the results
plot(draws, forecast = fore)

## End(Not run)
```

---

exrates	<i>Euro exchange rate data</i>
---------	--------------------------------

---

### Description

The data set contains the daily bilateral prices of one Euro in 23 currencies from January 3, 2000, until April 4, 2012. Conversions to New Turkish Lira and Fourth Romanian Leu have been incorporated.

### Source

ECB Statistical Data Warehouse (<https://sdw.ecb.europa.eu>)

### See Also

[svsample](#)

### Examples

```
## Not run:
data(exrates)
dat <- logret(exrates$USD, demean = TRUE) ## de-meaned log-returns
res <- svsample(dat)                    ## run MCMC sampler
plot(res, forecast = 100)               ## display results

## End(Not run)
```

---

extractors	<i>Common Extractors for 'svdraws' and 'svpredict' Objects</i>
------------	----------------------------------------------------------------

---

### Description

Some simple extractors returning the corresponding element of an svdraws and svpredict object.

**Usage**

```
para(x, chain = "concatenated")  
latent0(x, chain = "concatenated")  
latent(x, chain = "concatenated")  
vola(x, chain = "concatenated")  
svbeta(x, chain = "concatenated")  
svtau(x, chain = "concatenated")  
priors(x)  
thinning(x)  
runtime(x)  
sampled_parameters(x)  
predy(y, chain = "concatenated")  
predlatent(y, chain = "concatenated")  
predvola(y, chain = "concatenated")
```

**Arguments**

x	svdraws object.
chain	<i>optional</i> either a positive integer or the string "concatenated" (default) or the string "all".
y	svpredict object.

**Value**

The return value depends on the actual function.

```
para(x, chain = "concatenated")  
    extracts the parameter draws.  
latent(x, chain = "concatenated")  
    extracts the latent contemporaneous log-volatility draws.  
latent0(x, chain = "concatenated")  
    extracts the latent initial log-volatility draws.  
svbeta(x, chain = "concatenated")  
    extracts the linear regression coefficient draws.  
svtau(x, chain = "concatenated")  
    extracts the tau draws.
```

`vola(x, chain = "concatenated")`  
 extracts standard deviation draws.

`priors(x)`  
 extracts the prior parameters used and returns them in a `prior_spec` object as generated by [specify\\_priors](#).

`thinning(x)`  
 extracts the thinning parameters used and returns them in a list.

`runtime(x)`  
 extracts the runtime and returns it as a `proc_time` object.

`sampled_parameters(x)`  
 returns the names of time independent model parameters that were actually sampled by `svsample`.

`predlatent(y, chain = "concatenated")`  
 extracts the predicted latent contemporaneous log-volatility draws.

`predvola(y, chain = "concatenated")`  
 extracts predicted standard deviation draws.

`predy(y, chain = "concatenated")`  
 extracts the predicted observation draws.

Functions that have input parameter `chain` return an `mcmc.list` object if `chain=="all"` and return an `mcmc` object otherwise. If `chain` is an integer, then the specified chain is selected from all chains. If `chain` is "concatenated", then all chains are merged into one `mcmc` object.

### See Also

[specify\\_priors](#), [svsample](#), [predict.svdraws](#)

### Examples

```
# Simulate data
sim <- svsim(150)

# Draw from vanilla SV
draws <- svsample(sim, draws = 2000)

## Summarize all estimated parameter draws as a merged mcmc object
summary(para(draws)[, sampled_parameters(draws)])
## Extract the draws as an mcmc.list object
params <- para(draws, chain = "all")[, sampled_parameters(draws)]

options(max.print = 100)
## Further short examples
summary(latent0(draws))
summary(latent(draws))
summary(vola(draws))
sampled_parameters(draws)
priors(draws)

# Draw 3 independent chains from heavy-tailed and asymmetric SV with AR(2) structure
draws <- svsample(sim, draws = 20000, burnin = 3000,
  designmatrix = "ar2",
  priornu = 0.1, priorrho = c(4, 4),
```

```
                                n_chains = 3)

## Extract beta draws from the second chain
svbeta(draws, chain = 2)
## ... tau draws from all chains merged/concatenated together
svtau(draws)
## Create a new svdraws object from the first and third chain
second_chain_excluded <- draws[c(1, 3)]

# Draw from the predictive distribution
pred <- predict(draws, steps = 2)

## Extract the predicted observations as an mcmc.list object
predicted_y <- predy(pred, chain = "all")
## ... the predicted standard deviations from the second chain
predicted_sd <- predvola(pred, chain = 2)
## Create a new svpredict object from the first and third chain
second_chain_excluded <- pred[c(1, 3)]
```

---

get\_default\_fast\_sv     *Default Values for the Expert Settings*

---

## Description

These functions define meaningful expert settings for argument `expert` of `svsample` and its derivatives. The result of `get_default_fast_sv` should be provided as `expert$fast_sv` and `get_default_general_sv` as `expert$general_sv` when relevant.

## Usage

```
get_default_fast_sv()

get_default_general_sv(priorspec)

default_fast_sv
```

## Arguments

`priorspec`     a `priorspec` object created by `specify_priors`

## Format

An object of class `list` of length 11.

## Note

`default_fast_sv` is deprecated.

**See Also**

[svsample](#), [specify\\_priors](#), [svsample\\_roll](#), [svsample\\_fast\\_cpp](#), [svsample\\_general\\_cpp](#)

---

logret	<i>Computes the Log Returns of a Time Series</i>
--------	--------------------------------------------------

---

**Description**

logret computes the log returns of a time series, with optional de-meaning and/or standardization.

**Usage**

```
logret(dat, demean = FALSE, standardize = FALSE, ...)
```

```
## Default S3 method:
```

```
logret(dat, demean = FALSE, standardize = FALSE, ...)
```

**Arguments**

dat	The raw data.
demean	Logical value indicating whether the data should be de-meanned.
standardize	Logical value indicating whether the data should be standardized (in the sense that each component series has an empirical variance equal to one).
...	Ignored.

**Value**

Log returns of the (de-meanned / standardized) data.

**Methods (by class)**

- logret(default): Log returns of vectors

---

paradensplot	<i>Probability Density Function Plot for the Parameter Posteriors</i>
--------------	-----------------------------------------------------------------------

---

**Description**

Displays a plot of the density estimate for the posterior distribution of the parameters  $\mu$ ,  $\phi$ ,  $\sigma$  (and potentially  $\nu$  or  $\rho$ ), computed by the [density](#) function.



**Usage**

```
paradensplot(
  x,
  showobs = TRUE,
  showprior = TRUE,
  showxlab = TRUE,
  mar = c(1.9, 1.9, 1.9, 0.5),
  mgp = c(2, 0.6, 0),
  simobj = NULL,
  ...
)
```

**Arguments**

x	svdraws object.
showobs	logical value, indicating whether the observations should be displayed along the x-axis. If many draws have been obtained, the default (TRUE) can render the plotting to be quite slow, and you might want to try setting showobs to FALSE.
showprior	logical value, indicating whether the prior distribution should be displayed. The default value is TRUE.
showxlab	logical value, indicating whether the x-axis should be labelled with the number of iterations and the bandwidth obtained from <a href="#">density</a> . The default value is TRUE.
mar	numerical vector of length 4, indicating the plot margins. See <a href="#">par</a> for details. The default value is <code>c(1.9, 1.9, 1.9, 0.5)</code> , which is slightly smaller than the R-defaults.
mgp	numerical vector of length 3, indicating the axis and label positions. See <a href="#">par</a> for details. The default value is <code>c(2, 0.6, 0)</code> , which is slightly smaller than the R-defaults.
simobj	object of class <code>svsim</code> as returned by the SV simulation function <a href="#">svsim</a> . If provided, “true” data generating values will be added to the plots.
...	further arguments are passed on to the invoked <code>plot</code> function.

**Details**

`paradensplot` is modeled after [densplot](#) in the `coda` package, with some modifications for parameters that have (half-)bounded support.

**Value**

Called for its side effects. Returns argument `x` invisibly.

**Note**

You can call this function directly, but it is more commonly called by the `plot.svdraws` method.

**See Also**

Other plotting: [paratraceplot.svdraws\(\)](#), [paratraceplot\(\)](#), [plot.svdraws\(\)](#), [plot.svpredict\(\)](#), [volplot\(\)](#)

---

paratraceplot *Trace Plot of MCMC Draws from the Parameter Posteriors*

---

**Description**

Generic function for plotting iterations vs. sampled parameter values. A detailed help for the method implemented in **stochvol** can be found in [paratraceplot.svdraws](#).

**Usage**

```
paratraceplot(x, ...)
```

**Arguments**

`x` An object used to select a method.  
`...` Further arguments passed to or from other methods.

**Value**

Called for its side effects. Returns argument `x` invisibly.

**See Also**

Other plotting: [paradensplot\(\)](#), [paratraceplot.svdraws\(\)](#), [plot.svdraws\(\)](#), [plot.svpredict\(\)](#), [volplot\(\)](#)

---

paratraceplot.svdraws *Trace Plot of MCMC Draws from the Parameter Posteriors*

---

**Description**

Displays a plot of iterations vs. sampled values the parameters  $\mu$ ,  $\phi$ ,  $\sigma$  (and potentially  $\nu$  or  $\rho$ ), with a separate plot per variable.

**Usage**

```
## S3 method for class 'svdraws'
paratraceplot(
  x,
  mar = c(1.9, 1.9, 1.9, 0.5),
  mgp = c(2, 0.6, 0),
  simobj = NULL,
  ...
)
```

**Arguments**

x	svdraws object.
mar	numerical vector of length 4, indicating the plot margins. See <a href="#">par</a> for details. The default value is <code>c(1.9, 1.9, 1.9, 0.5)</code> , which is slightly smaller than the R-defaults.
mgp	numerical vector of length 3, indicating the axis and label positions. See <a href="#">par</a> for details. The default value is <code>c(2, 0.6, 0)</code> , which is slightly smaller than the R-defaults.
simobj	object of class <code>svsim</code> as returned by the SV simulation function <a href="#">svsim</a> . If provided, “true” data generating values will be added to the plots.
...	further arguments are passed on to the invoked <code>matplot</code> function.

**Details**

`paratraceplot` is modeled after [traceplot](#) in the `coda` package, with very minor modifications.

**Value**

Called for its side effects. Returns argument `x` invisibly.

**Note**

You can call this function directly, but it is more commonly called by the `plot.svdraws` method.

**See Also**

Other plotting: [paradensplot\(\)](#), [paratraceplot\(\)](#), [plot.svdraws\(\)](#), [plot.svpredict\(\)](#), [volplot\(\)](#)

---

plot.svdraws

*Graphical Summary of the Posterior Distribution*

---

**Description**

`plot.svdraws` and `plot.svl draws` generate some plots visualizing the posterior distribution and can also be used to display predictive distributions of future volatilities.

**Usage**

```
## S3 method for class 'svdraws'
plot(
  x,
  forecast = NULL,
  dates = NULL,
  show0 = FALSE,
  showobs = TRUE,
  showprior = TRUE,
```

```

forecastlty = NULL,
tcl = -0.4,
mar = c(1.9, 1.9, 1.7, 0.5),
mgp = c(2, 0.6, 0),
simobj = NULL,
newdata = NULL,
...
)

```

### Arguments

x	svdraws object.
forecast	nonnegative integer or object of class svpredict, as returned by <a href="#">predict.svdraws</a> . If an integer greater than 0 is provided, <a href="#">predict.svdraws</a> is invoked to obtain the forecast-step-ahead prediction. The default value is 0.
dates	vector of length ncol(x\$latent), providing optional dates for labelling the x-axis. The default value is NULL; in this case, the axis will be labelled with numbers.
show0	logical value, indicating whether the initial volatility $\exp(h_0/2)$ should be displayed. The default value is FALSE. Only available for inputs x of class svdraws.
showobs	logical value, indicating whether the observations should be displayed along the x-axis. If many draws have been obtained, the default (TRUE) can render the plotting to be quite slow, and you might want to try setting showobs to FALSE.
showprior	logical value, indicating whether the prior distribution should be displayed. The default value is TRUE.
forecastlty	vector of line type values (see <a href="#">par</a> ) used for plotting quantiles of predictive distributions. The default value NULL results in dashed lines.
tcl	The length of tick marks as a fraction of the height of a line of text. See <a href="#">par</a> for details. The default value is -0.4, which results in slightly shorter tick marks than usual.
mar	numerical vector of length 4, indicating the plot margins. See <a href="#">par</a> for details. The default value is c(1.9, 1.9, 1.9, 0.5), which is slightly smaller than the R-defaults.
mgp	numerical vector of length 3, indicating the axis and label positions. See <a href="#">par</a> for details. The default value is c(2, 0.6, 0), which is slightly smaller than the R-defaults.
simobj	object of class svsim as returned by the SV simulation function <a href="#">svsim</a> . If provided, the “true” data generating values will be added to the plots.
newdata	corresponds to parameter newdata in <a href="#">predict.svdraws</a> . <i>Only if forecast is a positive integer and <a href="#">predict.svdraws</a> needs a newdata object.</i> Corresponds to input parameter designmatrix in <a href="#">svsample</a> . A matrix of regressors with number of rows equal to parameter forecast.
...	further arguments are passed on to the invoked plotting functions.

**Details**

These functions set up the page layout and call [volplot](#), [paratraceplot](#) and [paradensplot](#).

**Value**

Called for its side effects. Returns argument `x` invisibly.

**Note**

In case you want different quantiles to be plotted, use [updatesummary](#) on the `svdraws` object first. An example of doing so is given in the Examples section.

**Author(s)**

Gregor Kastner <[gregor.kastner@wu.ac.at](mailto:gregor.kastner@wu.ac.at)>

**See Also**

[updatesummary](#), [predict.svdraws](#)

Other plotting: [paradensplot\(\)](#), [paratraceplot.svdraws\(\)](#), [paratraceplot\(\)](#), [plot.svpredict\(\)](#), [volplot\(\)](#)

**Examples**

```
## Simulate a short and highly persistent SV process
sim <- svsim(100, mu = -10, phi = 0.99, sigma = 0.2)

## Obtain 5000 draws from the sampler (that's not a lot)
draws <- svsample(sim$y, draws = 5000, burnin = 1000,
  priormu = c(-10, 1), priorphi = c(20, 1.5), priorsigma = 0.2)

## Plot the latent volatilities and some forecasts
plot(draws, forecast = 10)

## Re-plot with different quantiles
newquants <- c(0.01, 0.05, 0.25, 0.5, 0.75, 0.95, 0.99)
draws <- updatesummary(draws, quantiles = newquants)

plot(draws, forecast = 20, showobs = FALSE,
  forecastlty = 3, showprior = FALSE)
```

---

`plot.svpredict`*Graphical Summary of the Posterior Predictive Distribution*

---

**Description**

`plot.svpredict` and `plot.svlpredict` generate some plots visualizing the posterior predictive distribution of future volatilities and future observations.

**Usage**

```
## S3 method for class 'svpredict'  
plot(x, quantiles = c(0.05, 0.25, 0.5, 0.75, 0.95), ...)
```

**Arguments**

<code>x</code>	svpredict or svlpredict object.
<code>quantiles</code>	Which quantiles to plot? Defaults to <code>c(.05, .25, .5, .75, .95)</code> .
<code>...</code>	further arguments are passed on to the invoked <a href="#">ts.plot</a> or <a href="#">boxplot</a> function.

**Value**

Called for its side effects. Returns argument `x` invisibly.

**Note**

Note that `svpredict` or `svlpredict` objects can also be used within [plot.svdraws](#) for a possibly more useful visualization. See the examples in [predict.svdraws](#) and those below for use cases.

**See Also**

Other plotting: [paradensplot\(\)](#), [paratraceplot.svdraws\(\)](#), [paratraceplot\(\)](#), [plot.svdraws\(\)](#), [volplot\(\)](#)

Other plotting: [paradensplot\(\)](#), [paratraceplot.svdraws\(\)](#), [paratraceplot\(\)](#), [plot.svdraws\(\)](#), [volplot\(\)](#)

**Examples**

```
## Simulate a short and highly persistent SV process  
sim <- svsim(100, mu = -10, phi = 0.99, sigma = 0.1)  
  
## Obtain 5000 draws from the sampler (that's not a lot)  
draws <- svsample(sim$y, draws = 5000, burnin = 1000)  
  
## Predict 10 steps ahead  
pred <- predict(draws, 10)  
  
## Visualize the predicted distributions
```

```

plot(pred)

## Plot the latent volatilities and some forecasts
plot(draws, forecast = pred)

```

---

predict.svdraws      *Prediction of Future Returns and Log-Volatilities*

---

### Description

Simulates draws from the predictive density of the returns and the latent log-volatility process. The same mean model is used for prediction as was used for fitting, which is either a) no mean parameter, b) constant mean, c) AR(k) structure, or d) general Bayesian regression. In the last case, new regressors need to be provided for prediction.

### Usage

```

## S3 method for class 'svdraws'
predict(object, steps = 1L, newdata = NULL, ...)

```

### Arguments

object	svdraws or svldraws object.
steps	<i>optional</i> single number, coercible to integer. Denotes the number of steps to forecast.
newdata	<i>only in case d) of the description</i> corresponds to input parameter designmatrix in <a href="#">svsample</a> . A matrix of regressors with number of rows equal to parameter steps.
...	currently ignored.

### Value

Returns an object of class svpredict, a list containing three elements:

vol	mcmc.list object of simulations from the predictive density of the standard deviations $sd_{(n+1)}, \dots, sd_{(n+steps)}$
h	mcmc.list object of simulations from the predictive density of $h_{(n+1)}, \dots, h_{(n+steps)}$
y	mcmc.list object of simulations from the predictive density of $y_{(n+1)}, \dots, y_{(n+steps)}$

### Note

You can use the resulting object within [plot.svdraws](#) (see example below), or use the list items in the usual coda methods for mcmc objects to print, plot, or summarize the predictions.

### See Also

[plot.svdraws](#), [volplot](#).

**Examples**

```

# Example 1
## Simulate a short and highly persistent SV process
sim <- svsim(100, mu = -10, phi = 0.99, sigma = 0.2)

## Obtain 5000 draws from the sampler (that's not a lot)
draws <- svsample(sim$y, draws = 5000, burnin = 100,
  priormu = c(-10, 1), priorphi = c(20, 1.5), priorsigma = 0.2)

## Predict 10 days ahead
fore <- predict(draws, 10)

## Check out the results
summary(predlatent(fore))
summary(predy(fore))
plot(draws, forecast = fore)

# Example 2
## Simulate now an SV process with an AR(1) mean structure
len <- 109L
simar <- svsim(len, phi = 0.93, sigma = 0.15, mu = -9)
for (i in 2:len) {
  simar$y[i] <- 0.1 - 0.7 * simar$y[i-1] + simar$vol[i] * rnorm(1)
}

## Obtain 7000 draws
drawsar <- svsample(simar$y, draws = 7000, burnin = 300,
  designmatrix = "ar1", priormu = c(-10, 1), priorphi = c(20, 1.5),
  priorsigma = 0.2)

## Predict 7 days ahead (using AR(1) mean for the returns)
forear <- predict(drawsar, 7)

## Check out the results
plot(forear)
plot(drawsar, forecast = forear)

## Not run:
# Example 3
## Simulate now an SV process with leverage and with non-zero mean
len <- 96L
regressors <- cbind(rep_len(1, len), rgamma(len, 0.5, 0.25))
betas <- rbind(-1.1, 2)
simreg <- svsim(len, rho = -0.42)
simreg$y <- simreg$y + as.numeric(regressors %*% betas)

## Obtain 12000 draws
drawsreg <- svsample(simreg$y, draws = 12000, burnin = 3000,
  designmatrix = regressors, priormu = c(-10, 1), priorphi = c(20, 1.5),
  priorsigma = 0.2, priorrho = c(4, 4))

```



```

## Predict 5 days ahead using new regressors
predlen <- 5L
predregressors <- cbind(rep_len(1, predlen), rgamma(predlen, 0.5, 0.25))
forereg <- predict(drawsreg, predlen, predregressors)

## Check out the results
summary(predlatent(forereg))
summary(predy(forereg))
plot(forereg)
plot(drawsreg, forecast = forereg)

## End(Not run)

```

specify\_priors

*Specify Prior Distributions for SV Models***Description**

This function gives access to a larger set of prior distributions in case the default choice is unsatisfactory.

**Usage**

```

specify_priors(
  mu = sv_normal(mean = 0, sd = 100),
  phi = sv_beta(shape1 = 5, shape2 = 1.5),
  sigma2 = sv_gamma(shape = 0.5, rate = 0.5),
  nu = sv_infinity(),
  rho = sv_constant(0),
  latent0_variance = "stationary",
  beta = sv_multinormal(mean = 0, sd = 10000, dim = 1)
)

```

**Arguments**

mu	one of sv_normal or sv_constant
phi	one of sv_beta, sv_normal, or sv_constant. If sv_beta, then the specified beta distribution is the prior for $(\phi+1)/2$
sigma2	one of sv_gamma, sv_inverse_gamma, or sv_constant
nu	one of sv_infinity, sv_exponential, or sv_constant. If sv_exponential, then the specified exponential distribution is the prior for $\nu-2$
rho	one of sv_beta or sv_constant. If sv_beta, then the specified beta distribution is the prior for $(\rho+1)/2$
latent0_variance	either the character string "stationary" or an sv_constant object. If "stationary", then $h_0 \sim N(\mu, \sigma^2/(1-\phi^2))$ . If an sv_constant object with value $v$ , then $h_0 \sim N(\mu, \sigma^2/v)$ . Here, $N(b, B)$ stands for mean $b$ and variance $B$
beta	an sv_multinormal object

**See Also**

Other priors: [sv\\_constant\(\)](#)

---

svlm	<i>Markov Chain Monte Carlo (MCMC) Sampling for the Stochastic Volatility (SV) Model</i>
------	------------------------------------------------------------------------------------------

---

**Description**

svlm is a wrapper around [svsample](#) with a formula interface. The name derives from SV and [lm](#) because a linear model with SV residuals is fitted. The function simulates from the joint posterior distribution of the regression coefficients and the SV parameters  $\mu$ ,  $\phi$ ,  $\sigma$  (and potentially  $\nu$  and  $\rho$ ), along with the latent log-volatilities  $h_0, \dots, h_n$  and returns the MCMC draws.

**Usage**

```
svlm(
  formula,
  data,
  draws = 10000,
  burnin = 1000,
  heavytails = FALSE,
  asymmetry = FALSE,
  priorspec = NULL,
  thin = 1,
  keeptime = "all",
  quiet = FALSE,
  startpara = NULL,
  startlatent = NULL,
  parallel = c("no", "multicore", "snow"),
  n_cpus = 1L,
  cl = NULL,
  n_chains = 1L,
  print_progress = "automatic",
  expert = NULL,
  ...
)
```

**Arguments**

formula	an object of class "formula", as in <a href="#">lm</a> .
data	an optional data frame, list or environment (or object coercible by <code>as.data.frame</code> to a data frame) containing the variables in the model. If not found in data, the variables are taken from <code>environment(formula)</code> , typically the environment from which <code>svlm</code> is called.

draws	single number greater or equal to 1, indicating the number of draws after burn-in (see below). Will be automatically coerced to integer. The default value is 10000.
burnin	single number greater or equal to 0, indicating the number of draws discarded as burn-in. Will be automatically coerced to integer. The default value is 1000.
heavytails	if TRUE, then the residuals of the linear model will follow a t-distribution conditional on the latent volatility process. This model is usually called SV-t. If priorspec is given, then heavytails is ignored.
asymmetry	if TRUE, then the residuals of the linear model will follow an SV process with leverage. If priorspec is given, then heavytails is ignored.
priorspec	using the smart constructor <code>specify_priors</code> , one can set the details of the prior distribution.
thin	single number greater or equal to 1, coercible to integer. Every thinparath parameter and latent draw is kept and returned. The default value is 1, corresponding to no thinning of the parameter draws i.e. every draw is stored.
keeptime	Either 'all' (the default) or 'last'. Indicates which latent volatility draws should be stored.
quiet	logical value indicating whether the progress bar and other informative output during sampling should be omitted. The default value is FALSE, implying verbose output.
startpara	<i>optional</i> named list, containing the starting values for the parameter draws. If supplied, startpara may contain elements named mu, phi, sigma, nu, rho, beta, and latent0. The default value is equal to the prior mean. In case of parallel execution with c1 provided, startpara can be a list of named lists that initialize the parallel chains.
startlatent	<i>optional</i> vector of length length(y), containing the starting values for the latent log-volatility draws. The default value is rep(-10, length(y)). In case of parallel execution with c1 provided, startlatent can be a list of named lists that initialize the parallel chains.
parallel	<i>optional</i> one of "no" (default), "multicore", or "snow", indicating what type of parallelism is to be applied. Option "multicore" is not available on Windows.
n_cpus	<i>optional</i> positive integer, the number of CPUs to be used in case of parallel computations. Defaults to 1L. Ignored if parameter c1 is supplied and parallel != "snow".
c1	<i>optional</i> so-called SNOW cluster object as implemented in package parallel. Ignored unless parallel == "snow".
n_chains	<i>optional</i> positive integer specifying the number of independent MCMC chains
print_progress	<i>optional</i> one of "automatic", "progressbar", or "iteration", controls the output. Ignored if quiet is TRUE.
expert	<i>optional</i> named list of expert parameters. For most applications, the default values probably work best. Interested users are referred to the literature provided in the References section. If expert is provided, it may contain the following named elements:

**interweave** Logical value. If TRUE (the default), then ancillarity-sufficiency interweaving strategy (ASIS) is applied to improve on the sampling efficiency for the parameters. Otherwise one parameterization is used.

**correct\_model\_misspecification** Logical value. If FALSE (the default), then auxiliary mixture sampling is used to sample the latent states. If TRUE, extra computations are made to correct for model misspecification either ex-post by reweighting or on-line using a Metropolis-Hastings step.

... Any extra arguments will be forwarded to [updatesummary](#), controlling the type of statistics calculated for the posterior draws.

## Details

For details concerning the algorithm please see the paper by Kastner and Frühwirth-Schnatter (2014) and Hosszejni and Kastner (2019).

## Value

The value returned is a list object of class `svdraws` holding

<code>para</code>	<code>mcmc.list</code> object containing the <i>parameter</i> draws from the posterior distribution.
<code>latent</code>	<code>mcmc.list</code> object containing the <i>latent instantaneous log-volatility</i> draws from the posterior distribution.
<code>latent0</code>	<code>mcmc.list</code> object containing the <i>latent initial log-volatility</i> draws from the posterior distribution.
<code>tau</code>	<code>mcmc.list</code> object containing the <i>latent variance inflation factors</i> for the sampler with conditional t-innovations ( <i>optional</i> ).
<code>beta</code>	<code>mcmc.list</code> object containing the <i>regression coefficient</i> draws from the posterior distribution ( <i>optional</i> ).
<code>y</code>	the left hand side of the observation equation, usually the argument <code>y</code> . In case of an AR(k) specification, the first k elements are removed.
<code>runtime</code>	<code>proc_time</code> object containing the run time of the sampler.
<code>priors</code>	a <code>priorspec</code> object containing the parameter values of the prior distributions for <code>mu</code> , <code>phi</code> , <code>sigma</code> , <code>nu</code> , <code>rho</code> , and <code>betas</code> , and the variance of specification for <code>latent0</code> .
<code>thinning</code>	<code>list</code> containing the thinning parameters, i.e. the arguments <code>thinpara</code> , <code>thinlatent</code> and <code>keeptime</code> .
<code>summary</code>	<code>list</code> containing a collection of summary statistics of the posterior draws for <code>para</code> , <code>latent</code> , and <code>latent0</code> .
<code>meanmodel</code>	character containing information about how <code>designmatrix</code> was employed.
<code>svlm</code>	a flag for the use of <code>svlm</code>
<code>model_terms</code>	helper object that represents the formula
<code>formula</code>	argument formula
<code>xlevels</code>	helper object that is needed to interpret the formula

To display the output, use `print`, `summary` and `plot`. The `print` method simply prints the posterior draws (which is very likely a lot of output); the `summary` method displays the summary statistics currently stored in the object; the `plot` method `plot.svdraws` gives a graphical overview of the posterior distribution by calling `volplot`, `traceplot` and `densplot` and displaying the results on a single page.

## References

Kastner, G. and Frühwirth-Schnatter, S. (2014). Ancillarity-sufficiency interweaving strategy (ASIS) for boosting MCMC estimation of stochastic volatility models. *Computational Statistics & Data Analysis*, **76**, 408–423, doi:10.1016/j.csda.2013.01.002.

Hosszejni, D. and Kastner, G. (2019). Approaches Toward the Bayesian Estimation of the Stochastic Volatility Model with Leverage. *Springer Proceedings in Mathematics & Statistics*, **296**, 75–83, doi:10.1007/9783030306113\_8.

## See Also

[svsample](#), [svsim](#), [specify\\_priors](#)

## Examples

```
# Simulate data
n <- 50L
dat <- data.frame(x = runif(n, 3, 4),
                 z = runif(n, -1, -0.5))
designmatrix <- matrix(c(dat$x, dat$x^2, log10(dat$x),
                       dat$z), ncol = 4)
betas <- matrix(c(-1, 1, 2, 0), ncol = 1)
y <- designmatrix %*% betas + svsim(n)$y
dat$y <- y
# Formula interface
res <- svlm(y ~ 0 + x + I(x^2) + log10(x) + z, data = dat)
# Prediction
predn <- 10L
preddat <- data.frame(x = runif(predn, 3, 4),
                    z = runif(predn, -1, -0.5))
pred <- predict(res, newdata = preddat, steps = predn)
```

---

svsample

---

*Markov Chain Monte Carlo (MCMC) Sampling for the Stochastic Volatility (SV) Model*


---

## Description

`svsample` simulates from the joint posterior distribution of the SV parameters  $\mu$ ,  $\phi$ ,  $\sigma$  (and potentially  $\nu$  and  $\rho$ ), along with the latent log-volatilities  $h_{-0}, \dots, h_{-n}$  and returns the MCMC draws. If a design matrix is provided, simple Bayesian regression can also be conducted. For similar functionality with a formula interface, see [svlm](#).

**Usage**

```
svsample(  
  y,  
  draws = 10000,  
  burnin = 1000,  
  designmatrix = NA,  
  priormu = c(0, 100),  
  priorphi = c(5, 1.5),  
  priorsigma = 1,  
  priornu = 0,  
  priorrho = NA,  
  priorbeta = c(0, 10000),  
  priorlatent0 = "stationary",  
  priorspec = NULL,  
  thin = 1,  
  thinpara = thin,  
  thinlatent = thin,  
  keeptime = "all",  
  quiet = FALSE,  
  startpara = NULL,  
  startlatent = NULL,  
  parallel = c("no", "multicore", "snow"),  
  n_cpus = 1L,  
  cl = NULL,  
  n_chains = 1L,  
  print_progress = "automatic",  
  expert = NULL,  
  ...  
)
```

```
svtsample(  
  y,  
  draws = 10000,  
  burnin = 1000,  
  designmatrix = NA,  
  priormu = c(0, 100),  
  priorphi = c(5, 1.5),  
  priorsigma = 1,  
  priornu = 0.1,  
  priorrho = NA,  
  priorbeta = c(0, 10000),  
  priorlatent0 = "stationary",  
  priorspec = NULL,  
  thin = 1,  
  thinpara = thin,  
  thinlatent = thin,  
  keeptime = "all",  
  quiet = FALSE,
```

```
    startpara = NULL,  
    startlatent = NULL,  
    parallel = c("no", "multicore", "snow"),  
    n_cpus = 1L,  
    cl = NULL,  
    n_chains = 1L,  
    print_progress = "automatic",  
    expert = NULL,  
    ...  
)
```

```
svlsample(  
  y,  
  draws = 20000,  
  burnin = 2000,  
  designmatrix = NA,  
  priormu = c(0, 100),  
  priorphi = c(5, 1.5),  
  priorsigma = 1,  
  priornu = 0,  
  priorrho = c(4, 4),  
  priorbeta = c(0, 10000),  
  priorlatent0 = "stationary",  
  priorspec = NULL,  
  thin = 1,  
  thinpara = thin,  
  thinlatent = thin,  
  keeptime = "all",  
  quiet = FALSE,  
  startpara = NULL,  
  startlatent = NULL,  
  parallel = c("no", "multicore", "snow"),  
  n_cpus = 1L,  
  cl = NULL,  
  n_chains = 1L,  
  print_progress = "automatic",  
  expert = NULL,  
  ...  
)
```

```
svtlsample(  
  y,  
  draws = 20000,  
  burnin = 2000,  
  designmatrix = NA,  
  priormu = c(0, 100),  
  priorphi = c(5, 1.5),  
  priorsigma = 1,
```

```

    priornu = 0.1,
    priorrho = c(4, 4),
    priorbeta = c(0, 10000),
    priorlatent0 = "stationary",
    priorspec = NULL,
    thin = 1,
    thinpara = thin,
    thinlatent = thin,
    keeptime = "all",
    quiet = FALSE,
    startpara = NULL,
    startlatent = NULL,
    parallel = c("no", "multicore", "snow"),
    n_cpus = 1L,
    cl = NULL,
    n_chains = 1L,
    print_progress = "automatic",
    expert = NULL,
    ...
)

svsample2(
  y,
  draws = 10000,
  burnin = 1000,
  designmatrix = NA,
  priormu = c(0, 100),
  priorphi = c(5, 1.5),
  priorsigma = 1,
  priornu = 0,
  priorrho = NA,
  priorbeta = c(0, 10000),
  priorlatent0 = "stationary",
  thinpara = 1,
  thinlatent = 1,
  keeptime = "all",
  quiet = FALSE,
  startpara = NULL,
  startlatent = NULL
)

```

### Arguments

- |       |                                                                                                                                                                                                                       |
|-------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| y     | numeric vector containing the data (usually log-returns), which must not contain zeros. Alternatively, y can be an <code>svsim</code> object. In this case, the returns will be extracted and a message is signalled. |
| draws | single number greater or equal to 1, indicating the number of draws after burn-in (see below). Will be automatically coerced to integer. The default value is                                                         |



	10000.
burnin	single number greater or equal to 0, indicating the number of draws discarded as burn-in. Will be automatically coerced to integer. The default value is 1000.
designmatrix	regression design matrix for modeling the mean. Must have $\text{length}(y)$ rows. Alternatively, <code>designmatrix</code> may be a string of the form "arX", where X is a nonnegative integer. To fit a constant mean model, use <code>designmatrix = "ar0"</code> (which is equivalent to <code>designmatrix = matrix(1, nrow = length(y))</code> ). To fit an AR(1) model, use <code>designmatrix = "ar1"</code> , and so on. If some elements of <code>designmatrix</code> are NA, the mean is fixed to zero (pre-1.2.0 behavior of <b>stochvol</b> ).
priormu	numeric vector of length 2, indicating mean and standard deviation for the Gaussian prior distribution of the parameter mu, the level of the log-volatility. The default value is <code>c(0, 100)</code> , which constitutes a practically uninformative prior for common exchange rate datasets, stock returns and the like.
priorphi	numeric vector of length 2, indicating the shape parameters for the Beta prior distribution of the transformed parameter $(\text{phi} + 1) / 2$ , where phi denotes the persistence of the log-volatility. The default value is <code>c(5, 1.5)</code> , which constitutes a prior that puts some belief in a persistent log-volatility but also encompasses the region where phi is around 0.
priorsigma	single positive real number, which stands for the scaling of the transformed parameter $\text{sigma}^2$ , where sigma denotes the volatility of log-volatility. More precisely, $\text{sigma}^2 \sim \text{priorsigma} * \text{chisq}(\text{df} = 1)$ . The default value is 1, which constitutes a reasonably vague prior for many common exchange rate datasets, stock returns and the like.
priornu	single non-negative number, indicating the rate parameter for the exponential prior distribution of the parameter; can be Inf nu, the degrees-of-freedom parameter of the conditional innovations t-distribution. The default value is 0, fixing the degrees-of-freedom to infinity. This corresponds to conditional standard normal innovations, the pre-1.1.0 behavior of <b>stochvol</b> .
priorrho	either NA for the no-leverage case or a numeric vector of length 2 that specify the beta prior distribution for $(\text{rho}+1)/2$
priorbeta	numeric vector of length 2, indicating the mean and standard deviation of the Gaussian prior for the regression parameters. The default value is <code>c(0, 10000)</code> , which constitutes a very vague prior for many common datasets. Not used if <code>designmatrix</code> is NA.
priorlatent0	either a single non-negative number or the string 'stationary' (the default, also the behavior before version 1.3.0). When <code>priorlatent0</code> is equal to 'stationary', the stationary distribution of the latent AR(1)-process is used as the prior for the initial log-volatility $h_0$ . When <code>priorlatent0</code> is equal to a number B, we have $h_0 \sim N(\mu, B\sigma^2)$ a priori.
priorspec	in case one needs different prior distributions than the ones specified by <code>priormu</code> , ..., <code>priorrho</code> , a <code>priorspec</code> object can be supplied here. A smart constructor for this usecase is <a href="#">specify_priors</a> .
thin	single number greater or equal to 1, coercible to integer. Every <code>thinparath</code> parameter and latent draw is kept and returned. The default value is 1, corresponding to no thinning of the parameter draws i.e. every draw is stored.

thinpara	single number greater or equal to 1, coercible to integer. Every thinparath parameter draw is kept and returned. The default value is thin.
thinlatent	single number greater or equal to 1, coercible to integer. Every thinlatentth latent variable draw is kept and returned. The default value is thin
keeptime	Either 'all' (the default) or 'last'. Indicates which latent volatility draws should be stored.
quiet	logical value indicating whether the progress bar and other informative output during sampling should be omitted. The default value is FALSE, implying verbose output.
startpara	<i>optional</i> named list, containing the starting values for the parameter draws. If supplied, startpara may contain elements named mu, phi, sigma, nu, rho, beta, and latent0. The default value is equal to the prior mean. In case of parallel execution with c1 provided, startpara can be a list of named lists that initialize the parallel chains.
startlatent	<i>optional</i> vector of length length(y), containing the starting values for the latent log-volatility draws. The default value is rep(-10, length(y)). In case of parallel execution with c1 provided, startlatent can be a list of numeric vectors that initialize the parallel chains.
parallel	<i>optional</i> one of "no" (default), "multicore", or "snow", indicating what type of parallelism is to be applied. Option "multicore" is not available on Windows.
n_cpus	<i>optional</i> positive integer, the number of CPUs to be used in case of parallel computations. Defaults to 1L. Ignored if parameter c1 is supplied and parallel != "snow".
c1	<i>optional</i> so-called SNOW cluster object as implemented in package parallel. Ignored unless parallel == "snow".
n_chains	<i>optional</i> positive integer specifying the number of independent MCMC chains
print_progress	<i>optional</i> one of "automatic", "progressbar", or "iteration", controls the output. Ignored if quiet is TRUE.
expert	<i>optional</i> named list of expert parameters. For most applications, the default values probably work best. Interested users are referred to the literature provided in the References section. If expert is provided, it may contain the following named elements: <ul style="list-style-type: none"> <li><b>interweave</b> Logical value. If TRUE (the default), then ancillarity-sufficiency interweaving strategy (ASIS) is applied to improve on the sampling efficiency for the parameters. Otherwise one parameterization is used.</li> <li><b>correct_model_misspecification</b> Logical value. If FALSE (the default), then auxiliary mixture sampling is used to sample the latent states. If TRUE, extra computations are made to correct for model misspecification either ex-post by reweighting or on-line using a Metropolis-Hastings step.</li> </ul>
...	Any extra arguments will be forwarded to <a href="#">updatesummary</a> , controlling the type of statistics calculated for the posterior draws.

## Details

Functions `svtsample`, `svlsample`, and `svtllsample` are wrappers around `svsample` with convenient default values for the SV model with t-errors, leverage, and both t-errors and leverage, respectively.

For details concerning the algorithm please see the paper by Kastner and Frühwirth-Schnatter (2014) and Hosszejni and Kastner (2019).

## Value

The value returned is a list object of class `svdraws` holding

<code>para</code>	<code>mcmc.list</code> object containing the <i>parameter</i> draws from the posterior distribution.
<code>latent</code>	<code>mcmc.list</code> object containing the <i>latent instantaneous log-volatility</i> draws from the posterior distribution.
<code>latent0</code>	<code>mcmc.list</code> object containing the <i>latent initial log-volatility</i> draws from the posterior distribution.
<code>tau</code>	<code>mcmc.list</code> object containing the <i>latent variance inflation factors</i> for the sampler with conditional t-innovations ( <i>optional</i> ).
<code>beta</code>	<code>mcmc.list</code> object containing the <i>regression coefficient</i> draws from the posterior distribution ( <i>optional</i> ).
<code>y</code>	the left hand side of the observation equation, usually the argument <code>y</code> . In case of an AR(k) specification, the first k elements are removed.
<code>runtime</code>	<code>proc_time</code> object containing the run time of the sampler.
<code>priors</code>	a <code>priorspec</code> object containing the parameter values of the prior distributions for <code>mu</code> , <code>phi</code> , <code>sigma</code> , <code>nu</code> , <code>rho</code> , and <code>betas</code> , and the variance of specification for <code>latent0</code> .
<code>thinning</code>	list containing the thinning parameters, i.e. the arguments <code>thinpara</code> , <code>thinlatent</code> and <code>keeptime</code> .
<code>summary</code>	list containing a collection of summary statistics of the posterior draws for <code>para</code> , <code>latent</code> , and <code>latent0</code> .
<code>meanmodel</code>	character containing information about how <code>designmatrix</code> was employed.

To display the output, use `print`, `summary` and `plot`. The `print` method simply prints the posterior draws (which is very likely a lot of output); the `summary` method displays the summary statistics currently stored in the object; the `plot` method `plot.svdraws` gives a graphical overview of the posterior distribution by calling `volplot`, `traceplot` and `densplot` and displaying the results on a single page.

## Note

If `y` contains zeros, you might want to consider de-meaning your returns or use `designmatrix = "ar0"`.

`svsample2` is deprecated.

## References

Kastner, G. and Frühwirth-Schnatter, S. (2014). Ancillarity-sufficiency interweaving strategy (ASIS) for boosting MCMC estimation of stochastic volatility models. *Computational Statistics & Data Analysis*, **76**, 408–423, doi:10.1016/j.csda.2013.01.002.

Hosszejni, D. and Kastner, G. (2019). Approaches Toward the Bayesian Estimation of the Stochastic Volatility Model with Leverage. *Springer Proceedings in Mathematics & Statistics*, **296**, 75–83, doi:10.1007/9783030306113\_8.

## See Also

[svlm](#), [svsim](#), [specify\\_priors](#)

## Examples

```
#####
# Full examples
#####

# Example 1
## Simulate a short and highly persistent SV process
sim <- svsim(100, mu = -10, phi = 0.99, sigma = 0.2)

## Obtain 5000 draws from the sampler (that's not a lot)
draws <-
  svsample(sim, draws = 5000, burnin = 100,
           priormu = c(-10, 1), priorphi = c(20, 1.5), priorsigma = 0.2)

## Check out the results
summary(draws)
plot(draws)

# Example 2
## Simulate an asymmetric and conditionally heavy-tailed SV process
sim <- svsim(150, mu = -10, phi = 0.96, sigma = 0.3, nu = 10, rho = -0.3)

## Obtain 10000 draws from the sampler
## Use more advanced prior settings
## Run two parallel MCMC chains
advanced_draws <-
  svsample(sim, draws = 10000, burnin = 5000,
           priorspec = specify_priors(mu = sv_normal(-10, 1),
                                     sigma2 = sv_gamma(0.5, 2),
                                     rho = sv_beta(4, 4),
                                     nu = sv_constant(5)),
           parallel = "snow", n_chains = 2, n_cpus = 2)

## Check out the results
summary(advanced_draws)
plot(advanced_draws)
```

```

# Example 3
## AR(1) structure for the mean
data(exrates)
len <- 3000
ahead <- 100
y <- head(exrates$USD, len)

## Fit AR(1)-SVL model to EUR-USD exchange rates
res <- svsample(y, designmatrix = "ar1")

## Use predict.svdraws to obtain predictive distributions
preddraws <- predict(res, steps = ahead)

## Calculate predictive quantiles
predquants <- apply(predy(preddraws), 2, quantile, c(.1, .5, .9))

## Visualize
expost <- tail(head(exrates$USD, len+ahead), ahead)
ts.plot(y, xlim = c(length(y)-4*ahead, length(y)+ahead),
        ylim = range(c(predquants, expost, tail(y, 4*ahead))))
for (i in 1:3) {
  lines((length(y)+1):(length(y)+ahead), predquants[i,],
        col = 3, lty = c(2, 1, 2)[i])
}
lines((length(y)+1):(length(y)+ahead), expost,
      col = 2)

# Example 4
## Predicting USD based on JPY and GBP in the mean
data(exrates)
len <- 3000
ahead <- 30
## Calculate log-returns
logreturns <- apply(exrates[, c("USD", "JPY", "GBP")], 2,
                    function(x) diff(log(x)))
logretUSD <- logreturns[2:(len+1), "USD"]
regressors <- cbind(1, as.matrix(logreturns[1:len, ])) # lagged by 1 day

## Fit SV model to EUR-USD exchange rates
res <- svsample(logretUSD, designmatrix = regressors)

## Use predict.svdraws to obtain predictive distributions
predregressors <- cbind(1, as.matrix(logreturns[(len+1):(len+ahead), ]))
preddraws <- predict(res, steps = ahead,
                    newdata = predregressors)
predprice <- exrates[len+2, "USD"] * exp(t(apply(predy(preddraws), 1, cumsum)))

## Calculate predictive quantiles
predquants <- apply(predprice, 2, quantile, c(.1, .5, .9))

```

```

## Visualize
priceUSD <- exrates[3:(len+2), "USD"]
expost <- exrates[(len+3):(len+ahead+2), "USD"]
ts.plot(priceUSD, xlim = c(len-4*ahead, len+ahead+1),
        ylim = range(c(expost, predquants, tail(priceUSD, 4*ahead))))
for (i in 1:3) {
  lines(len:(len+ahead), c(tail(priceUSD, 1), predquants[i,]),
        col = 3, lty = c(2, 1, 2)[i])
}
lines(len:(len+ahead), c(tail(priceUSD, 1), expost),
      col = 2)

#####
# Further short examples
#####

y <- svsim(50, nu = 10, rho = -0.1)$y

# Supply initial values
res <- svsample(y,
               startpara = list(mu = -10, sigma = 1))

# Supply initial values for parallel chains
res <- svsample(y,
               startpara = list(list(mu = -10, sigma = 1),
                               list(mu = -11, sigma = .1, phi = 0.9),
                               list(mu = -9, sigma = .3, phi = 0.7)),
               parallel = "snow", n_chains = 3, n_cpus = 2)

# Parallel chains with a pre-defined cluster object
cl <- parallel::makeCluster(2, "PSOCK", outfile = NULL) # print to console
res <- svsample(y,
               parallel = "snow", n_chains = 3, cl = cl)
parallel::stopCluster(cl)

# Turn on correction for model misspecification
## Since the approximate model is fast and it is working very
## well in practice, this is turned off by default
res <- svsample(y,
               expert = list(correct_model_misspecification = TRUE))
print(res)

## Not run:
# Parallel multicore chains (not available on Windows)
res <- svsample(y, draws = 30000, burnin = 10000,
               parallel = "multicore", n_chains = 3, n_cpus = 2)

# Plot using a color palette
palette(rainbow(coda::nchain(para(res, "all"))))
plot(res)

```

```

# Use functionality from package 'coda'
## E.g. Geweke's convergence diagnostics
coda::geweke.diag(para(res, "all")[, c("mu", "phi", "sigma")])

# Use functionality from package 'bayesplot'
bayesplot::mcmc_pairs(res, pars = c("sigma", "mu", "phi", "h_0", "h_15"))

## End(Not run)

```

---

svsample\_fast\_cpp      *Bindings to C++ Functions in stochvol*

---

## Description

All the heavy lifting in `stochvol` is implemented in C++ with the help of R packages `Rcpp` and `RcppArmadillo`. These functions call the MCMC samplers in C++ directly without any any validation and transformations, expert use only!

## Usage

```

svsample_fast_cpp(
  y,
  draws = 1,
  burnin = 0,
  designmatrix = matrix(NA),
  priorspec = specify_priors(),
  thinpara = 1,
  thinlatent = 1,
  keeptime = "all",
  startpara,
  startlatent,
  keeptau = !inherits(priorspec$nu, "sv_infinity"),
  print_settings = list(quiet = TRUE, n_chains = 1, chain = 1),
  correct_model_misspecification = FALSE,
  interweave = TRUE,
  myoffset = 0,
  fast_sv = get_default_fast_sv()
)

```

```

svsample_general_cpp(
  y,
  draws = 1,
  burnin = 0,
  designmatrix = matrix(NA),
  priorspec = specify_priors(),
  thinpara = 1,

```

```

thinlatent = 1,
keeptime = "all",
startpara,
startlatent,
keeptau = !inherits(priorspec$nu, "sv_infinity"),
print_settings = list(quiet = TRUE, n_chains = 1, chain = 1),
correct_model_misspecification = FALSE,
interweave = TRUE,
myoffset = 0,
general_sv = get_default_general_sv(priorspec)
)

```

### Arguments

y	numeric vector of the observations
draws	single positive integer, the number of draws to return (after the burn-in)
burnin	single positive integer, length of warm-up period, this number of draws are discarded from the beginning
designmatrix	numeric matrix of covariates. Dimensions: length(y) times the number of covariates. If there are no covariates then this should be matrix(NA)
priorspec	a priorspec object created by <a href="#">specify_priors</a>
thinpara	single number greater or equal to 1, coercible to integer. Every thinparath parameter draw is kept and returned. The default value is 1, corresponding to no thinning of the parameter draws i.e. every draw is stored.
thinlatent	single number greater or equal to 1, coercible to integer. Every thinlatentth latent variable draw is kept and returned. The default value is 1, corresponding to no thinning of the latent variable draws, i.e. every draw is kept.
keeptime	Either 'all' (the default) or 'last'. Indicates which latent volatility draws should be stored.
startpara	named list, containing the starting values for the parameter draws. It must contain elements <ul style="list-style-type: none"> <li>• mu: an arbitrary numerical value</li> <li>• phi: real number between -1 and 1</li> <li>• sigma: a positive real number</li> <li>• nu: a number larger than 2; can be Inf</li> <li>• rho: real number between -1 and 1</li> <li>• beta: a numeric vector of the same length as the number of covariates</li> <li>• latent0: a single number, the initial value for <math>h_0</math></li> </ul>
startlatent	vector of length length(y), containing the starting values for the latent log-volatility draws.
keeptau	Logical value indicating whether the 'variance inflation factors' should be stored (used for the sampler with conditional t innovations only). This may be useful to check at what point(s) in time the normal disturbance had to be 'upscaled' by a mixture factor and when the series behaved 'normally'.



print_settings	List of three elements: <ul style="list-style-type: none"> <li>• quiet: logical value indicating whether the progress bar and other informative output during sampling should be omitted</li> <li>• n_chains: number of independent MCMC chains</li> <li>• chain: index of this chain</li> </ul> Please note that this function does not run multiple independent chains but <code>svsample</code> offers different printing functionality depending on whether it is executed as part of several MCMC chains in parallel (chain specific messages) or simply as a single chain (progress bar).
correct_model_misspecification	Logical value. If FALSE, then auxiliary mixture sampling is used to sample the latent states. If TRUE, extra computations are made to correct for model misspecification either ex-post by reweighting or on-line using a Metropolis-Hastings step.
interweave	Logical value. If TRUE, then ancillarity-sufficiency interweaving strategy (ASIS) is applied to improve on the sampling efficiency for the parameters. Otherwise one parameterization is used.
myoffset	Single non-negative number that is used in $\log(y^2 + \text{myoffset})$ to prevent $-\text{Inf}$ values in the auxiliary mixture sampling scheme.
fast_sv	named list of expert settings. We recommend the use of <code>get_default_fast_sv</code> .
general_sv	named list of expert settings. We recommend the use of <code>get_default_general_sv</code> .

## Details

The sampling functions are separated into fast SV and general SV. See more details in the sections below.

## Fast SV

Fast SV was developed in Kastner and Fruehwirth-Schnatter (2014). Fast SV estimates an approximate SV model without leverage, where the approximation comes in through auxiliary mixture approximations to the exact SV model. The sampler uses the ancillarity-sufficiency interweaving strategy (ASIS) to improve on the sampling efficiency of the model parameters, and it employs all-without-a-loop (AWOL) for computationally efficient Kalman filtering of the conditionally Gaussian state space. Correction for model misspecification happens as a post-processing step.

Fast SV employs sampling strategies that have been fine-tuned and specified for vanilla SV (no leverage), and hence it can be fast and efficient but also more limited in its feature set. The conditions for the fast SV sampler:  $\rho == 0$ ;  $\mu$  has either a normal prior or it is also constant  $0$ ; the prior for  $\phi$  is a beta distribution; the prior for  $\sigma^2$  is either a gamma distribution with shape  $0.5$  or a mean- and variance-matched inverse gamma distribution; either `keep_time == 'all'` or `correct_model_misspecification == FALSE`. These criteria are NOT VALIDATED by fast SV on the C++ level!

## General SV

General SV also estimates an approximate SV model without leverage, where the approximation comes in through auxiliary mixture approximations to the exact SV model. The sampler uses both ASIS and AWOL.

General SV employs adapted random walk Metropolis-Hastings as the proposal for the parameters  $\mu$ ,  $\phi$ ,  $\sigma$ , and  $\rho$ . Therefore, more general prior distributions are allowed in this case.

### Examples

```
# Draw one sample using fast SV and general SV
y <- svsim(40)$y
params <- list(mu = -10, phi = 0.9, sigma = 0.1,
              nu = Inf, rho = 0, beta = NA,
              latent0 = -10)
res_fast <- svsample_fast_cpp(y,
                             startpara = params, startlatent = rep(-10, 40))
res_gen <- svsample_general_cpp(y,
                                startpara = params, startlatent = rep(-10, 40))

# Embed SV in another sampling scheme
## vanilla SV
len <- 40L
draws <- 1000L
burnin <- 200L
param_store <- matrix(NA, draws, 3,
                     dimnames = list(NULL,
                                      c("mu", "phi", "sigma")))
startpara <- list(mu = 0, phi = 0.9, sigma = 0.1,
                 nu = Inf, rho = 0, beta = NA,
                 latent0 = 0)
startlatent <- rep(0, len)
for (i in seq_len(burnin+draws)) {
  # draw the data in the bigger sampling scheme
  # now we simulate y from vanilla SV
  y <- svsim(len, mu = 0, phi = 0.9, sigma = 0.1)$y
  # call SV sampler
  res <- svsample_fast_cpp(y, startpara = startpara,
                          startlatent = startlatent)

  # administrate values
  startpara[c("mu", "phi", "sigma")] <-
    as.list(res$para[, c("mu", "phi", "sigma")])
  startlatent <- drop(res$latent)
  # store draws after the burnin
  if (i > burnin) {
    param_store[i-burnin, ] <-
      res$para[, c("mu", "phi", "sigma")]
  }
}
### quick look at the traceplots
ts.plot(param_store, col = 1:3)
```

**Description**

svsample\_roll performs rolling window estimation based on [svsample](#). A convenience function for backtesting purposes.

**Usage**

```
svsample_roll(  
  y,  
  designmatrix = NA,  
  n_ahead = 1,  
  forecast_length = 500,  
  n_start = NULL,  
  refit_every = 1,  
  refit_window = c("moving", "expanding"),  
  calculate_quantile = c(0.01),  
  calculate_predictive_likelihood = TRUE,  
  keep_draws = FALSE,  
  parallel = c("no", "multicore", "snow"),  
  n_cpus = 1L,  
  cl = NULL,  
  ...  
)
```

```
svtsample_roll(  
  y,  
  designmatrix = NA,  
  n_ahead = 1,  
  forecast_length = 500,  
  n_start = NULL,  
  refit_every = 1,  
  refit_window = c("moving", "expanding"),  
  calculate_quantile = c(0.01),  
  calculate_predictive_likelihood = TRUE,  
  keep_draws = FALSE,  
  parallel = c("no", "multicore", "snow"),  
  n_cpus = 1L,  
  cl = NULL,  
  ...  
)
```

```
svlsample_roll(  
  y,  
  designmatrix = NA,  
  n_ahead = 1,  
  forecast_length = 500,  
  n_start = NULL,  
  refit_every = 1,  
  refit_window = c("moving", "expanding"),
```

```

    calculate_quantile = c(0.01),
    calculate_predictive_likelihood = TRUE,
    keep_draws = FALSE,
    parallel = c("no", "multicore", "snow"),
    n_cpus = 1L,
    cl = NULL,
    ...
)

svtlsample_roll(
  y,
  designmatrix = NA,
  n_ahead = 1,
  forecast_length = 500,
  n_start = NULL,
  refit_every = 1,
  refit_window = c("moving", "expanding"),
  calculate_quantile = c(0.01),
  calculate_predictive_likelihood = TRUE,
  keep_draws = FALSE,
  parallel = c("no", "multicore", "snow"),
  n_cpus = 1L,
  cl = NULL,
  ...
)

```

### Arguments

<code>y</code>	numeric vector containing the data (usually log-returns), which must not contain zeros. Alternatively, <code>y</code> can be an <code>svsim</code> object. In this case, the returns will be extracted and a message is signalled.
<code>designmatrix</code>	regression design matrix for modeling the mean. Must have <code>length(y)</code> rows. Alternatively, <code>designmatrix</code> may be a string of the form <code>"arX"</code> , where <code>X</code> is a nonnegative integer. To fit a constant mean model, use <code>designmatrix = "ar0"</code> (which is equivalent to <code>designmatrix = matrix(1, nrow = length(y))</code> ). To fit an AR(1) model, use <code>designmatrix = "ar1"</code> , and so on. If some elements of <code>designmatrix</code> are <code>NA</code> , the mean is fixed to zero (pre-1.2.0 behavior of <b>stochvol</b> ).
<code>n_ahead</code>	number of time steps to predict from each time window.
<code>forecast_length</code>	the time horizon at the end of the data set that is used for backtesting.
<code>n_start</code>	<i>optional</i> the starting time point for backtesting. Computed from <code>forecast_length</code> if omitted.
<code>refit_every</code>	the SV model is refit every <code>refit_every</code> time steps. Only the value 1 is allowed.
<code>refit_window</code>	one of "moving" or "expanding". If "expanding", then the start of the time window stays at the beginning of the data set. If "moving", then the length of the time window is constant throughout backtesting.

calculate_quantile	vector of numbers between 0 and 1. These quantiles are predicted using <code>predict.svdraws</code> for each time window.
calculate_predictive_likelihood	boolean. If TRUE, the <code>n_ahead</code> predictive density is evaluated at the <code>n_ahead</code> time observation after each time window.
keep_draws	boolean. If TRUE, the <code>svdraws</code> and the <code>svpredict</code> objects are kept from each time window.
parallel	one of "no" (default), "multicore", or "snow", indicating what type of parallelism is to be applied. Option "multicore" is not available on Windows.
n_cpus	<i>optional</i> positive integer, the number of CPUs to be used in case of parallel computations. Defaults to 1L. Ignored if parameter <code>cl</code> is supplied and <code>parallel != "snow"</code> .
cl	<i>optional</i> so-called SNOW cluster object as implemented in package <code>parallel</code> . Ignored unless <code>parallel == "snow"</code> .
...	Any extra arguments will be forwarded to <code>svsample</code> , controlling the prior setup, the starting values for the MCMC chains, the number of independent MCMC chains, thinning and other expert settings.

## Details

Functions `svtssample_roll`, `svlsample_roll`, and `svtlssample_roll` are wrappers around `svsample_roll` with convenient default values for the SV model with t-errors, leverage, and both t-errors and leverage, respectively.

## Value

The value returned is a list object of class `svdraws_roll` holding a list item for every time window. The elements of these list items are

indices	a list object containing two elements: <code>train</code> is the vector of indices used for fitting the model, and <code>test</code> is the vector of indices used for prediction. The latter is mainly useful if a <code>designmatrix</code> is provided.
quantiles	the input parameter <code>calculate_quantiles</code> .
refit_every	the input parameter <code>refit_every</code> .
predictive_likelihood	present only if <code>calculate_predictive_likelihood</code> is TRUE. Then it is a number, the expected predictive density of the observation. The expectation is taken over the joint <code>n_ahead</code> predictive distribution of all model parameters.
predictive_quantile	present only if <code>calculate_quantile</code> is a non-empty vector. Then it is a vector of quantiles from the <code>n_ahead</code> predictive distribution of <code>y</code> . It is based on MCMC simulation by using <code>predict</code> .
fit	present only if <code>keep_draws</code> is TRUE. Then it is an <code>svdraws</code> object as returned by <code>svsample</code> .
prediction	present only if <code>keep_draws</code> is TRUE. Then it is an <code>svpredict</code> object as returned by <code>predict.svdraws</code> .

To display the output, use `print` and `summary`. The `print` method simply prints a short summary of the setup; the `summary` method displays the summary statistics of the backtesting.

### Note

The function executes `svsample` (`length(y) - arorder - n_ahead - n_start + 2`) `%%` `refit_every` times.

### See Also

[svsim](#), [specify\\_priors](#), [svsample](#)

### Examples

```
# Simulate from the true model
sim <- svsim(200)

# Perform rolling estimation using the vanilla SV
# model and default priors
roll <- svsample_roll(sim, draws = 5000, burnin = 2000,
  keep_draws = TRUE,
  forecast_length = 10,
  n_ahead = 1, refit_every = 1,
  refit_window = "moving",
  calculate_predictive_likelihood = TRUE,
  calculate_quantile = c(0.01, 0.05))

# Perform rolling estimation by making use
# of two CPU cores, advanced priors, and multiple
# chains with pre-set initial values. Let us combine
# that with an AR(2) specification
prior_beta <- sv_multinormal(c(1,0,-1), rbind(c(1, 0, 0.1),
  c(0, 0.3, -0.04),
  c(0.1, -0.04, 0.1)))
priorspec <- specify_priors(rho = sv_beta(4, 4),
  latent0_variance = sv_constant(1),
  beta = prior_beta,
  nu = sv_exponential(0.05))
startpara <- list(list(mu = -9, phi = 0.3),
  list(mu = -11, sigma = 0.1, phi = 0.95),
  list(phi = 0.99))
roll <- svsample_roll(sim, draws = 5000, burnin = 2000,
  designmatrix = "ar2",
  priorspec = priorspec,
  startpara = startpara,
  parallel = "snow", n_cpus = 2,
  n_chains = 3,
  keep_draws = TRUE,
  forecast_length = 10,
  n_ahead = 1, refit_every = 1,
  refit_window = "expanding",
```

```
calculate_predictive_likelihood = TRUE,
calculate_quantile = c(0.01, 0.05))
```

svsim

*Simulating a Stochastic Volatility Process***Description**

svsim is used to produce realizations of a stochastic volatility (SV) process.

**Usage**

```
svsim(len, mu = -10, phi = 0.98, sigma = 0.2, nu = Inf, rho = 0)
```

**Arguments**

len	length of the simulated time series.
mu	level of the latent log-volatility AR(1) process. The default value is -10.
phi	persistence of the latent log-volatility AR(1) process. The default value is 0.98.
sigma	volatility of the latent log-volatility AR(1) process. The default value is 0.2.
nu	degrees-of-freedom for the conditional innovations distribution. The default value is Inf, corresponding to standard normal conditional innovations.
rho	correlation between the observation and the increment of the log-volatility. The default value is 0, corresponding to the basic SV model with symmetric “log-returns”.

**Details**

This function draws an initial log-volatility  $h_0$  from the stationary distribution of the AR(1) process defined by  $\phi$ ,  $\sigma$ , and  $\mu$ . Then the function jointly simulates the log-volatility series  $h_1, \dots, h_n$  with the given AR(1) structure, and the “log-return” series  $y_1, \dots, y_n$  with mean 0 and standard deviation  $\exp(h/2)$ . Additionally, for each index  $i$ ,  $y_i$  can be set to have a conditionally heavy-tailed residual (through  $\nu$ ) and/or to be correlated with  $(h_{i+1} - h_i)$  (through  $\rho$ , the so-called leverage effect, resulting in asymmetric “log-returns”).

**Value**

The output is a list object of class `svsim` containing

- y** vector of length `len` containing the simulated data, usually interpreted as “log-returns”.
- vol** vector of length `len` containing the simulated instantaneous volatilities. These are  $e^{h_t/2}$  if  $\nu == \text{Inf}$ , and they are  $e^{h_t/2} \sqrt{\tau_t}$  for finite  $\nu$ .
- vol0** The initial volatility  $\exp(h_0/2)$ , drawn from the stationary distribution of the latent AR(1) process.

**para** a named list with five elements mu, phi, sigma, nu, and rho, containing the corresponding arguments.

**latent** vector of the latent state space  $h_t$  for  $t > 0$ .

**latent0** initial element of the latent state space  $h_0$ .

**tau** vector of length len containing the simulated auxiliary variables for the Student-t residuals when nu is finite. More precisely,  $\tau_t \sim \text{Gamma}^{-1}(\text{shape} = \nu/2, \text{rate} = \nu/2 - 1)$ .

### Note

The function generates the “log-returns” by `y <- exp(-h/2)*rt(h, df=nu)`. That means that in the case of  $\nu < \text{Inf}$  the (conditional) volatility is  $\sqrt{\nu/(\nu-2)} \cdot \exp(h/2)$ , and that corrected value is shown in the `print`, `summary` and `plot` methods.

To display the output use `print`, `summary` and `plot`. The `print` method simply prints the content of the object in a moderately formatted manner. The `summary` method provides some summary statistics (in %), and the `plot` method plots the the simulated ‘log-returns’ `y` along with the corresponding volatilities `vol`.

### Author(s)

Gregor Kastner <gregor.kastner@wu.ac.at>

### See Also

[svsample](#)

### Examples

```
## Simulate a highly persistent SV process of length 500
sim <- svsim(500, phi = 0.99, sigma = 0.1)
```

```
print(sim)
summary(sim)
plot(sim)
```

```
## Simulate an SV process with leverage
sim <- svsim(200, phi = 0.94, sigma = 0.15, rho = -0.6)
```

```
print(sim)
summary(sim)
plot(sim)
```

```
## Simulate an SV process with conditionally heavy-tails
sim <- svsim(250, phi = 0.91, sigma = 0.05, nu = 5)
```

```
print(sim)
summary(sim)
plot(sim)
```



---

sv\_constant

*Prior Distributions in stochvol*


---

### Description

The functions below can be supplied to `specify_priors` to overwrite the default set of prior distributions in `svsample`. The functions have mean, range, density, and print methods.

### Usage

```
sv_constant(value)
```

```
sv_normal(mean = 0, sd = 1)
```

```
sv_multinormal(mean = 0, precision = NULL, sd = 1, dim = NA)
```

```
sv_gamma(shape, rate)
```

```
sv_inverse_gamma(shape, scale)
```

```
sv_beta(shape1, shape2)
```

```
sv_exponential(rate)
```

```
sv_infinity()
```

### Arguments

value	The constant value for the degenerate constant distribution
mean	Expected value for the univariate normal distribution or mean vector of the multivariate normal distribution
sd	Standard deviation for the univariate normal distribution or constant scale of the multivariate normal distribution
precision	Precision matrix for the multivariate normal distribution
dim	(optional) Dimension of the multivariate distribution
shape	Shape parameter for the distribution
rate	Rate parameter for the distribution
scale	Scale parameter for the distribution
shape1	First shape parameter for the distribution
shape2	Second shape parameter for the distribution

## Multivariate Normal

Multivariate normal objects can be specified several ways. The most general way is by calling `sv_multinormal(mean, precision)`, which allows for arbitrary mean and (valid) precision arguments. Constant mean vectors and constant diagonal precision matrices of dimension  $D$  can be created two ways: either `sv_multinormal(mean, sd, dim = D)` or `rep(sv_normal(mean, sd), length.out = D)`.

## See Also

Other priors: [specify\\_priors\(\)](#)

---

updatesummary

*Updating the Summary of MCMC Draws*

---

## Description

Creates or updates a summary of an `svdraws` object.

## Usage

```
updatesummary(
  x,
  quantiles = c(0.05, 0.5, 0.95),
  esspara = TRUE,
  esslatent = FALSE
)
```

## Arguments

<code>x</code>	<code>svdraws</code> object.
<code>quantiles</code>	numeric vector of posterior quantiles to be computed. The default is <code>c(0.05, 0.5, 0.95)</code> .
<code>esspara</code>	logical value which indicates whether the effective sample size (ESS) should be calculated for the <i>parameter draws</i> . This is achieved by calling <a href="#">effectiveSize</a> from the coda package. The default is TRUE.
<code>esslatent</code>	logical value which indicates whether the effective sample size (ESS) should be calculated for the <i>latent log-volatility draws</i> . This is achieved by calling <a href="#">effectiveSize</a> from the coda package. The default is FALSE, because this can be quite time-consuming when many latent variables are present.

## Details

`updatesummary` will always calculate the posterior mean and the posterior standard deviation of the raw draws and some common transformations thereof. Moreover, the posterior quantiles, specified by the argument `quantiles`, are computed. If `esspara` and/or `esslatent` are TRUE, the corresponding effective sample size (ESS) will also be included.

**Value**

The value returned is an updated list object of class `svdraws` holding

<code>para</code>	mcmc object containing the <i>parameter</i> draws from the posterior distribution.
<code>latent</code>	mcmc object containing the <i>latent instantaneous log-volatility</i> draws from the posterior distribution.
<code>latent0</code>	mcmc object containing the <i>latent initial log-volatility</i> draws from the posterior distribution.
<code>y</code>	argument <code>y</code> .
<code>runtime</code>	" <code>proc_time</code> " object containing the run time of the sampler.
<code>priors</code>	list containing the parameter values of the prior distribution, i.e. the arguments <code>priormu</code> , <code>priorphi</code> , <code>priorsigma</code> (and potentially <code>nu</code> ).
<code>thinning</code>	list containing the thinning parameters, i.e. the arguments <code>thinpara</code> , <code>thinlatent</code> and <code>keeptime</code> .
<code>summary</code>	list containing a collection of summary statistics of the posterior draws for <code>para</code> , <code>latent</code> , and <code>latent0</code> .

To display the output, use `print`, `summary` and `plot`. The `print` method simply prints the posterior draws (which is very likely a lot of output); the `summary` method displays the summary statistics currently stored in the object; the `plot` method gives a graphical overview of the posterior distribution by calling [volplot](#), [traceplot](#) and [densplot](#) and displaying the results on a single page.

**Note**

`updatesummary` does not actually overwrite the object's current summary, but in fact creates a new object with an updated summary. Thus, don't forget to overwrite the old object if this is what you intend to do. See the examples below for more details.

**See Also**

[svsample](#)

**Examples**

```
## Here is a baby-example to illustrate the idea.
## Simulate an SV time series of length 51 with default parameters:
sim <- svsim(51)

## Draw from the posterior:
res <- svsample(sim$y, draws = 2000, priorphi = c(10, 1.5))

## Check out the results:
summary(res)
plot(res)

## Look at other quantiles and calculate ESS of latents:
newquants <- c(0.01, 0.05, 0.25, 0.5, 0.75, 0.95, 0.99)
res <- updatesummary(res, quantiles = newquants, esslatent = TRUE)
```

```
## See the difference?
summary(res)
plot(res)
```

---

update\_fast\_sv

*Single MCMC Update Using Fast SV*


---

### Description

Samples the mixture indicators, the latent variables, and the model independent parameters  $\mu$ ,  $\phi$ , and  $\sigma$ . The input is the logarithm of the squared de-meaned observations. An approximate SV model is estimated instead of the exact SV model by the use of auxiliary mixture sampling. Depending on the prior specification,  $\mu$  might not be updated. Depending on the expert settings, the function might follow the ancillarity-sufficiency interweaving strategy (ASIS, Yu and Meng, 2011) for sampling  $\mu$ ,  $\phi$ , and  $\sigma$ . Furthermore, the user can turn off the sampling of the parameters, the latents, or the mixture indicators in the expert settings.

### Usage

```
update_fast_sv(log_data2, mu, phi, sigma, h0, h, r, prior_spec, expert)
```

### Arguments

log_data2	log(data <sup>2</sup> ), where data is the vector of de-meaned observations
mu	parameter $\mu$ . Level of the latent process $h$ . Updated in place
phi	parameter $\phi$ , persistence of the latent process $h$ . Updated in place
sigma	parameter $\sigma$ , volatility of the latent process $h$ , also called volvol. Updated in place
h0	parameter $h_0$ , the initial value of the latent process $h$ . Updated in place
h	the vector of the latent process. Updated in place
r	the vector of the mixture indicators. Updated in place
prior_spec	prior specification object. See type_definitions.h
expert	expert settings for this function. See type_definitions.h

### See Also

Other stochvol\_cpp: [update\\_general\\_sv\(\)](#), [update\\_regressors\(\)](#), [update\\_t\\_error\(\)](#)

---

update\_general\_sv      *Single MCMC Update Using General SV*

---

### Description

Samples the latent variables and the model independent parameters  $\mu$ ,  $\phi$ ,  $\sigma$ , and  $\rho$ . The observations need to be provided in different formats for efficiency. An approximate SV model is as the default posterior distribution for the latent vector; however, there is the option to correct for model misspecification through the expert settings. Depending on the prior specification, some of  $\mu$ ,  $\phi$ ,  $\sigma$ , and  $\rho$  might not be updated. Depending on the expert settings, the function might follow the ancillarity-sufficiency interweaving strategy (ASIS, Yu and Meng, 2011) for sampling  $\mu$ ,  $\phi$ ,  $\sigma$ , and  $\rho$ . Also controlled by the expert settings, Furthermore, the user can turn off the sampling of the parameters, the latents, or the mixture indicators in the expert settings.

### Usage

```
update_general_sv(
  data,
  log_data2,
  sign_data,
  mu,
  phi,
  sigma,
  rho,
  h0,
  h,
  adaptation,
  prior_spec,
  expert
)
```

### Arguments

data	the vector of de-meanded observations
log_data2	$\log(\text{data}^2)$ , where data is the vector of de-meanded observations
sign_data	the sign of the data
mu	parameter $\mu$ . Level of the latent process $h$ . Updated in place
phi	parameter $\phi$ , persistence of the latent process $h$ . Updated in place
sigma	parameter $\sigma$ , volatility of the latent process $h$ , also called volvol. Updated in place
rho	parameter $\rho$ . Accounts for asymmetry/the leverage effect. Updated in place
h0	parameter $h_0$ , the initial value of the latent process $h$ . Updated in place
h	the vector of the latent process. Updated in place
adaptation	object implementing the adaptive Metropolis-Hastings scheme. Updated in place. See adaptation.hpp

prior\_spec      prior specification object. See type\_definitions.h  
 expert          expert settings for this function. See type\_definitions.h

### See Also

Other stochvol\_cpp: [update\\_fast\\_sv\(\)](#), [update\\_regressors\(\)](#), [update\\_t\\_error\(\)](#)

---

update\_regressors      *Single MCMC update of Bayesian linear regression*

---

### Description

Samples the coefficients of a linear regression. The prior distribution is multivariate normal and it is specified in prior\_spec.

### Usage

```
update_regressors(dependent_variable, independent_variables, beta, prior_spec)
```

### Arguments

dependent\_variable      the left hand side  
 independent\_variables    the matrix of the independent variables. Has to be of same height as the length of the dependent variable  
 beta                      the vector of the latent states used in MDA. Updated in place  
 prior\_spec                prior specification object. See type\_definitions.h

### See Also

Other stochvol\_cpp: [update\\_fast\\_sv\(\)](#), [update\\_general\\_sv\(\)](#), [update\\_t\\_error\(\)](#)

---

update\_t\_error          *Single MCMC update to Student's t-distribution*

---

### Description

Samples the degrees of freedom parameter of standardized and homoskedastic t-distributed input variates. Marginal data augmentation (MDA) is applied, tau is the vector of auxiliary latent states. Depending on the prior specification, nu might not be updated, just tau.

**Usage**

```
update_t_error(
  homosked_data,
  tau,
  mean,
  sd,
  nu,
  prior_spec,
  do_tau_acceptance_rejection = TRUE
)
```

**Arguments**

homosked_data	de-meaned and homoskedastic observations
tau	the vector of the latent states used in MDA. Updated in place
mean	the vector of the conditional means // TODO update docs in R
sd	the vector of the conditional standard deviations
nu	parameter nu. The degrees of freedom for the t-distribution. Updated in place
prior_spec	prior specification object. See type_definitions.h
do_tau_acceptance_rejection	boolean. If TRUE, there is a correction for non-zero mean and non-unit sd, otherwise the proposal distribution is used

**Details**

The function samples tau and nu from the following hierarchical model:  $\text{homosked\_data}_i = \sqrt{\text{tau}_i} * (\text{mean}_i + \text{sd}_i * N(0, 1))$   $\text{tau}_i \sim \text{InvGamma}(.5 * \text{nu}, .5 * (\text{nu} - 2))$  Naming: The data is homoskedastic ex ante in the model,  $\text{mean}_i$  and  $\text{sd}_i$  are conditional on some other parameter in the model. The prior on tau corresponds to a standardized t-distributed heavy tail on the data.

**See Also**

Other stochvol\_cpp: [update\\_fast\\_sv\(\)](#), [update\\_general\\_sv\(\)](#), [update\\_regressors\(\)](#)

---

validate\_and\_process\_expert

*Validate and Process Argument 'expert'*

---

**Description**

A helper function that validates the input and extends it with default values if there are missing parts for argument 'expert'.

**Usage**

```
validate_and_process_expert(expert = NULL, priorspec = specify_priors())
```

**Arguments**

expert            list, the input values for expert.  
 priorspec        a priorspec object created by [specify\\_priors](#)

**Value**

A list that is the input extended by default values. If the input is invalid, an error is thrown.

**See Also**

[specify\\_priors](#)

---

 volplot

---

*Plotting Quantiles of the Latent Volatilities*


---

**Description**

Displays quantiles of the posterior distribution of the volatilities over time as well as predictive distributions of future volatilities.

**Usage**

```
volplot(
  x,
  forecast = 0,
  dates = NULL,
  show0 = FALSE,
  forecastlty = NULL,
  tcl = -0.4,
  mar = c(1.9, 1.9, 1.9, 0.5),
  mgp = c(2, 0.6, 0),
  simobj = NULL,
  newdata = NULL,
  ...
)
```

**Arguments**

x                    svdraws object.  
 forecast            nonnegative integer or object of class svpredict, as returned by [predict.svdraws](#).  
 If an integer greater than 0 is provided, [predict.svdraws](#) is invoked to obtain the forecast-step-ahead prediction. The default value is 0.  
 dates                vector of length `ncol(x$latent)`, providing optional dates for labeling the x-axis. The default value is NULL; in this case, the axis will be labeled with numbers.



show0	logical value, indicating whether the initial volatility $\exp(h_0/2)$ should be displayed. The default value is FALSE. Only available for inputs <code>x</code> of class <code>svdraws</code> .
forecastlty	vector of line type values (see <a href="#">par</a> ) used for plotting quantiles of predictive distributions. The default value NULL results in dashed lines.
tc1	The length of tick marks as a fraction of the height of a line of text. See <a href="#">par</a> for details. The default value is <code>-0.4</code> , which results in slightly shorter tick marks than usual.
mar	numerical vector of length 4, indicating the plot margins. See <a href="#">par</a> for details. The default value is <code>c(1.9, 1.9, 1.9, 0.5)</code> , which is slightly smaller than the R-defaults.
mgp	numerical vector of length 3, indicating the axis and label positions. See <a href="#">par</a> for details. The default value is <code>c(2, 0.6, 0)</code> , which is slightly smaller than the R-defaults.
simobj	object of class <code>svsim</code> as returned by the SV simulation function <code>svsim</code> . If provided, “true” data generating values will be added to the plot(s).
newdata	corresponds to parameter <code>newdata</code> in <code>predict.svdraws</code> . <i>Only if forecast is a positive integer and predict.svdraws needs a newdata object.</i> Corresponds to input parameter <code>designmatrix</code> in <code>svsample</code> . A matrix of regressors with number of rows equal to parameter <code>forecast</code> .
...	further arguments are passed on to the invoked <code>ts.plot</code> function.

**Value**

Called for its side effects. Returns argument `x` invisibly.

**Note**

In case you want different quantiles to be plotted, use `updatesummary` on the `svdraws` object first. An example of doing so is given below.

**Author(s)**

Gregor Kastner <[gregor.kastner@wu.ac.at](mailto:gregor.kastner@wu.ac.at)>

**See Also**

[updatesummary](#), [predict.svdraws](#)

Other plotting: [paradensplot\(\)](#), [paratraceplot.svdraws\(\)](#), [paratraceplot\(\)](#), [plot.svdraws\(\)](#), [plot.svpredict\(\)](#)

**Examples**

```
## Simulate a short and highly persistent SV process
sim <- svsim(100, mu = -10, phi = 0.99, sigma = 0.2)

## Obtain 5000 draws from the sampler (that's not a lot)
draws <- svsample(sim$y, draws = 5000, burnin = 100,
```

```
priormu = c(-10, 1), priorphi = c(20, 1.5),  
priorsigma = 0.2)  
  
## Plot the latent volatilities and some forecasts  
volplot(draws, forecast = 10)  
  
## Re-plot with different quantiles  
newquants <- c(0.01, 0.05, 0.25, 0.5, 0.75, 0.95, 0.99)  
draws <- updatesummary(draws, quantiles = newquants)  
  
volplot(draws, forecast = 10)
```

# Index

- \* **backtesting**
    - svsample\_roll, 34
  - \* **datagen**
    - svsim, 39
  - \* **datasets**
    - exrates, 4
    - get\_default\_fast\_sv, 7
  - \* **estimation**
    - svsample\_roll, 34
  - \* **hplot**
    - paradensplot, 8
    - paratraceplot, 10
    - paratraceplot.svdraws, 10
    - plot.svdraws, 11
    - plot.svpredict, 14
    - volplot, 48
  - \* **models**
    - stochvol-package, 2
    - svlm, 18
    - svsample, 21
    - svsample\_roll, 34
  - \* **package**
    - stochvol-package, 2
  - \* **plotting**
    - paradensplot, 8
    - paratraceplot, 10
    - paratraceplot.svdraws, 10
    - plot.svdraws, 11
    - plot.svpredict, 14
    - volplot, 48
  - \* **priors**
    - specify\_priors, 17
    - sv\_constant, 41
  - \* **rolling**
    - svsample\_roll, 34
  - \* **stochvol\_cpp**
    - update\_fast\_sv, 44
    - update\_general\_sv, 45
    - update\_regressors, 46
    - update\_t\_error, 46
  - \* **ts**
    - predict.svdraws, 15
    - stochvol-package, 2
    - svlm, 18
    - svsample, 21
    - svsample\_roll, 34
    - svsim, 39
    - volplot, 48
  - \* **update**
    - update\_fast\_sv, 44
    - update\_general\_sv, 45
    - update\_regressors, 46
    - update\_t\_error, 46
  - \* **utilities**
    - extractors, 4
    - logret, 8
    - updatesummary, 42
  - \* **validation**
    - validate\_and\_process\_expert, 47
  - \* **window**
    - svsample\_roll, 34
- boxplot, 14
- default\_fast\_sv, 7
- default\_fast\_sv (get\_default\_fast\_sv), 7
- density, 8, 9
- densplot, 9, 21, 27, 43
- effectiveSize, 42
- exrates, 4
- extractors, 4
- get\_default\_fast\_sv, 7, 33
- get\_default\_general\_sv, 33
- get\_default\_general\_sv  
(get\_default\_fast\_sv), 7
- latent (extractors), 4
- latent0 (extractors), 4

- lm, [18](#)
- logret, [8](#)
- observations (extractors), [4](#)
- par, [9](#), [11](#), [12](#), [49](#)
- para (extractors), [4](#)
- paradensplot, [8](#), [10](#), [11](#), [13](#), [14](#), [49](#)
- paratraceplot, [10](#), [10](#), [11](#), [13](#), [14](#), [49](#)
- paratraceplot.svdraws, [10](#), [10](#), [13](#), [14](#), [49](#)
- plot.svdraws, [9–11](#), [11](#), [14](#), [15](#), [21](#), [27](#), [49](#)
- plot.svpredict, [10](#), [11](#), [13](#), [14](#), [49](#)
- predict, [37](#)
- predict.svdraws, [6](#), [12–14](#), [15](#), [37](#), [48](#), [49](#)
- predlatent (extractors), [4](#)
- predvola (extractors), [4](#)
- predy (extractors), [4](#)
- priors (extractors), [4](#)
- runtime (extractors), [4](#)
- sampld\_parameters (extractors), [4](#)
- specify\_priors, [6–8](#), [17](#), [19](#), [21](#), [25](#), [28](#), [32](#), [38](#), [41](#), [42](#), [48](#)
- stochvol (stochvol-package), [2](#)
- stochvol-package, [2](#)
- sv\_beta (sv\_constant), [41](#)
- sv\_constant, [18](#), [41](#)
- sv\_exponential (sv\_constant), [41](#)
- sv\_gamma (sv\_constant), [41](#)
- sv\_infinity (sv\_constant), [41](#)
- sv\_inverse\_gamma (sv\_constant), [41](#)
- sv\_multinormal (sv\_constant), [41](#)
- sv\_normal (sv\_constant), [41](#)
- svbeta (extractors), [4](#)
- svlm, [18](#), [21](#), [28](#)
- svlsample (svsample), [21](#)
- svlsample\_roll (svsample\_roll), [34](#)
- svsample, [4](#), [6–8](#), [12](#), [15](#), [18](#), [21](#), [21](#), [33](#), [35](#), [37](#), [38](#), [40](#), [41](#), [43](#), [49](#)
- svsample2, [27](#)
- svsample2 (svsample), [21](#)
- svsample\_fast\_cpp, [8](#), [31](#)
- svsample\_general\_cpp, [8](#)
- svsample\_general\_cpp (svsample\_fast\_cpp), [31](#)
- svsample\_roll, [8](#), [34](#)
- svsim, [9](#), [11](#), [12](#), [21](#), [28](#), [38](#), [39](#), [49](#)
- svttau (extractors), [4](#)
- svtlsample (svsample), [21](#)
- svtlsample\_roll (svsample\_roll), [34](#)
- svtsample (svsample), [21](#)
- svtsample\_roll (svsample\_roll), [34](#)
- thinning (extractors), [4](#)
- traceplot, [11](#), [21](#), [27](#), [43](#)
- ts.plot, [14](#), [49](#)
- update\_fast\_sv, [44](#), [46](#), [47](#)
- update\_general\_sv, [44](#), [45](#), [46](#), [47](#)
- update\_regressors, [44](#), [46](#), [46](#), [47](#)
- update\_t\_error, [44](#), [46](#), [46](#)
- updatesummary, [13](#), [20](#), [26](#), [42](#), [49](#)
- validate\_and\_process\_expert, [47](#)
- vola (extractors), [4](#)
- volplot, [10](#), [11](#), [13–15](#), [21](#), [27](#), [43](#), [48](#)