

Package: bayesdfa (via r-universe)

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Type Package

Title Bayesian Dynamic Factor Analysis (DFA) with 'Stan'

Version 1.3.3

Description Implements Bayesian dynamic factor analysis with 'Stan'.

Dynamic factor analysis is a dimension reduction tool for multivariate time series. 'bayesdfa' extends conventional dynamic factor models in several ways. First, extreme events may be estimated in the latent trend by modeling process error with a student-t distribution. Second, alternative constraints (including proportions are allowed). Third, the estimated dynamic factors can be analyzed with hidden Markov models to evaluate support for latent regimes.

License GPL (>=3)

Encoding UTF-8

Depends R (>= 3.5.0)

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URL <https://fate-ewi.github.io/bayesdfa/>

BugReports <https://github.com/fate-ewi/bayesdfa/issues>

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bayesdfa-package *The 'bayesdfa' package.*

Description

A DESCRIPTION OF THE PACKAGE

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References

Stan Development Team (2020). RStan: the R interface to Stan. R package version 2.21.2.
<https://mc-stan.org>

See Also

Useful links:

- <https://fate-ewi.github.io/bayesdfa/>
- Report bugs at <https://github.com/fate-ewi/bayesdfa/issues>

dfa_cv

Apply cross validation to DFA model

Description

Apply cross validation to DFA model

Usage

```
dfa_cv(  
  stanfit,  
  cv_method = c("loocv", "lfocv"),  
  fold_ids = NULL,  
  n_folds = 10,  
  estimation = c("sampling", "optimizing", "vb"),  
  iter = 2000,  
  chains = 4,  
  thin = 1,  
  ...  
)
```

Arguments

stanfit	A stanfit object, to preserve the model structure from a call to fit_dfa()
cv_method	The method used for cross validation. The options are 'loocv', where time is ignored and each data point is assigned randomly to a fold. The method 'lto cv' is leave time out cross validation, and time slices are iteratively held out. Finally the method 'lfocv' implements leave future out cross validation to do one-step ahead predictions.
fold_ids	A vector whose length is the same as the number of total data points. Elements are the fold id of each data point. If not all data points are used (e.g. the lfocv or lto cv approach might only use 10 time steps) the value can be something other than a number, e.g. NA
n_folds	Number of folds, defaults to 10
estimation	Character string. Should the model be sampled using <code>rstan::sampling()</code> ("sampling", default), <code>rstan::optimizing()</code> ("optimizing"), variational inference <code>rstan::vb()</code> ("vb").
iter	Number of iterations in Stan sampling, defaults to 2000.
chains	Number of chains in Stan sampling, defaults to 4.
thin	Thinning rate in Stan sampling, defaults to 1.
...	Any other arguments to pass to <code>rstan::sampling()</code> .

Examples

```
## Not run:
set.seed(42)
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
obs <- c(s$y_sim[1, ], s$y_sim[2, ], s$y_sim[3, ])
long <- data.frame("obs" = obs, "ts" = sort(rep(1:3, 20)),
"time" = rep(1:20, 3))
m <- fit_dfa(y = long, data_shape = "long", estimation="none")
# random folds
fit_cv <- dfa_cv(m, cv_method = "loocv", n_folds = 5, iter = 50,
chains = 1, estimation="sampling")

# folds can also be passed in
fold_ids <- sample(1:5, size = nrow(long), replace = TRUE)
m <- fit_dfa(y = long, data_shape = "long", estimation="none")
fit_cv <- dfa_cv(m, cv_method = "loocv", n_folds = 5, iter = 50, chains = 1,
fold_ids = fold_ids, estimation="sampling")

# do an example of leave-time-out cross validation where years are dropped
fold_ids <- long$time
m <- fit_dfa(y = long, data_shape = "long", estimation="none")
fit_cv <- dfa_cv(m, cv_method = "loocv", iter = 100, chains = 1,
fold_ids = fold_ids)

# example with covariates and long format data
obs_covar <- expand.grid("time" = 1:20, "timeseries" = 1:3,
"covariate" = 1:2)
```

```

obs_covar$value <- rnorm(nrow(obs_covar), 0, 0.1)
obs <- c(s$y_sim[1, ], s$y_sim[2, ], s$y_sim[3, ])
m <- fit_dfa(y = long, obs_covar = obs_covar,
  data_shape = "long", estimation="none")
fit_cv <- dfa_cv(m, cv_method = "loocv", n_folds = 5,
  iter = 50, chains = 1, estimation="sampling")

## End(Not run)

```

dfa_fitted	<i>Get the fitted values from a DFA as a data frame</i>
------------	---

Description

Get the fitted values from a DFA as a data frame

Usage

```
dfa_fitted(modelfit, conf_level = 0.95, names = NULL)
```

Arguments

modelfit	Output from fit_dfa .
conf_level	Probability level for CI.
names	Optional vector of names for time series labels. Should be same length as the number of time series.

Value

A data frame with the following columns: ID is an identifier for each time series, time is the time step, y is the observed values standardized to mean 0 and unit variance, estimate is the mean fitted value, lower is the lower CI, and upper is the upper CI.

See Also

[predicted](#) [plot_fitted](#) [fit_dfa](#)

Examples

```

y <- sim_dfa(num_trends = 2, num_years = 20, num_ts = 4)
m <- fit_dfa(y = y$y_sim, num_trends = 2, iter = 50, chains = 1)
fitted <- dfa_fitted(m)

```

`dfa_loadings`*Get the loadings from a DFA as a data frame*

Description

Get the loadings from a DFA as a data frame

Usage

```
dfa_loadings(rotated_model_fit, names = NULL, summary = TRUE, conf_level = 0.95)
```

Arguments

<code>rotated_model_fit</code>	Output from rotate_trends .
<code>names</code>	An optional vector of names for plotting the loadings.
<code>summary</code>	Logical. Should the full posterior densities be returned? Defaults to TRUE.
<code>conf_level</code>	Confidence level for credible intervals. Defaults to 0.95.

Value

A data frame with the following columns: `name` is an identifier for each loading, `trend` is the trend for the loading, `median` is the posterior median loading, `lower` is the lower CI, `upper` is the upper CI, and `prob_diff0` is the probability the loading is different than 0. When `summary = FALSE`, there is no lower or upper columns and instead there are columns `chain` and `draw`.

See Also

`plot_loadings` `fit_dfa` `rotate_trends`

Examples

```
set.seed(42)
s <- sim_dfa(num_trends = 2, num_ts = 4, num_years = 10)
# only 1 chain and 180 iterations used so example runs quickly:
m <- fit_dfa(y = s$y_sim, num_trends = 2, iter = 50, chains = 1)
r <- rotate_trends(m)
loadings <- dfa_loadings(r, summary = TRUE)
loadings <- dfa_loadings(r, summary = FALSE)
```

dfa_trends	<i>Get the trends from a DFA as a data frame</i>
------------	--

Description

Get the trends from a DFA as a data frame

Usage

```
dfa_trends(rotated_model_fit, years = NULL)
```

Arguments

`rotated_model_fit`
Output from [rotate_trends](#).

`years`
Optional numeric vector of years.

Value

A data frame with the following columns: `time` is the time step, `trend_number` is an identifier for each trend, `estimate` is the trend mean, `lower` is the lower CI, and `upper` is the upper CI.

See Also

[plot_trends](#) [fit_dfa](#) [rotate_trends](#)

Examples

```
set.seed(1)
s <- sim_dfa(num_trends = 1)
m <- fit_dfa(y = s$y_sim, num_trends = 1, iter = 50, chains = 1)
r <- rotate_trends(m)
trends <- dfa_trends(r)
```

find_dfa_trends	<i>Find the best number of trends according to LOOIC</i>
---------------------------------	--

Description

Fit a DFA with different number of trends and return the leave one out (LOO) value as calculated by the [loo](#) package.

Usage

```
find_dfa_trends(
  y = y,
  kmin = 1,
  kmax = 5,
  iter = 2000,
  thin = 1,
  compare_normal = FALSE,
  convergence_threshold = 1.05,
  variance = c("equal", "unequal"),
  ...
)
```

Arguments

y	A matrix of data to fit. Columns represent time element.
kmin	Minimum number of trends, defaults to 1.
kmax	Maximum number of trends, defaults to 5.
iter	Iterations when sampling from each Stan model, defaults to 2000.
thin	Thinning rate when sampling from each Stan model, defaults to 1.
compare_normal	If TRUE, does model selection comparison of Normal vs. Student-t errors
convergence_threshold	The maximum allowed value of Rhat to determine convergence of parameters
variance	Vector of variance arguments for searching over large groups of models. Can be either or both of ("equal","unequal")
...	Other arguments to pass to fit_dfa()

Examples

```
set.seed(42)
s <- sim_dfa(num_trends = 2, num_years = 20, num_ts = 3)
# only 1 chain and 180 iterations used so example runs quickly:
m <- find_dfa_trends(
  y = s$y_sim, iter = 50,
  kmin = 1, kmax = 2, chains = 1, compare_normal = FALSE,
  variance = "equal", convergence_threshold = 1.1,
  control = list(adapt_delta = 0.95, max_treedepth = 20)
)
m$summary
m$best_model
```

find_inverted_chains *Find which chains to invert*

Description

Find which chains to invert by checking the sum of the squared deviations between the first chain and each other chain.

Usage

```
find_inverted_chains(model, trend = 1, plot = FALSE)
```

Arguments

model	A Stan model, rstanfit object
trend	Which trend to check
plot	Logical: should a plot of the trend for each chain be made? Defaults to FALSE

See Also

invert_chains

Examples

```
set.seed(2)
s <- sim_dfa(num_trends = 2)
set.seed(1)
m <- fit_dfa(y = s$y_sim, num_trends = 1, iter = 30, chains = 2)
# chains were already inverted, but we can redo that, as an example, with:
find_inverted_chains(m$model, plot = TRUE)
```

find_regimes *Fit multiple models with differing numbers of regimes to trend data*

Description

Fit multiple models with differing numbers of regimes to trend data

Usage

```
find_regimes(
  y,
  sds = NULL,
  min_regimes = 1,
  max_regimes = 3,
  iter = 2000,
  thin = 1,
  chains = 1,
  ...
)
```

Arguments

y	Data, time series or trend from fitted DFA model.
sds	Optional time series of standard deviations of estimates. If passed in, residual variance not estimated.
min_regimes	Smallest of regimes to evaluate, defaults to 1.
max_regimes	Biggest of regimes to evaluate, defaults to 3.
iter	MCMC iterations, defaults to 2000.
thin	MCMC thinning rate, defaults to 1.
chains	MCMC chains; defaults to 1 (note that running multiple chains may result in a "label switching" problem where the regimes are identified with different IDs across chains).
...	Other parameters to pass to <code>rstan::sampling()</code> .

Examples

```
data(Nile)
find_regimes(log(Nile), iter = 50, chains = 1, max_regimes = 2)
```

find_swans

Find outlying "black swan" jumps in trends

Description

Find outlying "black swan" jumps in trends

Usage

```
find_swans(rotated_model_fit, threshold = 0.01, plot = FALSE)
```

Arguments

rotated_modelfit
 Output from `rotate_trends()`.

threshold
 A probability threshold below which to flag trend events as extreme

plot
 Logical: should a plot be made?

Value

Prints a ggplot2 plot if `plot = TRUE`; returns a data frame indicating the probability that any given point in time represents a "black swan" event invisibly.

References

Anderson, S.C., Branch, T.A., Cooper, A.B., and Dulvy, N.K. 2017. Black-swan events in animal populations. *Proceedings of the National Academy of Sciences* 114(12): 3252–3257. <https://doi.org/10.1073/pnas.1611525114>

Examples

```
set.seed(1)
s <- sim_dfa(num_trends = 1, num_ts = 3, num_years = 30)
s$y_sim[1, 15] <- s$y_sim[1, 15] - 6
plot(s$y_sim[1, ], type = "o")
abline(v = 15, col = "red")
# only 1 chain and 250 iterations used so example runs quickly:
m <- fit_dfa(y = s$y_sim, num_trends = 1, iter = 50, chains = 1, nu_fixed = 2)
r <- rotate_trends(m)
p <- plot_trends(r) #+ geom_vline(xintercept = 15, colour = "red")
print(p)
# a 1 in 1000 probability if was from a normal distribution:
find_swans(r, plot = TRUE, threshold = 0.001)
```

fit_dfa

*Fit a Bayesian DFA***Description**

Fit a Bayesian DFA

Usage

```
fit_dfa(
  y = y,
  num_trends = 1,
  varIndx = NULL,
  scale = c("zscore", "center", "none"),
  iter = 2000,
  chains = 4,
```

```

thin = 1,
control = list(adapt_delta = 0.99, max_treedepth = 20),
nu_fixed = 101,
est_correlation = FALSE,
estimate_nu = FALSE,
estimate_trend_ar = FALSE,
estimate_trend_ma = FALSE,
estimate_process_sigma = FALSE,
equal_process_sigma = TRUE,
estimation = c("sampling", "optimizing", "vb", "none"),
data_shape = c("wide", "long"),
obs_covar = NULL,
pro_covar = NULL,
offset = NULL,
z_bound = NULL,
z_model = c("dfa", "proportion"),
trend_model = c("rw", "bs", "ps", "gp"),
n_knots = NULL,
knot_locs = NULL,
par_list = NULL,
family = "gaussian",
verbose = FALSE,
inv_var_weights = NULL,
likelihood_weights = NULL,
gp_theta_prior = c(3, 1),
expansion_prior = FALSE,
...
)

```

Arguments

<code>y</code>	A matrix of data to fit. See <code>data_shape</code> option to specify whether this is long or wide format data. Wide format data (default) is a matrix with time across columns and unique time series across rows, and can only contain 1 observation per time series - time combination. In contrast, long format data is a data frame that includes observations ("obs"), time ("time") and time series ("ts") identifiers – the benefit of long format is that multiple observations per time series can be included. Correlation matrix currently not estimated if data shape is long.
<code>num_trends</code>	Number of trends to fit.
<code>varIndx</code>	Indices indicating which timeseries should have shared variances.
<code>scale</code>	Character string, used to standardized data. Can be "zscore" to center and standardize data, "center" to just standardize data, or "none". Defaults to "zscore"
<code>iter</code>	Number of iterations in Stan sampling, defaults to 2000. Used for both <code>rstan::sampling()</code> and <code>rstan::vb()</code>
<code>chains</code>	Number of chains in Stan sampling, defaults to 4.
<code>thin</code>	Thinning rate in Stan sampling, defaults to 1.

control	A list of options to pass to Stan sampling. Defaults to <code>list(adapt_delta = 0.99, max_treedepth = 20)</code> .
nu_fixed	Student t degrees of freedom parameter. If specified as greater than 100, a normal random walk is used instead of a random walk with a t-distribution. Defaults to 101.
est_correlation	Boolean, whether to estimate correlation of observation error matrix R. Defaults to FALSE. Currently can't be estimated if data are in long format.
estimate_nu	Logical. Estimate the student t degrees of freedom parameter? Defaults to FALSE,
estimate_trend_ar	Logical. Estimate AR(1) parameters on DFA trends? Defaults to 'FALSE', in which case AR(1) parameters are set to 1
estimate_trend_ma	Logical. Estimate MA(1) parameters on DFA trends? Defaults to 'FALSE', in which case MA(1) parameters are set to 0.
estimate_process_sigma	Logical. Defaults FALSE, whether or not to estimate process error sigma. If not estimated, sigma is fixed at 1, like conventional DFAs.
equal_process_sigma	Logical. If process sigma is estimated, whether or not to estimate a single shared value across trends (default) or estimate equal values for each trend
estimation	Character string. Should the model be sampled using <code>rstan::sampling()</code> ("sampling", default), <code>rstan::optimizing()</code> ("optimizing"), variational inference <code>rstan::vb()</code> ("vb"), or no estimation done ("none"). No estimation may be useful for debugging and simulation.
data_shape	If wide (the current default) then the input data should have rows representing the various timeseries and columns representing the values through time. This matches the MARSS input data format. If long then the long format data is a data frame that includes observations ("obs"), time ("time") and time series ("ts") identifiers – the benefit of long format is that multiple observations per time series can be included
obs_covar	Optional dataframe of data with 4 named columns ("time", "timeseries", "covariate", "value"), representing: (1) time, (2) the time series affected, (3) the covariate number for models with more than one covariate affecting each trend, and (4) the value of the covariate
pro_covar	Optional dataframe of data with 4 named columns ("time", "trend", "covariate", "value"), representing: (1) time, (2) the trend affected, (3) the covariate number for models with more than one covariate affecting each trend, and (4) the value of the covariate
offset	a string argument representing the name of the offset variable to be included. The variable name is in the data frame passed in, e.g. "offset". This only works when the data shape is "long". All transformations (such as log transformed effort) to the offset must be done before passing in the data.
z_bound	Optional hard constraints for estimated factor loadings – really only applies to model with 1 trend. Passed in as a 2-element vector representing the lower and upper bound, e.g. (0, 100) to constrain positive

z_model	Optional argument allowing for elements of Z to be constrained to be proportions (each time series modeled as a mixture of trends). Arguments can be "dfa" (default) or "proportion"
trend_model	Optional argument to change the model of the underlying latent trend. By default this is set to 'rw', where the trend is modeled as a random walk - as in conventional DFA. Alternative options are 'bs', where B-splines are used to model the trends, "ps" where P-splines are used to model the trends, or 'gp', where gaussian predictive processes are used. If models other than 'rw' are used, there are some key points. First, the MA and AR parameters on these models will be turned off. Second, for B-splines and P-splines, the process_sigma becomes an optional scalar on the spline coefficients, and is turned off by default. Third, the number of knots can be specified (more knots = more wiggleness, and n_knots < N). For models with > 2 trends, each trend has their own spline coefficients estimated though the knot locations are assumed shared. If knots aren't specified, the default is N/3. By default both the B-spline and P-spline models use 3rd degree functions for smoothing, and include an intercept term. The P-spline model uses a difference penalty of 2.
n_knots	The number of knots for the B-spline, P-spline, or Gaussian predictive process models. Optional, defaults to round(N/3)
knot_locs	Locations of knots (optional), defaults to uniform spacing between 1 and N
par_list	A vector of parameter names of variables to be estimated by Stan. If NULL, this will default to c("x", "Z", "sigma", "log_lik", "psi", "xstar") for most models – though if AR / MA, or Student-t models are used additional parameters will be monitored. If you want to use diagnostic tools in rstan, including moment_matching, you will need to pass in a larger list. Setting this argument to "all" will monitor all parameters, enabling the use of diagnostic functions – but making the models a lot larger for storage. Finally, this argument may be a custom string of parameters to monitor, e.g. c("x", "sigma")
family	String describing the observation model. Default is "gaussian", but included options are "gamma", "lognormal", negative binomial ("nbinom2"), "poisson", or "binomial". The binomial family is assumed to have logit link, gaussian family is assumed to be identity, and the rest are log-link.
verbose	Whether to print iterations and information from Stan, defaults to FALSE.
inv_var_weights	Optional name of inverse variance weights argument in data frame. This is only implemented when data are in long format. If not entered, defaults to inv_var_weights = 1 for all observations. The implementation of inv_var_weights relies on inverse variance weightings, so that if you have standard errors associated with each observation, the inverse variance weights are calculated as $inv_var_weights \leftarrow 1 / (standard_errors^2)$. The observation error sigma in the likelihood then becomes $\sigma / \sqrt{inv_var_weights}$
likelihood_weights	Optional name of likelihood weights argument in data frame. These are used in the same way weights are implemented in packages glmmTMB, brms, sdmTMB, etc. Weights are used as multipliers on the log-likelihood, with higher weights allowing observations to contribute more. Currently only implemented with univariate distributions, when data is in long format

`gp_theta_prior` A 2-element vector controlling the prior on the Gaussian process parameter in `cov_exp_quad`. This prior is a half-Student t prior, with the first argument of `gp_theta_prior` being the degrees of freedom (`nu`), and the second element being the standard deviation

`expansion_prior` Defaults to `FALSE`, if `TRUE` uses the parameter expansion prior of Ghosh & Dunson 2009

... Any other arguments to pass to `rstan::sampling()`.

Details

Note that there is nothing restricting the loadings and trends from being inverted (i.e. multiplied by -1) for a given chain. Therefore, if you fit multiple chains, the package will attempt to determine which chains need to be inverted using the function `find_inverted_chains()`.

See Also

`plot_loadings` `plot_trends` `rotate_trends` `find_swans`

Examples

```
set.seed(42)
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
# only 1 chain and 250 iterations used so example runs quickly:
m <- fit_dfa(y = s$y_sim, iter = 50, chains = 1)
## Not run:
# example of observation error covariates
set.seed(42)
obs_covar <- expand.grid("time" = 1:20, "timeseries" = 1:3, "covariate" = 1)
obs_covar$value <- rnorm(nrow(obs_covar), 0, 0.1)
m <- fit_dfa(y = s$y_sim, iter = 50, chains = 1, obs_covar = obs_covar)

# example of process error covariates
pro_covar <- expand.grid("time" = 1:20, "trend" = 1:2, "covariate" = 1)
pro_covar$value <- rnorm(nrow(pro_covar), 0, 0.1)
m <- fit_dfa(y = s$y_sim, iter = 50, chains = 1, num_trends = 2, pro_covar = pro_covar)

# example of long format data
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
obs <- c(s$y_sim[1, ], s$y_sim[2, ], s$y_sim[3, ])
long <- data.frame("obs" = obs, "ts" = sort(rep(1:3, 20)), "time" = rep(1:20, 3))
m <- fit_dfa(y = long, data_shape = "long", iter = 50, chains = 1)

# example of long format data with obs covariates
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
obs <- c(s$y_sim[1, ], s$y_sim[2, ], s$y_sim[3, ])
long <- data.frame("obs" = obs, "ts" = sort(rep(1:3, 20)), "time" = rep(1:20, 3))
obs_covar <- expand.grid("time" = 1:20, "timeseries" = 1:3, "covariate" = 1:2)
obs_covar$value <- rnorm(nrow(obs_covar), 0, 0.1)
m <- fit_dfa(y = long, data_shape = "long", iter = 50, chains = 1, obs_covar = obs_covar)
```

```

# example of model with Z constrained to be proportions and wide format data
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
m <- fit_dfa(y = s$y_sim, z_model = "proportion", iter = 50, chains = 1)

# example of model with Z constrained to be proportions and long format data
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
obs <- c(s$y_sim[1, ], s$y_sim[2, ], s$y_sim[3, ])
long <- data.frame("obs" = obs, "ts" = sort(rep(1:3, 20)), "time" = rep(1:20, 3))
m <- fit_dfa(y = long, data_shape = "long", z_model = "proportion", iter = 50, chains = 1)

#' # example of B-spline model with wide format data
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
m <- fit_dfa(y = s$y_sim, iter = 50, chains = 1, trend_model = "bs", n_knots = 10)

#' #' # example of P-spline model with wide format data
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
m <- fit_dfa(y = s$y_sim, iter = 50, chains = 1, trend_model = "ps", n_knots = 10)

# example of Gaussian process model with wide format data
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
m <- fit_dfa(y = s$y_sim, iter = 50, chains = 1, trend_model = "gp", n_knots = 5)

# example of long format data
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
obs <- c(s$y_sim[1, ], s$y_sim[2, ], s$y_sim[3, ])
long <- data.frame("obs" = obs, "ts" = sort(rep(1:3, 20)),
"time" = rep(1:20, 3), "offset" = rep(0.1,length(obs)))
m <- fit_dfa(y = long, data_shape = "long", offset = "offset", iter = 50, chains = 1)

## End(Not run)

```

fit_regimes

Fit models with differing numbers of regimes to trend data

Description

Fit models with differing numbers of regimes to trend data

Usage

```

fit_regimes(
  y,
  sds = NULL,
  n_regimes = 2,
  iter = 2000,
  thin = 1,
  chains = 1,
  ...
)

```


Arguments

y	Data, time series or trend from fitted DFA model.
sds	Optional time series of standard deviations of estimates. If passed in, residual variance not estimated. Defaults to NULL.
n_regimes	Number of regimes to evaluate, defaults 2
iter	MCMC iterations, defaults to 2000.
thin	MCMC thinning rate, defaults to 1.
chains	MCMC chains, defaults to 1 (note that running multiple chains may result in a label switching problem where the regimes are identified with different IDs across chains).
...	Other parameters to pass to <code>rstan::sampling()</code> .

Examples

```
data(Nile)
fit_regimes(log(Nile), iter = 50, n_regimes = 1)
```

hmm_init	<i>Create initial values for the HMM model.</i>
----------	---

Description

Create initial values for the HMM model.

Usage

```
hmm_init(K, x_t)
```

Arguments

K	The number of regimes or clusters to fit. Called by <code>rstan::sampling()</code> .
x_t	A matrix of values. Called by <code>rstan::sampling()</code> .

Value

list of initial values (mu, sigma)

invert_chains	<i>Invert chains</i>
---------------	----------------------

Description

Invert chains

Usage

```
invert_chains(model, trends = 1, print = FALSE, ...)
```

Arguments

model	A Stan model, rstanfit object
trends	The number of trends in the DFA, defaults to 1
print	Logical indicating whether the summary should be printed. Defaults to FALSE.
...	Other arguments to pass to find_inverted_chains() .

See Also

[find_inverted_chains](#)

is_converged	<i>Summarize Rhat convergence statistics across parameters</i>
--------------	--

Description

Pass in rstanfit model object, and a threshold Rhat value for convergence. Returns boolean.

Usage

```
is_converged(fitted_model, threshold = 1.05, parameters = c("sigma", "x", "Z"))
```

Arguments

fitted_model	Samples extracted (with permuted = FALSE) from a Stan model. E.g. output from invert_chains() .
threshold	Threshold for maximum Rhat.
parameters	Vector of parameters to be included in convergence determination. Defaults = c("sigma", "x", "Z"). Other elements can be added including "pred", "log_lik", or "lp__"

loo.bayesdfa	<i>LOO information criteria</i>
--------------	---------------------------------

Description

Extract the LOOIC (leave-one-out information criterion) using `loo::loo()`. Note that we've implemented slightly different variants of `loo`, based on whether the DFA observation model includes correlation between time series or not (default is no correlation). Importantly, these different versions are not directly comparable to evaluate data support for including correlation or not in a DFA. If time series are not correlated, the point-wise log-likelihood for each observation is calculated and used in the `loo` calculations. However if time series are correlated, then each time slice is assumed to be a joint observation of all variables, and the point-wise log-likelihood is calculated as the joint likelihood of all variables under the multivariate normal distribution.

Usage

```
## S3 method for class 'bayesdfa'
loo(x, ...)
```

Arguments

```
x           Output from fit_dfa().
...         Arguments for loo::relative_eff() and loo::loo.array().
```

Examples

```
set.seed(1)
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
m <- fit_dfa(y = s$y_sim, iter = 50, chains = 1, num_trends = 1)
loo(m)
```

plot_fitted	<i>Plot the fitted values from a DFA</i>
-------------	--

Description

Plot the fitted values from a DFA

Usage

```
plot_fitted(
  modelfit,
  conf_level = 0.95,
  names = NULL,
  spaghetti = FALSE,
  time_labels = NULL
)
```

Arguments

modelfit	Output from <code>fit_dfa</code> , a rstanfit object
conf_level	Probability level for CI.
names	Optional vector of names for plotting labels TODO. Should be same length as the number of time series
spaghetti	Defaults to FALSE, but if TRUE puts all raw time series (grey) and fitted values on a single plot
time_labels	Optional vector of time labels for plotting, same length as number of time steps

See Also

plot_loadings fit_dfa rotate_trends dfa_fitted

Examples

```
y <- sim_dfa(num_trends = 2, num_years = 20, num_ts = 4)
m <- fit_dfa(y = y$y_sim, num_trends = 2, iter = 50, chains = 1)
p <- plot_fitted(m)
print(p)

p <- plot_fitted(m, spaghetti = TRUE)
print(p)
```

plot_loadings

Plot the loadings from a DFA

Description

Plot the loadings from a DFA

Usage

```
plot_loadings(
  rotated_modelfit,
  names = NULL,
  facet = TRUE,
  violin = TRUE,
  conf_level = 0.95,
  threshold = NULL
)
```

Arguments

rotated_model_fit	Output from <code>rotate_trends()</code> .
names	An optional vector of names for plotting the loadings.
facet	Logical. Should there be a separate facet for each trend? Defaults to TRUE.
violin	Logical. Should the full posterior densities be shown as a violin plot? Defaults to TRUE.
conf_level	Confidence level for credible intervals. Defaults to 0.95.
threshold	Numeric (0-1). Optional for plots, if included, only plot loadings who have $\Pr(<0)$ or $\Pr(>0) > \text{threshold}$. For example <code>threshold = 0.8</code> would only display estimates where 80% of posterior density was above/below zero. Defaults to NULL (not used).

See Also

`plot_trends` `fit_dfa` `rotate_trends`

Examples

```
set.seed(42)
s <- sim_dfa(num_trends = 2, num_ts = 4, num_years = 10)
# only 1 chain and 180 iterations used so example runs quickly:
m <- fit_dfa(y = s$y_sim, num_trends = 2, iter = 50, chains = 1)
r <- rotate_trends(m)
plot_loadings(r, violin = FALSE, facet = TRUE)
plot_loadings(r, violin = FALSE, facet = FALSE)
plot_loadings(r, violin = TRUE, facet = FALSE)
plot_loadings(r, violin = TRUE, facet = TRUE)
```

`plot_regime_model` *Plot the state probabilities from `find_regimes()`*

Description

Plot the state probabilities from `find_regimes()`

Usage

```
plot_regime_model(
  model,
  probs = c(0.05, 0.95),
  type = c("probability", "means"),
  regime_prob_threshold = 0.9,
  plot_prob_indices = NULL,
  flip_regimes = FALSE
)
```

Arguments

model	A model returned by <code>find_regimes()</code> .
probs	A numeric vector of quantiles to plot the credible intervals at. Defaults to <code>c(0.05, 0.95)</code> .
type	Whether to plot the probabilities (default) or means.
regime_prob_threshold	The probability density that must be above 0.5. Defaults to 0.9 before we classify a regime (only affects "means" plot).
plot_prob_indices	Optional indices of probability plots to plot. Defaults to showing all.
flip_regimes	Optional whether to flip regimes in plots, defaults to FALSE

Details

Note that the original timeseries data (dots) are shown scaled between 0 and 1.

Examples

```
data(Nile)
m <- fit_regimes(log(Nile), n_regimes = 2, chains = 1, iter = 50)
plot_regime_model(m)
plot_regime_model(m, plot_prob_indices = c(2))
plot_regime_model(m, type = "means")
```

plot_trends

Plot the trends from a DFA

Description

Plot the trends from a DFA

Usage

```
plot_trends(
  rotated_model_fit,
  years = NULL,
  highlight_outliers = FALSE,
  threshold = 0.01
)
```

Arguments

rotated_model_fit	Output from rotate_trends
years	Optional numeric vector of years for the plot
highlight_outliers	Logical. Should trend events that exceed the probability of occurring with a normal distribution as defined by <code>threshold</code> be highlighted? Defaults to FALSE
threshold	A probability threshold below which to flag trend events as extreme. Defaults to 0.01

See Also

[dfa_trends](#) [plot_loadings](#) [fit_dfa](#) [rotate_trends](#)

Examples

```
set.seed(1)
s <- sim_dfa(num_trends = 1)
m <- fit_dfa(y = s$y_sim, num_trends = 1, iter = 50, chains = 1)
r <- rotate_trends(m)
p <- plot_trends(r)
print(p)
```

predicted

Calculate predicted value from DFA object

Description

Pass in `rstanfit` model object. Returns array of predictions, dimensioned number of MCMC draws x number of MCMC chains x time series length x number of time series

Usage

```
predicted(fitted_model)
```

Arguments

fitted_model	Samples extracted (with <code>permuted = FALSE</code>) from a Stan model. E.g. output from invert_chains() .
--------------	---

Examples

```
## Not run:
set.seed(42)
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
# only 1 chain and 1000 iterations used so example runs quickly:
m <- fit_dfa(y = s$y_sim, iter = 2000, chains = 3, num_trends = 1)
```

```
pred <- predicted(m)
## End(Not run)
```

rotate_trends	<i>Rotate the trends from a DFA</i>
---------------	-------------------------------------

Description

Rotate the trends from a DFA

Usage

```
rotate_trends(fitted_model, conf_level = 0.95, invert = FALSE)
```

Arguments

fitted_model	Output from fit_dfa() .
conf_level	Probability level for CI.
invert	Whether to invert the trends and loadings for plotting purposes

Examples

```
set.seed(42)
s <- sim_dfa(num_trends = 1, num_years = 20, num_ts = 3)
# only 1 chain and 800 iterations used so example runs quickly:
m <- fit_dfa(y = s$y_sim, iter = 50, chains = 1)
r <- rotate_trends(m)
plot_trends(r)
```

sim_dfa	<i>Simulate from a DFA</i>
---------	----------------------------

Description

Simulate from a DFA

Usage

```

sim_dfa(
  num_trends = 1,
  num_years = 20,
  num_ts = 4,
  loadings_matrix = matrix(nrow = num_ts, ncol = num_trends, rnorm(num_ts * num_trends,
    0, 1)),
  sigma = rlnorm(1, meanlog = log(0.2), 0.1),
  varIndx = rep(1, num_ts),
  trend_model = c("rw", "bs"),
  spline_weights = matrix(ncol = 6, nrow = num_trends, data = rnorm(6 * num_trends)),
  extreme_value = NULL,
  extreme_loc = NULL,
  nu_fixed = 100,
  user_supplied_deviations = NULL
)

```

Arguments

num_trends	The number of trends.
num_years	The number of years.
num_ts	The number of timeseries.
loadings_matrix	A loadings matrix. The number of rows should match the number of timeseries and the number of columns should match the number of trends. Note that this loadings matrix will be internally manipulated by setting some elements to 0 and constraining some elements to 1 so that the model can be fitted. See fit_dfa() . See the outfit element Z in the returned list is to see the manipulated loadings matrix. If not specified, a random matrix $\sim N(0, 1)$ is used.
sigma	A vector of standard deviations on the observation error. Should be of the same length as the number of trends. If not specified, random numbers are used $rlnorm(1, meanlog = \log(0.2), 0.1)$.
varIndx	Indices of unique observation variances. Defaults to <code>c(1, 1, 1, 1)</code> . Unique observation error variances would be specified as <code>c(1, 2, 3, 4)</code> in the case of 4 time series.
trend_model	The type of trend model. Random walk ("rw") or basis spline ("bs")
spline_weights	A matrix of basis function weights that is used if <code>trend_model = "bs"</code> . The number of columns should correspond to the number of knots and the number of rows should correspond to the number of trends.
extreme_value	Value added to the random walk in the extreme time step. Defaults to not included.
extreme_loc	Location of single extreme event in the process. The same for all processes, and defaults to <code>round(n_t/2)</code> where <code>n_t</code> is the time series length
nu_fixed	Nu is the degrees of freedom parameter for the t-distribution, defaults to 100, which is effectively normal.

user_supplied_deviations

An optional matrix of deviations for the trend random walks. Columns are for trends and rows are for each time step.

Value

A list with the following elements: `y_sim` is the simulated data, `pred` is the true underlying data without observation error added, `x` is the underlying trends, `Z` is the manipulated loadings matrix that is fed to the model.

Examples

```
x <- sim_dfa(num_trends = 2)
names(x)
matplot(t(x$y_sim), type = "l")
matplot(t(x$x), type = "l")

set.seed(42)
x <- sim_dfa(extreme_value = -4, extreme_loc = 10)
matplot(t(x$x), type = "l")
abline(v = 10)
matplot(t(x$pred), type = "l")
abline(v = 10)

set.seed(42)
x <- sim_dfa()
matplot(t(x$x), type = "l")
abline(v = 10)
matplot(t(x$pred), type = "l")
abline(v = 10)
```

trend_cor	<i>Estimate the correlation between a DFA trend and some other time-series</i>
-----------	--

Description

Fully incorporates the uncertainty from the posterior of the DFA trend

Usage

```
trend_cor(
  rotated_model_fit,
  y,
  trend = 1,
  time_window = seq_len(length(y)),
  trend_samples = 100,
  stan_iter = 300,
  stan_chains = 1,
  ...
)
```

Arguments

rotated_modelfit	Output from <code>rotate_trends()</code> .
y	A numeric vector to correlate with the DFA trend. Must be the same length as the DFA trend.
trend	A number corresponding to which trend to use, defaults to 1.
time_window	Indices indicating a time window slice to use in the correlation. Defaults to using the entire time window. Can be used to walk through the timeseries and test the cross correlations.
trend_samples	The number of samples from the trend posterior to use. A model will be run for each trend sample so this value shouldn't be too large. Defaults to 100.
stan_iter	The number of samples from the posterior with each Stan model run, defaults to 300.
stan_chains	The number of chains for each Stan model run, defaults to 1.
...	Other arguments to pass to <code>sampling</code>

Details

Uses a $\sigma \sim \text{half_t}(3, 0, 2)$ prior on the residual standard deviation and a $\text{uniform}(-1, 1)$ prior on the correlation coefficient. Fitted as a linear regression of $y \sim x$, where y represents the y argument to `trend_cor()` and x represents the DFA trend, and both y and x have been scaled by subtracting their means and dividing by their standard deviations. Samples are drawn from the posterior of the trend and repeatedly fed through the Stan regression to come up with a combined posterior of the correlation.

Value

A numeric vector of samples from the correlation coefficient posterior.

Examples

```
set.seed(1)
s <- sim_dfa(num_trends = 1, num_years = 15)
m <- fit_dfa(y = s$y_sim, num_trends = 1, iter = 50, chains = 1)
r <- rotate_trends(m)
n_years <- ncol(r$trends[, 1, ])
fake_dat <- rnorm(n_years, 0, 1)
correlation <- trend_cor(r, fake_dat, trend_samples = 25)
hist(correlation)
correlation <- trend_cor(r,
  y = fake_dat, time_window = 5:15,
  trend_samples = 25
)
hist(correlation)
```

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