Package ‘Rbeast’

December 8, 2023

Type Package

Version 1.0.0

Date 2023-12-08

Title Bayesian Change-Point Detection and Time Series Decomposition

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Depends R (>= 2.10.0),methods, utils

Description Interpretation of time series data is affected by model choices. Different models can give different or even contradicting estimates of patterns, trends, and mechanisms for the same data--a limitation alleviated by the Bayesian estimator of abrupt change,seasonality, and trend (BEAST) of this package. BEAST seeks to improve time series decomposition by forgoing the ``single-best-model'' concept and embracing all competing models into the inference via a Bayesian model averaging scheme. It is a flexible tool to uncover abrupt changes (i.e., change-points), cyclic variations (e.g., seasonality), and nonlinear trends in time-series observations. BEAST not just tells when changes occur but also quantifies how likely the detected changes are true. It detects not just piecewise linear trends but also arbitrary nonlinear trends. BEAST is applicable to real-valued time series data of all kinds, be it for remote sensing, economics, climate sciences, ecology, and hydrology. Example applications include its use to identify regime shifts in ecological data, map forest disturbance and land degradation from satellite imagery, detect market trends in economic data, pinpoint anomaly and extreme events in climate data, and unravel system dynamics in biological data. Details on BEAST are reported in Zhao et al. (2019) <doi:10.1016/j.rse.2019.04.034>.

LazyData true

Imports grid

License GPL (>= 2)

URL https://github.com/zhaokg/Rbeast

NeedsCompilation yes

Repository CRAN

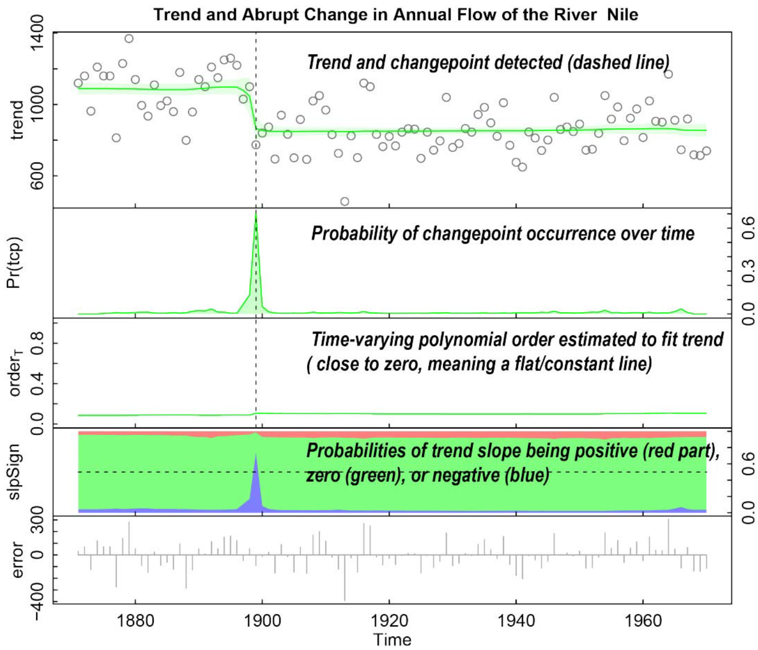
Date/Publication 2023-12-08 10:30:05 UTC

R topics documented:

`beast` *Bayesian changepoint detection detection and time series decomposition for trend, periodicity or seasonality, and abrupt changes*

Description

A Bayesian model averaging algorithm called BEAST to decompose time series or 1D sequential data into individual components, such as abrupt changes, trends, and periodic/seasonal variations. BEAST is useful for changepoint detection (e.g., breakpoints or structural breaks), nonlinear trend analysis, time series decomposition, and time series segmentation.



Usage

```
beast(
       y,
       start          = 1,
       deltat         = 1,
       season         = c("harmonic", "svd", "dummy", "none"),
       period         = NULL,
       scp.minmax     = c(0,10), sorder.minmax   = c(0,5),
       tcp.minmax     = c(0,10), torder.minmax   = c(0,1),
   sseg.min       = NULL,    sseg.leftmargin = NULL,  sseg.rightmargin = NULL,
   tseg.min       = NULL,    tseg.leftmargin = NULL,  tseg.rightmargin = NULL,
       method         = c('bayes','bic', 'aic','aicc','hic'),
       detrend        = FALSE,
       deseasonalize  = FALSE,
       mcmc.seed      = 0,
       mcmc.burnin    = 200,
       mcmc.chains    = 3,
       mcmc.thin      = 5,
       mcmc.samples   = 8000,
       ci             = FALSE,
       precValue      = 1.5,
       precPriorType  = c('componentwise','uniform','constant','orderwise'),
       print.options  = TRUE,
       print.progress = TRUE,
       quiet          = FALSE,
       gui            = FALSE,
```

```
      ...
  )
```

Arguments

`y` a vector for an evenly-spaced regular time series. Missing values such as NA and NaN are allowed.

- If `y` is irregular or unordered in time (e.g., multiple years of daily data spanning across leap years: 365 points in some years, and 366 in others), use the `beast.irreg` function instead.
- If `y` is a matrix or 3D array consisting of multiple regular or irregular time series (e.g., stacked images), use `beast123` instead.
- If `y` is an object of class 'ts','xts', or 'zoo', its time attributes (i.e.,start, end, frequency) will be used to specify the next several args such as `start`,`detlta`,`period`, and `season`: No need to provide them explicitly; even if provided, the values are ignored to honor the time attributes of `y`. For example, if `y` has a frequency = 1, `season = 'none'` is always assumed; if `y` has a frequency > 1 (i.e., with a periodic component) but `season='none'` is specified by the user, 'none' will be replaced by 'harmonic'.

If a list of multiple time series is provided for `y`, the multivariate version of the BEAST algorithm will be invoked to decompose the multiple time series and detect common changepoints altogether. This feature is `experimental` only and under further development. Check `ohio` for a working example.

`start` numeric (default to 1.0) or `Date`; the time of the 1st datapoint of `y`. It can be specified as a scalar (e.g., 2021.0644), a vector of three values in the order of Year, Month, and Day (e.g., `c(2021,1,24)`), or a R's Date object (e.g., `as.Date('2021-1-24')`).

`deltat` numeric (default to 1.0) or string; the time interval between consecutive data points. Its unit should be consistent with `start`. If `start` takes a numeric scalar, the unit is arbitrary and irrelevant to beast (e.g., 2021.3 can be of any unit: Year 2021.3, 2021.3 meters, 2021.3 degrees ...). If `start` is a vector of Year, Month, and Day or an R's Date, `deltat` has the unit of YEAR. For example, if `start=c(2021,1,24)` for a monthly time series, `start` is converted to a fractional year 2021+(24-0.5)/365=2021.0644 and `deltat=1/12` needs to be set in order to specify the monthly interval. Alternatively, `deltat` can be provided as a string to specify whether its unit is day, month, or year. Examples include '7 days', '7d', '1/2 months', '1 mn', '1.0 year', and '1y'.

`season` characters (default to 'harmonic'); specify if `y` has a periodic component or not. Four strings are possible.

- `'none'`: `y` is trend-only; no periodic components are present in the time series. The args for the seasonal component (i.e.,`sorder.minmax`, `scp.minmax` and `sseg.max`) will be irrelevant and ignored.
- `'harmonic'`: `y` has a periodic/seasonal component. The term `season` is a misnomer, being used here to broadly refer to any periodic variations present in `y`. The periodicity is NOT a model parameter estimated by BEAST but a known constant given by the user through `freq`. By default,

the periodic component is modeled as a harmonic curve–a combination of sins and cosines.

- `'dummy'`: the same as `'harmonic'` except that the periodic/seasonal component is modeled as a non-parametric curve. The harmonic order arg `sorder.minmax` is irrelevant and is ignored.
- `'svd'`: (experimental feature) the same as `'harmonic'` except that the periodic/seasonal component is modeled as a linear combination of function bases derived from a Single-value decomposition. The SVD-based basis functions are more parsimonious than the harmonic sin/cos bases in parameterizing the seasonal variations; therefore, more subtle changepoints are likely to be detected.

`period` numeric or string. Specify the period for the periodic/seasonal component in `y`. Needed only for data with a periodic/cyclic component (i.e., season=`'harmonic'` or `'dummy'`) and not used for trend-only data (i.e., `season='none'`). The period of the cyclic component should have a unit consisent with the unit of `deltat`. It holds that `period=deltat*freq` where `freq` is the number of data samples per period. (Note that the `freq` argument in earlier versions becomes obsolete and now is replaced by `period`. `freq` is still supported but`period` takes precedence if both are provided.) `period` or the number of data points per period is not a BEAST model parameter and it has to be specified by the user. But if `period` is missing, BEAST first attempts to guess its value via auto-correlation before fitting the model. If `period` <= 0, `season='none'` is assumed, and the trend-only model is fitted without a seasonal/cyclic component. If needed, use a string to specify whether the unit of period is day, month, or year. Examples are '1.0 year', '12 months', '365d', '366 days'.

`scp.minmax` a vector of 2 integers (>=0); the min and max number of seasonal changepoints (scp) allowed in segmenting the seasonal component. `scp.minmax` is used only if `y` has a seasonal component (i.e., `season='harmonic' or 'dummy'`) and ignored for trend-only data. If the min and max changepoint numbers are equal, BEAST assumes a constant number of scp and won't infer the posterior probability of the number of changepoints, but it still estimates the occurrence probability of the changepoints over time (i.e., the most likely times at which these changepoints occur). If both the min and max numbers are set to 0, no changepoints are allowed; then a global harmonic model is used to fit the seasonal component, but still, the most likely harmonic order will be inferred if sorder.minmax[1] is not equal to sorder.minmax[2].

`sorder.minmax` a vector of 2 integers (>=1); the min and max harmonic orders considered to fit the seasonal component. `sorder.minmax` is used only used if the time series has a seasonal component (i.e., `season='harmonic'`) and ignored for trend-only data or when `season='dummy'`. If the min and max orders are equal (`sorder.minmax[1]=sorder.minmax[2]`), BEAST assumes a constant harmonic order used and won't infer the posterior probability of harmonic orders.

`tcp.minmax` a vector of 2 integers (>=0); the min and max number of trend changepoints (tcp) allowed in segmenting the trend component. If the min and max changepoint numbers are equal, BEAST assumes a constant number of changepoints and won't infer the posterior probability of the number of changepoints for the trend, but it still estimates the occurrence probability of the changepoints over time (i.e., the most likely times at which these changepoints occur in the trend). If both the min and max numbers are set to 0, no changepoints are allowed; then a global polynomial trend is used to fit the trend component, but still, the most likely polynomial order will be inferred if torder.minmax[1] is not equal to torder.minmax[2].

`torder.minmax` a vector of 2 integers (>=0); the min and max orders of the polynomials considered to fit the trend component. The 0-th order corresponds to a constant term/a flat line and the 1st order is a line. If `torder.minmax[1]=torder.minmax[2]`, BEAST assumes a constant polynomial order used and won't infer the posterior probability of polynomial orders.

`sseg.min` an integer (>0); the min segment length allowed between two neighboring season changepoints. That is, when fitting a piecewise harmonic seasonal model, two changepoints are not allowed to occur within a time window of length `sseg.min`. `sseg.min` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `sseg.min*deltat`. `sseg.min` defaults to NULL and its value will be given a default value in reference to `freq`.

`sseg.leftmargin`
an integer (>=0); the number of leftmost data points excluded for seasonal changepoint detection. That is, when fitting a piecewise harmonic seasonal model, no changepoints are allowed in the starting window/segment of length `sseg.leftmargin`. `sseg.leftmargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `sseg.leftmargin*deltat`. If missing, `sseg.leftmargin` defaults to `sseg.min`.

`sseg.rightmargin`
an integer (>=0); the number of rightmost data points excluded for seasonal changepoint detection. That is, when fitting a piecewise harmonic seasonal model, no changepoints are allowed in the ending window/segment of length `sseg.rightmargin`. `sseg.rightmargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `sseg.rightmargin*deltat`. If missing, `sseg.rightmargin` defaults to `sseg.min`.

`tseg.min` an integer (>0); the min segment length allowed between two neighboring trend changepoints. That is, when fitting a piecewise polynomial trend model, two changepoints are not allowed to occur within a time window of length `tseg.min`. `tseg.min` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `tseg.min*deltat`. `tseg.min` defaults to NULL and its value will be given a default value in reference to `freq` if the time series has a cyclic component.

`tseg.leftmargin`
an integer (>=0); the number of leftmost data points excluded for trend changepoint detection. That is, when fitting a piecewise polynomial trend model, no changepoints are allowed in the starting window/segment of length `tseg.leftmargin`. `tseg.leftmargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `tseg.leftmargin*deltat`. If missing, `tseg.leftmargin` defaults to `tseg.min`.

`tseg.rightmargin`
an integer (>=0); the number of rightmost data points excluded for trend changepoint detection. That is, when fitting a piecewise polynomial trend model, no

changepoints are allowed in the ending window/segment of length `tseg.rightmargin`. `tseg.rightmargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `tseg.rightmargin*deltat`. If missing, `tseg.rightmargin` defaults to `tseg.min`.

`method` an string (default to 'bayes'); specify which method is used to formulate model posterior probability.

- `'bayes'`: the full Bayesian formulation as described in Zhao et al. (2019).
- `'bic'`: approximation of posterior probability using the Bayesian information criterion (bic).
- `'aic'`: approximation of posterior probability using the Akaike information criterion (aic).
- `'aicc'`: approximation of posterior probability using the corrected Akaike information criterion (aicc).
- `'hic'`: approximation of posterior probability using the Hannan-Quinn information criterion (hic)

`detrend` logical; If `TRUE`, a global trend is first fitted and removed from the time series before running BEAST; after BEAST finishes, the global trend is added back to the BEAST result.

`deseasonalize` logical; If `TRUE`, a global seasonal model is first fitted and removed from the time series before running BEAST; after BEAST finishes, the global seasonal curve is added back to the BEAST result. `deseasonalize` is ignored if `season='none'` (i.e., trend-only data).

`mcmc.seed` integer (>=0); the seed for the random number generator used for Monte Carlo Markov Chain (mcmc). If `mcmc.seed=0`, an arbitrary seed is picked and the fitting results vary across runs. If fixed to the same non-zero integer, the result can be re-produced for different runs. But the results from the same seed may still vary if run on different computers because the random generator library depends on CPU's instruction sets.

`mcmc.chains` integer (>0); the number of MCMC chains.

`mcmc.thin` integer (>0); a factor to thin chains (e.g., if thinningFactor=5, samples will be taken every 3 iterations)

`mcmc.burnin` integer (>0); the number of burn-in samples discarded at the start of each chain

`mcmc.samples` integer (>=0); the number of samples collected per MCMC chain. The total number of iterations is `(burnin+samples*thin)*chains`.

`ci` boolean; If `TRUE`, credible intervals (i.e., out$season$CI or out$trend$CI) will be computed for the estimated seasonal and trend components. Computing CI is time-consuming, due to sorting, so set `ci` to FALSE if a symmetric credible interval (i.e., out$trend$SD and out$season$SD) suffices.

`precValue` numeric (>0); the hyperparameter of the precision prior; the default value is 1.5. `precValue` is useful only when `precPriorType`='constant', as further explained below

`precPriorType` characters. It takes one of 'constant', 'uniform', 'componentwise' (the default), and 'orderwise'. Below are the differences between them.

1. `'constant'`: the precision parameter used to parameterize the model coefficients is fixed to a constant specified by `precValue`. In other words, `precValue` is a user-defined hyperparameter and the fitting result may be sensitive to the chosen values of `precValue`.
2. `'uniform'`: the precision parameter used to parameterize the model coefficients is a random variable; its initial value is specified by `precValue`. In other words, `precValue` will be inferred by the MCMC, so the fitting result will be insensitive to the choice in `precValue`.
3. `'componentwise'`: multiple precision parameters are used to parameterize the model coefficients for individual components (e.g., one for season and another for trend); their initial values is specified by `precValue`. In other words, `precValue` will be inferred by the MCMC, so the fitting result will be insensitive to the choice in `precValue`.
4. `'orderwise'`: multiple precision parameters are used to parameterize the model coefficients not just for individual components but also for individual orders of each component; their initial values is specified by `precValue`. In other words, `precValue` will be inferred by the MCMC, so the fitting result will be insensitive to the choice in `precValue`.

`print.options` boolean. If `TRUE`,the full list of input parameters to BEAST will be printed out prior to the MCMC inference; the naming for this list (e.g., metadata, prior, and mcmc) differs slightly from the input to `beast`, but there is a one-to-one correspondence (e.g., prior$trendMinSepDist=tseg.min). Internally, beast converts the input parameters to the forms of metadata, prior,and mcmc. Type 'View(beast)' to see the details or check the `beast123` function.

`print.progress` boolean;If `TRUE`, a progressbar will be displayed.

`quiet` boolean. If `TRUE`, warning messages are suppressed and not printed.

`gui` boolean. If `TRUE`, BEAST will be run with a GUI window to show an animation of the MCMC sampling in the model space step by step; as an experimental feature, `"gui=TRUE"` works only for Windows x64 systems not Windows 32 or Linux/Mac.

`...` additional parameters. There are many more settings for the implementation but not made available in the beast() interface; please use the function `beast123()` instead

Value

The output is an object of class "beast". It is a list, consisting of the following variables. Its structure is the same as the outputs from the other two alternative functions `beast.irreg` and `beast123`. In the explanations below, we assume the input `y` is a single time series of length `N`:

`time` a vector of size `1xN`: the times at the `N` sampled locations. By default, it is simply set to `1:N`

`data` a vector, matrix, or 3D array; this is a copy of the input `y` if extra$dumpInputData = TRUE. If extra$dumpInputData=FALSE, it is set to NULL. If the original input `y` is irregular (as in `beast.irreg`), the copy here is the regular version aggregated from the original at the time interval specified by deltat (in `beast.irreg` or metadata$deltaTime (in `beast123`).

marg_lik
: numeric; the average of the model marginal likelihood; the larger marg_lik, the better the fitting for a given time series.

R2
: numeric; the R-square of the model fitting.

RMSE
: numeric; the RMSE of the model fitting.

sig2
: numeric; the estimated variance of the model error.

trend
: a list object consisting of various outputs related to the estimated trend component:

- `ncp`: [Number of ChangePoints]. a numeric scalar; the mean number of trend changepoints. Individual models sampled by BEAST has a varying dimension (e.g., number of changepoints or knots), so several alternative statistics (e.g., `ncp_mode`, `ncp_median`, and `ncp_pct90`) are also given to summarize the number of changepoints. For example, if `mcmc$samples=10`, the numbers of changepoints for the 10 sampled models are assumed to be c(0, 2, 4, 1, 1, 2, 7, 6, 6, 1). The mean ncp is 3.1 (rounded to 3), the median is 2.5 (2), the mode is 1, and the 90th percentile (ncp_pct90) is 6.5.
- `ncp_mode`: [Number of ChangePoints]. a numeric scalar; the mode for number of changepoints. See the above for explanations.
- `ncp_median`: [Number of ChangePoints]. a numeric scalar; the median for number of changepoints. See the above for explanations.
- `ncp_pct90`: [Number of ChangePoints]. a numeric scalar; the 90th percentile for number of changepoints. See the above for explanations.
- `ncpPr`: [Probability of the Number of ChangePoints]. A vector of length `(tcp.minmax[2]+1)=tcp.max+1`. It gives a probability distribution of having a certain number of trend changepoints over the range of [0,tcp.max]; for example, `ncpPr[1]` is the probability of having no trend changepoint; `ncpPr[i]` is the probability of having (i-1) changepoints: Note that it is `ncpPr[i]` not `ncpPr[i-1]` because ncpPr[1] is used for having zero changepoint.
- `cpOccPr`: [ChangePoint OCCurence PRobability]. a vector of length N; it gives a probability distribution of having a changepoint in the trend at each point of time. Plotting `cpOccPr` will depict a continious curve of probability-of-being-changepoint. ***Of particular note, in the curve, a higher peak indicates a higher chance of being a changepoint only at that particular SINGLE point in time and does not necessarily mean a higher chance of observing a changepoint AROUND that time. For example, a window of cpOccPr values*** `c(0,0,0.5,0,0)` ***(i.e., the peak prob is 0.5 and the summed prob is 0.5) is less likely to be a changepoint compared to another window*** `c(0.1,0.2,0.21,0.2,0.1)` ***(i.e., the peak prob is 0.21 but the summed prob is 0.71)***.
- `order`: a vector of length N; the average polynomial order needed to approximate the fitted trend. As an average over many sampled individual piece-wise polynomial trends, `order` is not necessarily an integer.
- `cp`: [Changepoints] a vector of length `tcp.max=tcp.minmax[2]`; the most possible changepoint locations in the trend component. The locations are obtained by first applying a sum-filtering to the `cpOccPr` curve with a filter window size of `tseg.min` and then picking up to a total `prior$MaxKnotNum/tcp.max`

of the highest peaks in the filtered curve. NaNs are possible if no enough changepoints are identified. cp records all the possible changepoints identified and many of them are bound to be false positives. Do not blindly treat all of them as actual changepoints.

- cpPr: [Changepoints PRobability] a vector of length tcp.max=tcp.minmax[2]; the probabilities associated with the changepoints cp. Filled with NaNs for the remaining elements if ncp<tcp.max.
- cpCI: [Changepoints Credible Interval] a matrix of dimension tcp.max x 2; the credibable intervals for the detected changepoints cp.
- cpAbruptChange: [Abrupt change at Changepoints] a vector of length tcp.max; the jumps in the fitted trend curves at the detected changepoints cp.
- Y: a vector of length N; the estimated trend component. It is the Bayesian model averaging of all the individual sampled trend.
- SD: [Standard Deviation] a vector of length N; the estimated standard deviation of the estimated trend component.
- CI: [Standard Deviation] a matrix of dimension N x 2; the estimated credible interval of the estimated trend. One vector of the matrix is for the upper envelope and another for the lower envelope.
- slp: [Slope] a vector of length N; the time-varying slope of the fitted trend component .
- slpSD: [Standar Deviation of Slope] a vector of length N; the SD of the slope for the trend component.
- slpSgnPosPr: [PRobability of slope having a positive sign] a vector of length N; the probability of the slope being positive (i.e., increasing trend) for the trend component. For example, if slpSgnPosPr=0.80 at a given point in time, it means that 80% of the individual trend models sampled in the MCMC chain has a positive slope at that point.
- slpSgnZeroPr: [PRobability of slope being zero] a vector of length N; the probability of the slope being zero (i.e., a flat constant line) for the trend component. For example, if slpSgnZeroPr=0.10 at a given point in time, it means that 10% of the individual trend models sampled in the MCMC chain has a zero slope at that point. The probability of slope being negative can be obtained from 1-slpSgnZeroPr-slpSgnPosPr.
- pos_ncp:
- neg_ncp:
- pos_ncpPr:
- neg_ncpPr:
- pos_cpOccPr:
- neg_cpOccPr:
- pos_cp:
- neg_cp:
- pos_cpPr:
- neg_cpPr:
- pos_cpAbruptChange:
- neg_cpAbruptChange:

- pos_cpCI:
- neg_cpCI: The above variables have the same outputs as those variables without the prefix 'pos' and 'neg', except that we differentiate the changepoints with a POStive jump in the trend from those changepoints with a NEGative jump. For example, pos_ncp refers to the average number of trend changepoints that jump up (i.e., positively) in the trend.
- inc_ncp:
- dec_ncp:
- inc_ncpPr:
- dec_ncpPr:
- inc_cpOccPr:
- dec_cpOccPr:
- inc_cp:
- dec_cp:
- inc_cpPr:
- dec_cpPr:
- inc_cpAbruptChange:
- dec_cpAbruptChange:
- inc_cpCI:
- dec_cpCI: The above variables have the same outputs as those variables without the prefix 'inc' and 'dec', except that we differentiate the changepoints at which the trend slope increases from those changepoints at which the trend slope decreases. For example, if the trend slopes before and after a chngpt is 0.4 and 2.5, then the changepoint is counted toward inc_ncp.

season
: a list object consisting of various outputs related to the estimated seasonal/periodic component:

- ncp: [Number of ChangePoints]. a numeric scalar; the mean number of seasonal changepoints.
- ncpPr: [Probability of the Number of ChangePoints]. A vector of length (scp.minmax[2]+1)=scp.max+1. It gives a probability distribution of having a certain number of seasonal changepoints over the range of [0,scp.max]; for example, ncpPr[1] is the probability of having no seasonal changepoint; ncpPr[i] is the probability of having (i-1) changepoints: Note that the index is i rather than (i-1) because ncpPr[1] is used for having zero changepoint.
- cpOccPr: [ChangePoint OCCurence PRobability]. a vector of length N; it gives a probability distribution of having a changepoint in the seasonal component at each point of time. Plotting cpOccPr will depict a continious curve of probability-of-being-changepoint over the time. Of particular note, in the curve, a higher value at a peak indicates a higher chance of being a changepoint only at that particular SINGLE point in time, and does not necessarily mean a higher chance of observing a changepoint AROUND that time. For example, a window of cpOccPr values c(0,0,0.5,0,0) (i.e., the peak prob is 0.5 and the summed prob is 0.5) is less likely to be a changepoint compared to another window values c(0.1,0.2,0.3,0.2,0.1) (i.e., the peak prob is 0.3 but the summed prob is 0.8).

- `order`: a vector of length N; the average harmonic order needed to approximate the seasonal component. As an average over many sampled individual piece-wise harmonic curves, `order` is not necessarily an integer.
- `cp`: [Changepoints] a vector of length `scp.max=scp.minmax[2]`; the most possible changepoint locations in the seasonal component. The locations are obtained by first applying a sum-filtering to the `cpOccPr` curve with a filter window size of `sseg.min` and then picking up to a total `ncp` of the highest peaks in the filtered curve. If `ncp<scp.max`, the remaining of the vector is filled with NaNs.
- `cpPr`: [Changepoints PRobability] a vector of length `scp.max`; the probabilities associated with the changepoints `cp`. Filled with NaNs for the remaining elements if `ncp<scp.max`.
- `cpCI`: [Changepoints Credible Interval] a matrix of dimension `scp.max` x `2`; the credibable intervals for the detected changepoints `cp`.
- `cpAbruptChange`: [Abrupt change at Changepoints] a vector of length `scp.max`; the jumps in the fitted seasonal curves at the detected changepoints `cp`.
- `Y`: a vector of length N; the estimated seasonal component. It is the Bayesian model averaging of all the individual sampled signal.
- `SD`: [Standard Deviation] a vector of length N; the estimated standard deviation of the estimated seasonal component.
- `CI`: [Standard Deviation] a matrix of dimension `N` x `2`; the estimated credible interval of the estimated seasonal signal. One vector of the matrix is for the upper envelope and another for the lower envelope.
- `amp`: [AMPlitude] a vector of length N; the time-varying amplitude of the estimated seasonality.
- `ampSD`: [Standar Deviation of AMPlitude] a vector of length N; , the SD of the amplitude of the seasonality.
- `pos_ncp`:
- `neg_ncp`:
- `pos_ncpPr`:
- `neg_ncpPr`:
- `pos_cpOccPr`:
- `neg_cpOccPr`:
- `pos_cp`:
- `neg_cp`:
- `pos_cpPr`:
- `neg_cpPr`:
- `pos_cpAbruptChange`:
- `neg_cpAbruptChange`:
- `pos_cpCI`:
- `neg_cpCI`: The above variables have the same outputs as those variables without the prefix 'pos' and 'neg', except that we differentiate the changepoints with a POStive jump in the trend from those changepoints with a NEGative jump. For example, `pos_ncp` refers to the average number of trend changepoints that jump up (i.e., positively) in the trend.

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

See Also

`beast`, `beast.irreg`, `beast123`, `minesweeper`, `tetris`, `geeLandsat`

Examples

```
library(Rbeast)


#------------------------------------Example 1----------------------------------------#
# 'googletrend_beach' is the monthly Google Trend popularity of searching for 'beach'
# in the US from 2004 to 2022. Sudden changes in the time series coincide with known
# extreme  weather events (e.g., 2006 North American Blizzard, 2011 US hottest summer
# on record, Record warm January in 2016) or the covid19 outbreak.

 out <- beast(googletrend_beach)

 plot(out)
 plot(out, vars=c('t','slpsgn') ) # plot the trend and probability of slope sign only.
                                  # In the slpsgn panel, the upper red portion refers to
                                 # probability of trend slope being positive, the middle
                                  # green to the prob of slope being zero, and the lower
                                  # blue to the probability of slope being negative.
                                  # Run "?plot.beast" for details on the plot function.

#------------------------------------Example 2----------------------------------------#
# Yellowstone is a half-monthly satellite time series of 774 NDVI(vegetation greeness)
# observations starting from July 1-15,1981(i.e., start=c(1981,7,7)) at a Yellowstone
# forest site. It has 24 data points per year (i.e., freq=24). Note that the beast
# function  hanldes only evenly-spaced regular time series. Irregular data need to be
# first  aggegrated at a regular time interval of your choice--the aggregation
# functionality is implemented in beast.irreg() and beast123().

 data(Yellowstone)
 plot( 1981.5+(0:773)/24, Yellowstone, type='l')  # A sudden drop in greenness in 1988
```

```
                                                  # due to the 1988 Yellowstone Fire

# Yellowstone is not a object of class 'ts' but a pure vector without time attributes.
# Below, no extra argument is supplied, so default values (i.e.,start=1, deltat=1) are
# used and the time is 1:774. 'period' is missing and so is guessed via auto-correlation.
# Use of auto-correlation to compute the period of a cyclic time series is not always
# reliable, so it is suggested to always supply 'period' directly, as in Example 2 and
# Example 3.

 o = beast(Yellowstone)   # By defualt, the times assumed to be 1:length(Yellowstone)
                          # and a periodic component is assumed (season='harmonic')
 plot(o)

#o = beast(Yellowstone, quiet=TRUE)                        # print no warning messages
#o = beast(Yellowstone, quiet=TRUE, print.progress=FALSE)  # print nothing

#------------------------------------Example 3---------------------------------------#
# The time info such as start,delta,and period is explicitly provided. 'start' can be
# given as (1) a fractional number, (2) a vector comprising year, month,& day, or (3)
# a R's Date. In (1), the unit of start and deltat does not necessarily refer to time and can
# be arbitrary (e.g., a sequence of data observed at evenly-spaced distaces along a
# transect or a elevation gradient)

 # (1) Unknown unit such that 1981.5137 can be interpreted arbitrarily
 o=beast(Yellowstone, start=1981.5137,           deltat=1/24,  period=1.0)

 # Use a string to explictly specify a time unit so that times are intepreted as dates
 # o=beast(Yellowstone, start=1981.5137, deltat='1/24 year', period=1.0) # 1.0 = 1 yr
 # o=beast(Yellowstone, start=1981.5137, deltat='0.5 mon',   period=1.0) # 1.0 = 1 yr
 # o=beast(Yellowstone, start=1981.5137, deltat=1/24, period='1 yr')    # 1/24 = 1/24 yr
 # o=beast(Yellowstone, start=1981.5137, deltat=1/24, period='365 days')# 1/24 = 1/24 yr

 # (2) start is provided as YMD, the unit is year: deltat=1/24 year=0.5 month
 # o=beast(Yellowstone, start=c(1981,7,7),        deltat=1/24,  period=1.0)

 # (3) start is provided as Date, the unit is year: deltat=1/24 year=0.5 month
 #o=beast(Yellowstone, start=as.Date('1981-7-7'), deltat=1/24, period=1.0)

 print(o)                          # o is a R LIST object with many fields
 str(o)                            # See a list of fields in o

 plot(o)                           # plot many variables
 plot(o, vars=c('y','s','t') )     # plot the Y, seasonal, and trend components only
 plot(o, vars=c('s','scp','samp','t','tcp','tslp'))# Plot some selected variables in
                                                   # 'o'. Type "?plot.beast" to see
                                                   # more about vars
 plot(o, vars=c('s','t'),col=c('red','blue') )     # Specify colors of selected subplots

 plot(o$time, o$season$Y,type='l') # directly plot output: the fitted season
 plot(o$time, o$season$cpOccPr)    # directly plot output: season chgpt  prob
 plot(o$time, o$trend$Y,type='l')  # directly plot output: the fitted trend
 plot(o$time, o$trend$cpOccPr)     # directly plot output: trend chgpt occurrence prob
 plot(o$time, o$season$order)      # directly plot output: avg harmonic order
```

```
 plot(o, interactive=TRUE)        # manually choose which variables to plot




#-----------------------------------Example 4---------------------------------------#
# Specify other arguments explicitly.  Default values are used for missing parameters.
# Note that beast(), beast.irreg(), and beast123() call the same internal C/C++ library,
# so in beast(), the input parameters will be converted to metadata, prior, mcmc, and
# extra parameters as explained for the beast123() function. Or type 'View(beast)' to
# check the parameter assignment in the code.


 # In R's terminology, the  number of datapoints per period is also called 'freq'. In this
 # version, the 'freq' argument is obsolete and replaced by 'period'.

 # period=deltat*number_of_datapoints_per_period = 1.0*24=24 because deltat is set to 1.0 by
 # default and this signal has 24 samples per period.
 out = beast(Yellowstone, period=24.0, mcmc.samples=5000, tseg.min=20)

 # period=deltat*number_of_datapoints_per_period = 1/24*24=1.0.
 # out = beast(Yellowstone, deltat=1/24 period=1.0, mcmc.samples=5000, tseg.min=20)

 out = beast(
     Yellowstone,            # Yellowstone: a pure numeric vector wo time info
     start   = 1981.51,
     deltat  = 1/24,
     period  = 1.0,           # period=delta*number_of_datapoints_per_period
     season  = 'harmonic',    # periodic compnt exisits,fitted as a harmonic curve
     scp.minmax     = c(0,3), # min and max numbers of seasonal changpts allowed
     sorder.minmax  = c(1,5), # min and max harmonic orders allowed
     sseg.min       = 24,     # the min length of segments btw neighboring chnpts
                          # '24' means 24 datapoints; the unit is datapoint.
     sseg.leftmargin= 40,     # no seasonal chgpts allowed in the starting 40 datapoints
     tcp.minmax     = c(0,10),# min and max numbers of changpts allowed in the trend
     torder.minmax  = c(0,1), #  min and maxx polynomial orders to fit trend
     tseg.min       = 24,     # the min length of segments btw neighboring trend chnpts
     tseg.leftmargin= 10,     # no trend chgpts allowed in the starting 10 datapoints
    deseasonalize  = TRUE, # remove the global seasonality before fitting the beast model
     detrend        = TRUE, # remove the global trend before fitting the beast model
     mcmc.seed      = 0,    # a seed for mcmc's random nummber generator; use a
                           # non-zero integer to reproduce results across runs
     mcmc.burnin    = 500, # number of initial iterations discarded
     mcmc.chains    = 2,    # number of chains
     mcmc.thin      = 3,    # include samples every 3 iterations
     mcmc.samples   = 6000  # number of samples taken per chain
                           # total iteration: (500+3*6000)*2
     )
 plot(out)
 plot(out, interactive=TRUE)
```

```
#------------------------------------Example 5----------------------------------------#
# Run an interactive GUI to visualize how BEAST is samplinig from the possible model
# spaces in terms of the numbers and timings of seasonal and trend changepoints.
# The GUI inferface allows changing the option parameters interactively. This GUI is
# only available on Win x64 machines, not Mac or Linux.

## Not run:
 beast(Yellowstone, period=24, gui=TRUE)

## End(Not run)

#------------------------------------Example 6----------------------------------------#
# Apply beast to trend-only data. 'Nile' is the ANNUAL river flow of the river
# Nile at Aswan since 1871. It is a 'ts' object; its time attributes (start=1871,
# end=1970,frequency=1) are used to replace the user-supplied start,deltat, and freq,
# if any.


 data(Nile)
 plot(Nile)
 attributes(Nile) # a ts object with time attributes (i.e., tsp=(start,end,freq)

 o = beast(Nile)  # start=1871, delta=1, and freq=1 taken from Nile itself
 plot(o)

 o = beast(Nile,             # the same as above. The user-supplied values (i.e., 2023,
          start=2023,      # 9999) are ignored bcz Nile carries its own time attributes.
          period=9999,     # Its frequency tag is 1 (i.e., trend-only), so season='none'
           season='harmonic' # is used instead of the supplied 'harmonic'
   )


#------------------------------------Example 7----------------------------------------#
# NileVec is  a pure data vector. The first run below is WRONG bcz NileVec was assumed
# to have a perodic component by default and beast gets a best estimate of freq=6 while
# the true value is freq=1. To fit a trend-only model, season='none' has to be explicitly
# specified, as in the 2nd & 3rd funs.

 NileVec = as.vector(Nile) # NileVec is not a ts obj but a pure numeric data vector
 o       = beast(NileVec)  # WRONG WAY to call: No time attributes available to interpret
                         # NileVec. By default, beast assumes season='harmonic', start=1,
                           # & deltat=1. 'freq' is missing and guessed to be 6 (WRONG).

 plot(o)                   # WRONG Results: The result has a suprious seasonal component

 o=beast(NileVec,season='none') # The correct way to call: Use season='none' for trend-only
                                # analysis; the default time is the integer indices
                                # "1:length(NileVec)'.
 print(o$time)

 o=beast(NileVec,               # Recommended way to call: The true time attributes are
        start  = 1871,          # given explicitly through start and deltat (or freq if
```

```
        deltat = 1,            # there is a  cyclic/seasonal cmponent).
        season = 'none')
 print(o$time)
 plot(o)



#------------------------------------Example 8---------------------------------------#
# beast can handle missing data. co2 is a monthly time series (i.e.,freq=12) starting
# from Jan 1959. We generate some missing values at random indices

## Not run:

 data(co2)
 attributes(co2)                          # A ts object with time attributes (i.e., tsp)
 badIdx      = sample( 1:length(co2), 50) # Get a set of random indices
 co2[badIdx] = NA                         # Insert some data gaps

 out=beast(co2) # co2 is a ts object and its 'tsp' time attributes are used to get the
               # true time info. No need to specify 'start','deltat', & freq explicity.

 out=beast(co2,                  # The supplied time/period values will be ignored bcz
          start  = c(1959,1,15),# co2 is a ts object; the correct period = 1 will be
          deltat = 1/12,        # used.
          period = 365)
 print(out)
 plot(out)

## End(Not run)



#------------------------------------Example 9---------------------------------------#
# Apply beast to time seris-like sequence data: the unit of sequences is not
# necessarily time.


  data(CNAchrom11) # DNA copy number alterations in Chromesome 11 for cell line GM05296
                   # The data is orderd by genomic position (not time), and the values
                 # are the log2-based intensity ratio of copy numbers between the sample
                  # the reference. A value of zero means no gain or loss in copy number.
  o = beast(CNAchrom11,season='none') # season is a misnomer here bcz the data has nothing
                                     # to do with time. Regardless, we fit only a trend.
  plot(o)




#------------------------------------Example 10--------------------------------------#
# Apply beast to time seris-like data: the unit of sequences is not necessarily time.


  # Age of Death of Successive Kings of England
```

```
  # If the data link is deprecated, install the time series data library instead,
  # which is available at https://pkg.yangzhuoranyang.com/tsdl/
  # install.packages("devtools")
  # devtools::install_github("FinYang/tsdl")
  # kings = tsdl::tsdl[[293]]

  kings = scan("http://robjhyndman.com/tsdldata/misc/kings.dat",skip=3)
  out   = beast(kings,season='none')
  plot(out)



#------------------------------------Example 11-------------------------------------#
# Another example from the tsdl data library



  # Number of monthly births in New York from Jan 1946 to Dec 1959
  # If the data link becomes invalid, install the time series data package instead
  # install.packages("devtools")
  # devtools::install_github("FinYang/tsdl")
  # kings = tsdl::tsdl[[534]]

  births = scan("http://robjhyndman.com/tsdldata/data/nybirths.dat")
  out    = beast(births,start=c(1946,1,15), deltat=1/12 )
  plot(out) # the result is wrong bcz the guessed freq via auto-correlation by beast
            # is 2 rather than 12, so we recommend always specifying 'freq' explicitly
            # for those time series with a periodic component, as shown below.
  out    = beast(births,start=c(1946,1,15), deltat=1/12, freq  =12 )
  out    = beast(births,start=c(1946,1,15), deltat=1/12, period=1.0 )
  plot(out)



#------------------------------------Example 12-------------------------------------#
#    Daily confirmed COVID-19 new cases and deaths across the globe

 ## Not run:
 data(covid19)
 plot(covid19$date, covid19$newcases, type='l')

 newcases = sqrt( covid19$newcases )  # Apply a square root-transformation

 # This ts varies periodically every 7 days. 7 days can't be precisely represented
 # in  the unit of year bcz some years has 365 days and others has 366. BEAST can hanlde
 # this in two ways.


 #(1) Use the date number as the time unit--the num of days lapsed since 1970-01-01.

  datenum  = as.numeric(covid19$date)
  o        = beast(newcases, start=min(datenum), deltat=1, period=7)
```

```
  o$time   = as.Date(o$time, origin='1970-01-01') # Convert from integers to Date.
  plot(o)

 #(2) Use strings to explicitly specify deltat and period with a unit.

  startdate = covid19$date[1]
  o         = beast(newcases, start=startdate, deltat='1day', period='7days')
  plot(o)


## End(Not run)

#-----------------------------------Example 13---------------------------------------#
# The old API interface of beast is still made available but NOT recommended. It is
# kept mainly to ensure the working of the sample code on Page 475 in the text
# Ecological Metods by Drs. Southwood and Henderson.

## Not run:

  # The interface as shown here will be deprecated and NOT recommended.
  beast(Yellowstone, 24)  #24 is the freq: number of datapoints per period


  # Specify the model or MCMC parameters through opt as in Rbeast v0.2
  opt=list()             #Create an empty list to append individual model parameters
  opt$period=24          #Period of the cyclic component (i.e.,freq in the new version)
  opt$minSeasonOrder=2   #Min harmonic order allowed in fitting season component
  opt$maxSeasonOrder=8   #Max harmonic order allowed in fititing season component
  opt$minTrendOrder=0    #Min polynomial order allowed to fit trend (0 for constant)
  opt$maxTrendOrder=1    #Max polynomial order allowed to fit trend (1 for linear term)
  opt$minSepDist_Season=20#Min separation time btw neighboring season changepoints
  opt$minSepDist_Trend=20 #Min separation time btw neighboring trend  changepoints
  opt$maxKnotNum_Season=4 #Max number of season changepoints allowed
  opt$maxKnotNum_Trend=10 #Max number of trend changepoints allowed
  opt$omittedValue=NA    #A customized value to indicate bad/missing values in the time
                          #series, in additon to those NA or NaN values.

  # The following parameters used to configure the reverisible-jump MCMC (RJMCC) sampler
  opt$chainNumber=2       #Number of parallel MCMC chains
  opt$sample=1000         #Number of samples to be collected per chain
  opt$thinningFactor=3    #A factor to thin chains
  opt$burnin=500          #Number of burn-in samples discarded at the start
  opt$maxMoveStepSize=30  #For the move proposal, the max window allowed in jumping from
                           #the current changepoint
  opt$resamplingSeasonOrderProb=0.2 #The probability of selecting a re-sampling proposal
                                    #(e.g., resample seasonal harmonic order)
  opt$resamplingTrendOrderProb=0.2  #The probability of selecting a re-sampling proposal
                                    #(e.g., resample trend polynomial order)

  opt$seed=65654    #A seed for the random generator: If seed=0,random numbers differ
                   #for different BEAST runs. Setting seed to a chosen non-zero integer
                   #will allow reproducing the same result for different BEAST runs.
```

```
  beast(Yellowstone, opt)

## End(Not run)
```

`beast.irreg` *Bayesian time series decomposition for changepoint, trend, and periodicity or seasonality*

Description

A Bayesian model averaging algorithm called BEAST to decompose time series or 1D sequential data into individual components, such as abrupt changes, trends, and periodic/seasonal variations. BEAST is useful for changepoint detection (e.g., breakpoints or structural breaks), nonlinear trend analysis, time series decomposition, and time series segmentation.

Usage

```
beast.irreg(
     y,
     time,
     deltat         = NULL,
     period         = NULL,
     season         = c("harmonic", "svd", "dummy", "none"),
     scp.minmax     = c(0,10), sorder.minmax = c(0,5),
     tcp.minmax     = c(0,10), torder.minmax = c(0,1),
    sseg.min       = NULL,    sseg.leftmargin = NULL, sseg.rightmargin = NULL,
    tseg.min       = NULL,    tseg.leftmargin = NULL, tseg.rightmargin = NULL,
     method         = c( 'bayes', 'bic', 'aic', 'aicc','hic'),
     detrend        = FALSE,
     deseasonalize  = FALSE,
     mcmc.seed      = 0,
     mcmc.burnin    = 200,
     mcmc.chains    = 3,
     mcmc.thin      = 5,
     mcmc.samples   = 8000,
     ci             = FALSE,
     precValue      = 1.5,
     precPriorType  = c('componentwise','uniform','constant','orderwise'),
     print.options  = TRUE,
     print.progress = TRUE,
     quiet          = FALSE,
     gui            = FALSE,
     ...
    )
```

Arguments

`y` a vector for an irregular or unordered time series. Missing values such as NA and NaN are allowed.

- If `y` is regular and evenly-spaced in time, use the `beast`function instead.
- If `y` is a matrix or 3D array (e.g., stacked images) consisting of multiple regular or irregular time series, use `beast123` instead.

If `y` is a list of multiple time series, the multivariate version of the BEAST algorithm is invoked to decompose the multiple time series and detect common changepoints altogether. This feature is `experimental` and under further development. Check `ohio` for a working example.

`time` a vector of the same length as `y`'s time dimension to provide the times for datapoints. It can be a vector of numbers, Dates, or date strings; it can also be a list of vectors of year, months, and days. Possible formats include:

1. a vector of numerical values [e.g., c(1984.23, 1984.27, 1984.36, ...)]. The unit of the times is irrelevant to BEAST as long as it is consistent with the unit used for specifying `startTime`, `deltaTime`, and `period`.
2. a vector of R Dates [e.g., `as.Date`(c("1984-03-27", "1984-04-10", "1984-05-12",...)].
3. a vector of char strings. Examples are:
   - c("1984-03-27", "1984-04-10", "1984-05-12")
   - c("1984/03/27", "1984,04,10", "1984 05 12") (i.e., the delimiters differ as long as the YMD order is consistent)
   - c("LT4-1984-03-27", "LT4-1984-04-10", "LT4-1984+05,12")
   - c("LT4-1984087ndvi", "LT4-1984101ndvi", "LT4-1984133ndvi")
   - c("1984,,abc 3/ 27", "1984,,ddxfdd 4/ 10" "ggd1984,, 5/ ttt 12")

   BEAST uses several heuristics to automatically parse the date strings without a format specifier but may fail due to ambiguity (e.g., in "LC8-2020-09-20-1984", no way to tell if 2020 or 1984 is the year). To ensure correctness, use a list object as explained below to provide a date format specifier.
4. a list object `time=list(datestr=..., strfmat='...')` consisting of a vector of date strings (`time$datestr`) and a format specifier (`time$strFmt`). The string `time$strFmt` specifies how to parse `dateStr`. Three formats are currently supported:
   - (a). All the date strings have a fixed pattern in terms of the relative positions of Year, Month, and Day. For example, to extract 2001/12/02 etc from `time$dateStr` = c('P23R34-2001.1202333xd', 'O93X94-2002.1108133fd', 'TP3R34-2009.0122333td') use `time$strFmt='P23R34-yyyy.mmdd333xd'` where `yyyy`, `mm`, and `dd` are the specifiers and other positions are wildcards and can be filled with any other letters different from `yyyy, mm` and `dd`.
   - (b). All the date strings have a fixed pattern in terms of the relative positions of year and doy. For example, to extract 2001/045(day of year) from 'P23R342001888045', use strFmt='123123yyyy888doy' where `yyyy` and `doy` are the specifiers and other positions are wildcards and can be filled with any other letters different from yyyy, and doy. 'doy' must be three digit in length.

- (c). All the date strings have a fixed pattern in terms of the separation characters between year, month, and day. For example, to extract 2002/12/02 from '2002,12/02', ' 2002 , 12/2', '2002,12 /02 ', use strFmt='Y,M/D' where the whitespaces are ignored. To get 2002/12/02 from '2–12, 2012 ', use strmFmt='D–M,Y'.

5. a list object of vectors to specify individual dates of the time series. Use `time$year`,`time$month`,and `time$day` to give the dates; or alternatively use `time$year` and `time$doy` where each value of the doy vector is a number within 1 and 365/366. Each vector must have the same length as the time dimension of `Y`.

`deltat` a number or a string to specify a time interval for aggregating the irregular `y` into a regular time series. The BEAST model is currently formulated for regular data only for fast computational, so internally, the `beast.irreg` function will aggregate/re-bin irregular data into regular ones. For the aggregation, `deltat` is needed to specify the desired bin size or time interval; if missing, a best guess will be used. The unit of `deltat` needs to be consistent with `time`. If `time` takes a numeric vector, the unit of `deltat` is arbitrary and irrelevant to beast. If `time` takes a vector of Dates or date strings, the unit for `deltat` is assumed to Fractional YEAR. If needed, use a string instead of a number to specify whether the unit of deltat is day, month, or year. Examples include '7 days', '7d', '1/2 months', '1mn', '1.0 year', and '1y'.

`period` numeric or string. Specify the period for the periodic/seasonal component in `y`. Needed only for data with a periodic/cyclic component (i.e., season=`'harmonic'` or `'dummy'`) and not used for trend-only data (i.e., `season='none'`). The period of the cyclic component should have a unit consisent with the unit of `deltat`. It holds that `period=deltat*freq` where `freq` is the number of data samples per period. (Note that the `freq` argument in earlier versions becomes obsolete and now is replaced by `period`. `freq` is still supported but`period` takes precedence if both are provided.) `period` or the number of data points per period is not a BEAST model parameter and it has to be specified by the user. But if `period` is missing, BEAST first attempts to guess its value via auto-correlation before fitting the model. If `period` <= 0, `season='none'` is assumed, and the trend-only model is fitted without a seasonal/cyclic component. If needed, use a string to specify whether the unit of period is day, month, or year. Examples are '1.0 year', '12 months', '365d', '366 days'.

`season` characters (default to 'harmonic'); specify if `y` has a periodic component or not. Three strings are possible.

- `'none'`: `y` is trend-only; no periodic components are present in the time series. The args for the seasonal component (i.e.,sorder.minmax, scp.minmax and sseg.max) will be ignored.
- `'harmonic'`: `y` has a periodic/seasonal component. The term 'season' is a misnomer, being used here to broadly refer to any periodic variations present in `y`. The periodicity is NOT a model parameter estimated by beast but a known constant given by the user through `freq`. By default, the periodic component is modeled as a harmonic curve–a combination of sins and cosines.

- 'dummy': the same as 'harmonic' except that the periodic/seasonal component is modeled as a non-parametric curve. The arg sorder.minmax is irrelevant and is ignored.
- 'svd': (experimental feature) the same as 'harmonic' except that the periodic/seasonal component is modeled as a linear combination of function bases derived from a Single-value decomposition. The SVD-based basis functions are more parsimonious than the harmonic sin/cos bases in parameterizing the seasonal variations; therefore, more subtle changepoints are likely to be detected.

scp.minmax
: a vector of 2 integers (>=0); the min and max number of seasonal changepoints (scp) allowed in segmenting the seasonal component. scp.minmax is used only if y has a seasonal component (i.e., season='harmonic' or 'dummy') and ignored for trend-only data. If the min and max changepoint numbers are equal, BEAST assumes a constant number of scp and won't infer the posterior probability of the number of changepoints, but it still estimates the occurrence probability of the changepoints over time (i.e., the most likely times at which these changepoints occur). If both the min and max numbers are set to 0, no changepoints are allowed; then a global harmonic model is used to fit the seasonal component, but still, the most likely harmonic order will be inferred if sorder.minmax[1] is not equal to sorder.minmax[2].

sorder.minmax
: a vector of 2 integers (>=1); the min and max harmonic orders considered to fit the seasonal component. sorder.minmax is used only used if the time series has a seasonal component (i.e., season='harmonic') and ignored for trend-only data or when season='dummy'. If the min and max orders are equal (sorder.minmax[1]=sorder.minmax[2]), BEAST assumes a constant harmonic order used and won't infer the posterior probability of harmonic orders.

torder.minmax
: a vector of 2 integers (>=0); the min and max orders of the polynomials considered to fit the trend component. The 0-th order corresponds to a constant term/a flat line and the 1st order is a line. If torder.minmax[1]=torder.minmax[2], BEAST assumes a constant polynomial order used and won't infer the posterior probability of polynomial orders.

tcp.minmax
: a vector of 2 integers; the min and max number of trend changepoints (tcp) allowed in segmenting the trend component. If the min and max changepoint numbers are equal, BEAST assumes a constant number of changepoints and won't infer the posterior probability of the number of changepoints for the trend, but it still estimates the occurrence probability of the changepoints over time (i.e., the most likely times at which these changepoints occur in the trend). If both the min and max numbers are set to 0, no changepoints are allowed; then a global polynomial trend is used to fit the trend component, but still, the most likely polynomial order will be inferred if torder.minmax[1] is not equal to torder.minmax[2].

sseg.min
: an integer (>0); the min segment length allowed between two neighboring season changepoints. That is, when fitting a piecewise harmonic seasonal model, two changepoints are not allowed to occur within a time window of length sseg.min. sseg.min must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is sseg.min*deltat. sseg.min defaults to NULL and its value will be given a default value in reference to freq.

`sseg.leftmargin`
: an integer (>=0); the number of leftmost data points excluded for seasonal changepoint detection. That is, when fitting a piecewise harmonic seasonal model, no changepoints are allowed in the starting window/segment of length `tseg.leftmargin`. `sseg.leftmargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `sseg.leftmargin*deltat`. If missing, `sseg.leftmargin` defaults to `sseg.min`.

`sseg.rightmargin`
: an integer (>=0); the number of rightmost data points excluded for seasonal changepoint detection. That is, when fitting a piecewise harmonic seasonal model, no changepoints are allowed in the ending window/segment of length `sseg.rightmargin`. `sseg.rightmargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `sseg.rightmargin*deltat`. If missing, `sseg.rightmargin` defaults to `sseg.min`.

`tseg.min`
: an integer (>0); the min segment length allowed between two neighboring trend changepoints. That is, when fitting a piecewise polynomial trend model, two changepoints are not allowed to occur within a time window of length `tseg.min`. `tseg.min` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `tseg.min*deltat`. `tseg.min` defaults to NULL and its value will be given a default value in reference to `freq` if the time series has a cyclic component.

`tseg.leftmargin`
: an integer (>=0); the number of leftmost data points excluded for trend changepoint detection. That is, when fitting a piecewise polynomial trend model, no changepoints are allowed in the starting window/segment of length `tseg.leftmargin`. `tseg.leftmargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `tseg.leftmargin*deltat`. If missing, `tseg.leftmargin` defaults to `tseg.min`.

`tseg.rightmargin`
: an integer (>=0); the number of rightmost data points excluded for trend changepoint detection. That is, when fitting a piecewise polynomial trend model, no changepoints are allowed in the ending window/segment of length `tseg.rightmargin`. `tseg.rightmargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `tseg.rightmargin*deltat`. If missing, `tseg.rightmargin` defaults to `tseg.min`.

`method`
: an string (default to 'bayes'); specify which method is used to formulate model posterior probability.

  - `'bayes'`: the full Bayesian formulation as described in Zhao et al. (2019).
  - `'bic'`: approximation of posterior probability using the Bayesian information criterion (bic).
  - `'aic'`: approximation of posterior probability using the Akaike information criterion (aic).
  - `'aicc'`: approximation of posterior probability using the corrected Akaike information criterion (aicc).
  - `'hic'`: approximation of posterior probability using the Hannan-Quinn information criterion (hic)

`detrend` logical; If `TRUE`, a global trend is first fitted and removed from the time series before running BEAST; after BEAST finishes, the global trend is added back to the BEAST result.

`deseasonalize` logical; If `TRUE`, a global seasonal model is first fitted and removed from the time series before running BEAST; after BEAST finishes, the global seasonal curve is added back to the BEAST result. `deseasonalize` is ignored if `season='none'` (i.e., trend-only data).

`mcmc.seed` integer (>=0); the seed for the random number generator used for Monte Carlo Markov Chain (mcmc). If `mcmc.seed=0`, an arbitrary seed is picked and the fitting results vary across runs. If fixed to the same non-zero integer, the result can be re-produced for different runs. But the results from the same seed may still vary if run on different computers because the random generator library depends on CPU's instruction sets.

`mcmc.chains` integer (>0); the number of MCMC chains.

`mcmc.thin` integer (>0); a factor to thin chains (e.g., if thinningFactor=5, samples will be taken every 3 iterations)

`mcmc.burnin` integer (>0); the number of burn-in samples discarded at the start of each chain

`mcmc.samples` integer (>=0); the number of samples collected per MCMC chain. The total number of iterations is `(burnin+samples*thin)*chains`.

`ci` boolean; If `TRUE`, credible intervals (i.e., out$season$CI or out$trend$CI) will be computed for the estimated seasonal and trend components. Computing CI is time-consuming, due to sorting, so set `ci` to FALSE if a symmetric credible interval (i.e., out$trend$SD and out$season$SD) suffices.

`precValue` numeric (>0); the hyperparameter of the precision prior; the default value is 1.5. `precValue` is useful only when `precPriorType`='constant', as further explained below

`precPriorType` characters. It takes one of 'constant', 'uniform', 'componentwise' (the default), and 'orderwise'. Below are the differences between them.

1. `'constant'`: the precision parameter used to parameterize the model coefficients is fixed to a constant specified by `precValue`. In other words, `precValue` is a user-defined hyperparameter and the fitting result may be sensitive to the chosen values of `precValue`.
2. `'uniform'`: the precision parameter used to parameterize the model coefficients is a random variable; its initial value is specified by `precValue`. In other words, `precValue` will be inferred by the MCMC, so the fitting result will be insensitive to the choice in `precValue`.
3. `'componentwise'`: multiple precision parameters are used to parameterize the model coefficients for individual components (e.g., one for season and another for trend); their initial values is specified by `precValue`. In other words, `precValue` will be inferred by the MCMC, so the fitting result will be insensitive to the choice in `precValue`.
4. `'orderwise'`: multiple precision parameters are used to parameterize the model coefficients not just for individual components but also for individual orders of each component; their initial values is specified by `precValue`. In other words, `precValue` will be inferred by the MCMC, so the fitting result will be insensitive to the choice in `precValue`.

print.options
: boolean. If `TRUE`,the full list of input parameters to BEAST will be printed out prior to the MCMC inference; the naming for this list (e.g., metadata, prior, and mcmc) differs slightly from the input to `beast`, but there is a one-to-one correspondence (e.g., prior$trendMinSepDist=tseg.min). Internally, beast converts the input parameters to the forms of metadata, prior,and mcmc. Type 'View(beast)' to see the details or check the `beast123` function.

print.progress
: boolean;If `TRUE`, a progressbar will be displayed.

quiet
: boolean. If `TRUE`, warning messages are suppressed and not printed.

gui
: boolean. If `TRUE`, BEAST will be run in a GUI demonstration mode, with a GUI window to show an animation of the MCMC sampling in the model space step by step. Note that "`gui=TRUE`" works only for Windows x64 systems not Windows 32 or Linux/Mac systems.

...
: additional parameters. There are many more settings for the implementation but not made available in the beast() interface; please use the function `beast123()` instead

Value

The output is an object of class "beast". It is a list, consisting of the following variables. In the explanations below, we assume the input `y` is a single time series of length `N`:

time
: a vector of size `1xN`: the times at the `N` sampled locations. By default, it is simply set to `1:N`

if the input arguments `delta`, 'start', or `time` are missing.

data
: a vector, matrix, or 3D array; this is a copy of the input `data` if extra$dumpInputData = TRUE. If extra$dumpInputData=FALSE, it is set to NULL. If the original input `data` is irregular, the copy here is the regular version aggregated from the original at the time interval specified by metadata$deltaTime.

marg_lik
: numeric; the average of the model marginal likelihood; the larger marg_lik, the better the fitting for a given time series.

R2
: numeric; the R-square of the model fitting.

RMSE
: numeric; the RMSE of the model fitting.

sig2
: numeric; the estimated variance of the model error.

trend
: a list object consisting of various outputs related to the estimated trend component:

  - `ncp`: [Number of ChangePoints]. a numeric scalar; the mean number of trend changepoints. Individual models sampled by BEAST has a varying dimension (e.g., number of changepoints or knots), so several alternative statistics (e.g., `ncp_mode`, `ncp_median`, and `ncp_pct90`) are also given to summarize the number of changepoints. For example, if `mcmc$samples=10`, the numbers of changepoints for the 10 sampled models are assumed to be c(0, 2, 4, 1, 1, 2, 7, 6, 6, 1). The mean ncp is 3.1 (rounded to 3), the median is 2.5 (2), the mode is 1, and the 90th percentile (ncp_pct90) is 6.5.
  - `ncp_mode`: [Number of ChangePoints]. a numeric scalar; the mode for number of changepoints. See the above for explanations.

- `ncp_median`: [Number of ChangePoints]. a numeric scalar; the median for number of changepoints. See the above for explanations.
- `ncp_pct90`: [Number of ChangePoints]. a numeric scalar; the 90th percentile for number of changepoints. See the above for explanations.
- `ncpPr`: [Probability of the Number of ChangePoints]. A vector of length `(tcp.minmax[2]+1)=tcp.max+1`. It gives a probability distribution of having a certain number of trend changepoints over the range of [0,tcp.max]; for example, `ncpPr[1]` is the probability of having no trend changepoint; `ncpPr[i]` is the probability of having (i-1) changepoints: Note that it is `ncpPr[i]` not `ncpPr[i-1]` because ncpPr[1] is used for having zero changepoint.
- `cpOccPr`: [ChangePoint OCCurence PRobability]. a vector of length N; it gives a probability distribution of having a changepoint in the trend at each point of time. Plotting `cpOccPr` will depict a continious curve of probability-of-being-changepoint. Of particular note, in the curve, a higher peak indicates a higher chance of being a changepoint only at that particular SINGLE point in time and does not necessarily mean a higher chance of observing a changepoint AROUND that time. For example, a window of cpOccPr values `c(0,0,0.5,0,0)` (i.e., the peak prob is 0.5 and the summed prob is 0.5) is less likely to be a changepoint compared to another window `c(0.1,0.2,0.21,0.2,0.1)` (i.e., the peak prob is 0.21 but the summed prob is 0.71).
- `order`: a vector of length N; the average polynomial order needed to approximate the fitted trend. As an average over many sampled individual piece-wise polynomial trends, `order` is not necessarily an integer.
- `cp`: [Changepoints] a vector of length `tcp.max=tcp.minmax[2]`; the most possible changepoint locations in the trend component. The locations are obtained by first applying a sum-filtering to the `cpOccPr` curve with a filter window size of `tseg.min` and then picking up to a total `prior$MaxKnotNum/tcp.max` of the highest peaks in the filtered curve. NaNs are possible if no enough changepoints are identified. `cp` records all the possible changepoints identified and many of them are bound to be false positives. Do not blindly treat all of them as actual changepoints.
- `cpPr`: [Changepoints PRobability] a vector of length `tcp.max=tcp.minmax[2]`; the probabilities associated with the changepoints `cp`. Filled with NaNs for the remaining elements if `ncp<tcp.max`.
- `cpCI`: [Changepoints Credible Interval] a matrix of dimension `tcp.max x 2`; the credibable intervals for the detected changepoints `cp`.
- `cpAbruptChange`: [Abrupt change at Changepoints] a vector of length `tcp.max`; the jumps in the fitted trend curves at the detected changepoints `cp`.
- `Y`: a vector of length N; the estimated trend component. It is the Bayesian model averaging of all the individual sampled trend.
- `SD`: [Standard Deviation] a vector of length N; the estimated standard deviation of the estimated trend component.
- `CI`: [Standard Deviation] a matrix of dimension `N x 2`; the estimated credible interval of the estimated trend. One vector of the matrix is for the upper envelope and another for the lower envelope.

- slp: [Slope] a vector of length N; the time-varying slope of the fitted trend component .
- slpSD: [Standar Deviation of Slope] a vector of length N; the SD of the slope for the trend component.
- slpSgnPosPr: [PRobability of slope having a positive sign] a vector of length N; the probability of the slope being positive (i.e., increasing trend) for the trend component. For example, if slpSgnPosPr=0.80 at a given point in time, it means that 80% of the individual trend models sampled in the MCMC chain has a positive slope at that point.
- slpSgnZeroPr: [PRobability of slope being zero] a vector of length N; the probability of the slope being zero (i.e., a flat constant line) for the trend component. For example, if slpSgnZeroPr=0.10 at a given point in time, it means that 10% of the individual trend models sampled in the MCMC chain has a zero slope at that point. The probability of slope being negative can be obtained from 1-slpSgnZeroPr-slpSgnPosPr.
- pos_ncp:
- neg_ncp:
- pos_ncpPr:
- neg_ncpPr:
- pos_cpOccPr:
- neg_cpOccPr:
- pos_cp:
- neg_cp:
- pos_cpPr:
- neg_cpPr:
- pos_cpAbruptChange:
- neg_cpAbruptChange:
- pos_cpCI:
- neg_cpCI: The above variables have the same outputs as those variables without the prefix 'pos' and 'neg', except that we differentiate the changepoints with a POStive jump in the trend from those changepoints with a NEGative jump. For example, pos_ncp refers to the average number of trend changepoints that jump up (i.e., positively) in the trend.
- inc_ncp:
- dec_ncp:
- inc_ncpPr:
- dec_ncpPr:
- inc_cpOccPr:
- dec_cpOccPr:
- inc_cp:
- dec_cp:
- inc_cpPr:
- dec_cpPr:
- inc_cpAbruptChange:

- `dec_cpAbruptChange`:
- `inc_cpCI`:
- `dec_cpCI`: The above variables have the same outputs as those variables without the prefix 'inc' and 'dec', except that we differentiate the changepoints at which the trend slope increases from those changepoints at which the trend slope decreases. For example, if the trend slopes before and after a chngpt is 0.4 and 2.5, then the changepoint is counted toward `inc_ncp`.

`season` a list object consisting of various outputs related to the estimated seasonal/periodic component:

- `ncp`: [Number of ChangePoints]. a numeric scalar; the mean number of seasonal changepoints.
- `ncpPr`: [Probability of the Number of ChangePoints]. A vector of length `(scp.minmax[2]+1)=scp.max+1`. It gives a probability distribution of having a certain number of seasonal changepoints over the range of [0,scp.max]; for example, `ncpPr[1]` is the probability of having no seasonal changepoint; `ncpPr[i]` is the probability of having (i-1) changepoints: Note that the index is i rather than (i-1) because ncpPr[1] is used for having zero changepoint.
- `cpOccPr`: [ChangePoint OCCurence PRobability]. a vector of length N; it gives a probability distribution of having a changepoint in the seasonal component at each point of time. Plotting `cpOccPr` will depict a continious curve of probability-of-being-changepoint over the time. Of particular note, in the curve, a higher value at a peak indicates a higher chance of being a changepoint only at that particular SINGLE point in time, and does not necessarily mean a higher chance of observing a changepoint AROUND that time. For example, a window of cpOccPr values `c(0,0,0.5,0,0)` (i.e., the peak prob is 0.5 and the summed prob is 0.5) is less likely to be a changepoint compared to another window values `c(0.1,0.2,0.3,0.2,0.1)` (i.e., the peak prob is 0.3 but the summed prob is 0.8).
- `order`: a vector of length N; the average harmonic order needed to approximate the seasonal component. As an average over many sampled individual piece-wise harmonic curves, `order` is not necessarily an integer.
- `cp`: [Changepoints] a vector of length `scp.max=scp.minmax[2]`; the most possible changepoint locations in the seasonal component. The locations are obtained by first applying a sum-filtering to the `cpOccPr` curve with a filter window size of `sseg.min` and then picking up to a total `ncp` of the highest peaks in the filtered curve. If `ncp<scp.max`, the remaining of the vector is filled with NaNs.
- `cpPr`: [Changepoints PRobability] a vector of length `scp.max`; the probabilities associated with the changepoints `cp`. Filled with NaNs for the remaining elements if `ncp<scp.max`.
- `cpCI`: [Changepoints Credible Interval] a matrix of dimension `scp.max x 2`; the credibable intervals for the detected changepoints `cp`.
- `cpAbruptChange`: [Abrupt change at Changepoints] a vector of length `scp.max`; the jumps in the fitted seasonal curves at the detected changepoints `cp`.
- `Y`: a vector of length N; the estimated seasonal component. It is the Bayesian model averaging of all the individual sampled seasonal curve.

- SD: [Standard Deviation] a vector of length N; the estimated standard deviation of the estimated seasonal component.
- CI: [Standard Deviation] a matrix of dimension N x 2; the estimated credible interval of the estimated seasonal curve. One vector of the matrix is for the upper envelope and another for the lower envelope.
- amp: [AMPlitude] a vector of length N; the time-varying amplitude of the estimated seasonality.
- ampSD: [Standar Deviation of AMPlitude] a vector of length N; , the SD of the amplitude of the seasonality.
- pos_ncp:
- neg_ncp:
- pos_ncpPr:
- neg_ncpPr:
- pos_cpOccPr:
- neg_cpOccPr:
- pos_cp:
- neg_cp:
- pos_cpPr:
- neg_cpPr:
- pos_cpAbruptChange:
- neg_cpAbruptChange:
- pos_cpCI:
- neg_cpCI: The above variables have the same outputs as those variables without the prefix 'pos' and 'neg', except that we differentiate the changepoints with a POStive jump in the trend from those changepoints with a NEGative jump. For example, pos_ncp refers to the average number of trend changepoints that jump up (i.e., positively) in the trend.

Note

x

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

See Also

beast, beast123, minesweeper, tetris, geeLandsat

Examples

```
library(Rbeast)



#########################################################################################
# Note that the BEAST algorithm is currently implemented to handle only regular time
# series. 'beast.irreg' accepts irregular time series but internally it aggregates them
# into regular ones prior to applying the BEAST model. For the aggregation, both the
# "time" and "deltat" args are needed to specify indvidial times of data points and the
# regular time interval desired. If there is  a cyclic componet, 'period' should also be given;
# if not, a possible value is guessed via auto-correlation


#########################################################################################
# 'ohio' is a data.frame on an irregular Landsat time series of reflectances & ndvi
# (e.g., surface greenness) at an Ohio site. It has multiple columns of alternative date
# formats, such as year, month, day, doy (date of year), rdate (R's date class), and
# time (fractional year)

 data(ohio)
 str(ohio)
 plot(ohio$rdate, ohio$ndvi,type='o') # ndvi is irregularly spaced and unordered in time

#########################################################################################
# Below, 'time' is given as numeric values, which can be of any arbitray unit. Although
# here 1/12 can be interepreted as 1/12 year or 1 month, BEAST itself doesn't care about
# the time unit. So, the unit of 1/12 is irrelevant for BEAST. 'freq' or 'period' is missing
# and a guess of it is used.

 o=beast.irreg(ohio$ndvi, time=ohio$time,deltat=1/12)
 plot(o)
 print(o)

#########################################################################################
# Aggregrate the time series at a monthly interval (deltat=1/12) and explictly provide
# the 'freq' or 'period' arg

 o=beast.irreg(ohio$ndvi, time=ohio$time,deltat=1/12, period=1.0)
#o=beast.irreg(ohio$ndvi, time=ohio$time,deltat=1/12, freq  =12)



## Not run:
#########################################################################################
# Aggregate the time series at a half-monthly time interval, and the 'freq' becomes 24
# while the period is still 1. That is, PERIOD (1.0)=deltat(1/24) X  freq (24)
```

```
 o=beast.irreg(ohio$ndvi, time=ohio$time,deltat=1/24, freq   = 24)
#o=beast.irreg(ohio$ndvi, time=ohio$time,deltat=1/24, period = 1)

#####################################################################################
# 'time' is given as R's dates. The unit is YEAR. 1/12 refers to 1/12 year or 1 month

 o=beast.irreg(ohio$ndvi, time=ohio$rdate,deltat=1/12)

#####################################################################################
# 'time' is given as data strings. The unit is YEAR. 1/12 refers to 1/12 year or 1 month


 o=beast.irreg(ohio$ndvi, time=ohio$datestr1,deltat=1/12) #"LT4-1984-03-27" (YYYY-MM-DD)
 o=beast.irreg(ohio$ndvi, time=ohio$datestr2,deltat=1/12)  #"LT4-1984087ndvi" (YYYYDOY)
 o=beast.irreg(ohio$ndvi, time=ohio$datestr3,deltat=1/12)  #"1984,, 3/ 27"    (YYYY M D)



#####################################################################################
# 'time' is given as data strings, with a format specifier



 TIME =list()
 TIME$datestr = ohio$datestr1
 TIME$strfmt  = "LT4-YYYY-MM-DD"   # "LT4-1984-03-27"
 o=beast.irreg(ohio$ndvi, time=TIME,deltat=1/12)

 TIME =list()
 TIME$datestr = ohio$datestr2
 TIME$strfmt  = "LT4-YYYYDOYndvi"   # LT4-1984087ndvi
 o=beast.irreg(ohio$ndvi, time=TIME,deltat=1/12)


#####################################################################################
# 'time' is given as  a list object


 TIME = list()

 TIME$year  = ohio$Y
 TIME$month = ohio$M
 TIME$day   = ohio$D
 o=beast.irreg(ohio$ndvi, time=TIME,deltat=1/12)

 TIME = list()
 TIME$year  = ohio$Y
 TIME$doy   = ohio$doy
 o=beast.irreg(ohio$ndvi, time=TIME, deltat=1/12)
```

```
## End(Not run)
```

---

beast123 *Bayesian time series decomposition for changepoint, trend, and periodicity or seasonality*

Description

A Bayesian model averaging algorithm called BEAST to decompose time series or 1D sequential data into individual components, such as abrupt changes, trends, and periodic/seasonal variations. BEAST is useful for changepoint detection (e.g., breakpoints or structural breaks), nonlinear trend analysis, time series decomposition, and time series segmentation.

Usage

```
beast123( Y,
          metadata=list(),
          prior   =list(),
          mcmc    =list(),
          extra   =list(),
          season  = c('harmonic','svd','dummy','none'),
          method  = c( 'bayes', 'bic', 'aic', 'aicc','hic'),
          ...)
```

Arguments

`Y` a 1D vector, 2D matrix, or 3D array of numeric data. Missing values are allowed and can be indicated by `NA`, `NaN`, or a value customized in the 2nd argument `metadata` (e.g., `metadata$missingValue=-9999`).

- If `Y` is a vector of size `Nx1` or `1xN`, it is treated as a single time series of length `N`.
- If `Y` is a 2D matrix or 3D array of dimension `N1xN2` or `N1xN2xN3` (e.g., stacked images of geospatial data), it includes multiple time series of equal length: Which dimension is time has to be specified in the 2nd argument using `metadata$whichDimIsTime`. For example, `metadata$whichDimIsTime = 1` for a 190x35 2D input indicates 35 time series of length 190 each; `metadata$whichDimIsTime = 2` for a 100x200x300 3D input indicates 30000=100*300 time series of length 200 each.

`Y` can be either regular (i.e., evenly-spaced in time) or irregular/unordered in time.

- If regular, individual times are determined from the time of the 1st data point `startTime` and the time span between consecutive points `deltaTime`, which are specified in the 2nd arg through `metadata$startTime` and `metadata$deltaTime`; if not given, `startTime` and `deltaTime` take a default 1.0.

- If irregular or regular but unordered, the times have to be explicitly given through `metadata$time`. The BEAST model is currently formulated for regular data only, so internally, the `beast123` function will aggregate/re-bin irregular data into regular ones; for the aggregation, the `metadata$deltaTime` parameter should also be also provided to specify the desired bin size or time interval.

`Y` can have a periodic component or have a trend component only. Use the argument `season` to specify the cases.

- `season='none'`: `Y` is treated as trend-only; no periodic components are present in the time series.
- `season='harmonic'`: `Y` has a periodic/seasonal component. The term 'season' is a misnomer being used here to broad refer to any periodic variations present in `Y`. The periodicity is not a statistical parameter estimated by BEAST but a known constant given by the user through `metadata$freq`. The periodic component is modeled as a harmonic curve–a combination of sins and cosines.
- `season='dummy'`: the same as 'harmonic' except that the periodic/seasonal component is modeled as a non-parametric curve.
- `season='svd'`: (experimental feature) the same as `'harmonic'` except that the periodic/seasonal component is modeled as a linear combination of function bases derived from a Single-value decomposition. The SVD-based basis functions are more parsimonious than the harmonic sin/cos bases in parameterizing the seasonal variations; therefore, more subtle changepoints are likely to be detected.

`metadata` (optional). If present, `metadata` may (1) a scalar value to specify the period of the input Y, (2) a vector of numbers, strings, or R Dates to specify the times of Y, or (3) more often, a LIST object specifying various parameters to describe the 1st argument `Y`. If missing, default values will be used. But `metadata` should be explicitly provided if the input `Y` is a 2D matrix or 3D array to avoid misinterpreting the input Y. `metadata` is not part of BEAST's Bayesian formulation but just some additional info to interpret `Y`. If `metadata` is provided as a LIST, below are possible fields; not all of them are always needed, depending on the types of inputs (e.g., 1D, 2D or 3D; regular or irregular).

- `metadata$whichDimIsTime`: integer (<=3). Needed to specify which dimension of `Y` is time for a matrix or 3D array input. Ignored if the input `Y` is a vector.
- `metadata$isRegularOrdered`: logical. Obsolete and no longer used in this version. Now, `metadata$time` is analyzed to determine whether the input is irregular or not; if `metadata$time` is missing, `Y` is assumed to be regular.
- `metadata$time`: a vector of the same length as `Y`'s time dimension to provide the times for datapoints. It can be a vector of numbers, Dates, or date strings; it can also be a list of vectors of year, months, and days. Possible formats include:
  1. a vector of numerical values [e.g., c(1984.23, 1984.27, 1984.36, ...)]. The unit of the times is irrelevant to BEAST as long as it is consistent with the unit used for specifying `startTime`, `deltaTime`, and `period`.

2. a vector of R Dates [e.g., `as.Date(` c("1984-03-27", "1984-04-10", "1984-05-12",...)].
3. a vector of char strings. Examples are:
   - c("1984-03-27", "1984-04-10", "1984-05-12")
   - c("1984/03/27", "1984,04,10", "1984 05 12") (i.e., the delimiters differ as long as the YMD order is consistent)
   - c("LT4-1984-03-27", "LT4-1984-04-10", "LT4-1984+05,12")
   - c("LT4-1984087ndvi", "LT4-1984101ndvi", "LT4-1984133ndvi")
   - c("1984,,abc 3/ 27", "1984,,ddxfdd 4/ 10" "ggd1984,, 5/ ttt 12")

   BEAST uses several heuristics to automatically parse the date strings without a format specifier but may fail due to ambiguity (e.g., in "LC8-2020-09-20-1984", no way to tell if 2020 or 1984 is the year). To ensure correctness, use a list object as explained below to provide a date format specifier.
4. a list object `time=list(datestr=..., strfmat='...')` consisting of a vector of date strings (`time$datestr`) and a format specifier (`time$strFmt`). The string `time$strFmt` specifies how to parse `dateStr`. Three formats are currently supported:
   - (a). All the date strings have a fixed pattern in terms of the relative positions of Year, Month, and Day. For example, to extract 2001/12/02 etc from `time$dateStr` = c('P23R34-2001.1202333xd', 'O93X94-2002.1108133fd', 'TP3R34-2009.0122333td') use `time$strFmt='P23R34-yyyy.m` where `yyyy`, `mm`, and `dd` are the specifiers and other positions are wildcards and can be filled with any other letters different from `yyyy`, `mm and dd`.
   - (b). All the date strings have a fixed pattern in terms of the relative positions of year and doy. For example, to extract 2001/045(day of year) from 'P23R342001888045', use strFmt='123123yyyy888doy' where `yyyy` and `doy` are the specifiers and other positions are wildcards and can be filled with any other letters different from yyyy, and doy. 'doy' must be three digit in length.
   - (c). All the date strings have a fixed pattern in terms of the separation characters between year, month, and day. For example, to extract 2002/12/02 from '2002,12/02', ' 2002 , 12/2', '2002,12 /02 ', use strFmt='Y,M/D' where the whitespaces are ignored. To get 2002/12/02 from '2–12, 2012 ', use strmFmt='D–M,Y'.
5. a list object of vectors to specify individual dates of the time series. Use `time$year`,`time$month`,and `time$day` to give the dates; or alternatively use `time$year` and `time$doy` where each value of the doy vector is a number within 1 and 365/366. Each vector must have the same length as the time dimension of `Y`.

- `metadata$startTime`: numeric (default to 1.0 if missing). It gives the time of the 1st data point. It can be specified as a scalar (e.g., 2021.23) or a vector of three values in the order of year, month, and day (e.g., `metadata$startTime = c(2021,1,24)`). `metadata$startTime` is needed for regular input data but optional for irregular data: If missing, startTime will be computed from `metadata$time` for irregular `Y`.

- `metadata$deltaTime`: numeric or string. It specifies the time interval between consecutive data points. It is optional for regular data (default to 1.0 if not supplied), but should be specified for irregular data because deltaTime is needed to aggregate/resample the irregular time series into regular ones. The unit of `deltaTime` needs to be consistent with `metadata$time`. If `metadata$time` takes a numeric vector, the unit of `deltaTime` is arbitrary and irrelevant to BEAST. If `time` takes a vector of Dates or date strings, the unit for `deltaTime` is assumed to Fractional YEAR. If needed, use a string instead of a number to specify whether the unit of deltaTime is day, month, or year. Examples include '7 days', '7d', '1/2 months', '1mn', '1.0 year', and '1y'.
- `metadata$period`: numeric or string. Specify the period for the periodic/seasonal component in `Y`. Needed only for data with a periodic/cyclic component (i.e., season=`'harmonic'` or `'dummy'`) and not used for trend-only data (i.e., `season='none'`). The period of the cyclic component should have a unit consisent with the unit of `deltaTime`. It holds that `period=deltaTime*freq` where `freq` is the number of data samples per period. (Note that the `freq` argument in earlier versions becomes obsolete and now is replaced by `period`.) `period` or the number of data points per period is not a BEAST model parameter and it has to be specified by the user. But if `period` is missing, BEAST first attempts to guess its value via auto-correlation before fitting the model. If `period` <= 0, no seasonal/cyclic component is assumed (i.e, `season='none'`) and the trend-only model is used. If needed, use a string to specify whether the unit of period is day, month, or year. Examples are '1.0 year', '12 months', '365d', '366 days'.
- `metadata$missingValue`: numeric; a customized value to indicate bad/missing values in the time series, in addition to those NA or NaN values.
- `metadata$maxMissingRate` a fractional number within [0, 1] as the maximum percentage of missing values, above which the time series will be skipped and won't be fitted by BEAST.

`prior` (optional). a list object consisting of the hyperprior parameters in the Bayesian formulation of the BEAST model. Because they are part of the model, the fitting result may be sensitive to the choices of these hyperparameters. If `prior` is missing, a set of default values will be used and the exact values used will be printed to the console at the start of the BEAST run. Below are possible parameters:

- `prior$seasonMinOrder`: integer (>=1)
- `prior$seasonMaxOrder`: integer (>=1); the min and max harmonic orders considered to fit the seasonal component. `seasonMinOrder` and `seasonMaxOrder` are only used if the time series has a seasonal component (i.e., `season='harmonic'`) and ignored for trend-only data or when `season='dummy'`. If `seasonMinOrder=seasonMaxOrder`, BEAST assumes a constant harmonic order used and won't infer the posterior probability of harmonic orders.
- `prior$seasonMinKnotNum`: integer (>=0)
- `prior$seasonMaxKnotNum`: integer (>=0); the min and max number of seasonal changepoints allowed in segmenting and fitting the seasonal component. `seasonMinKnotNum` and `seasonMaxKnotNum` are only used if the time

series has a seasonal component (i.e., season='harmonic' or season='dummy') and ignored for trend-only data. If seasonMinOrder=seasonMaxOrder, BEAST assumes a constant number of changepoints and won't infer the posterior probability of the number of changepoints, but it will still estimate the occurrence probability of the changepoints over time (i.e., the most likely times at which these changepoints occur). If seasonMinOrder=seasonMaxOrder=0, no changepoints are allowed in the seasonal component; then a global harmonic model is used to fit the seasonal component.

- prior$seasonMinSepDist: integer (>0). the min separation time between two neighboring season changepoints. That is, when fitting a piecewise harmonic seasonal model, no two changepoints are allowed to occur within a time window of seasonMinSepDist. seasonMinSepDist must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is seasonMinSepDist*metadata$deltaTime.
- prior$seasonLeftMargin: integer (>=0); the number of leftmost data points excluded for seasonal changepoint detection. That is, when fitting a piecewise harmonic seasonal model, no changepoints are allowed in the starting window/segment of length seasonLeftMargin. seasonLeftMargin must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is seasonLeftMargin*deltat. If missing, seasonLeftMargin defaults to seasonMinSepDist.
- prior$seasonRightMargin: integer (>=0); the number of rightmost data points excluded for seasonal changepoint detection. That is, when fitting a piecewise harmonic seasonal model, no changepoints are allowed in the ending window/segment of length seasonRightMargin. seasonRightMargin must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is seasonRightMargin*deltat. If missing, seasonRightMargin defaults to seasonMinSepDist.
- prior$trendMinOrder: integer (>=0)
- prior$trendMaxOrder: integer (>=0); the min and max orders of the polynomials considered to fit the trend component. The zero-th order corresponds to a constant term/ a flat line and the 1st order is a line. If trendMinOrder=trendMaxOrder, BEAST assumes a constant polynomial order used and won't infer the posterior probability of polynomial orders.
- prior$trendMinKnotNum:
- prior$trendMaxKnotNum: integer (>=0); the min and max number of trend changepoints allowed in segmenting and fitting the trend component. If trendMinOrder=trendMaxOrder, BEAST assumes a constant number of changepoints in the fitted trend and won't infer the posterior probability of the number of trend changepoints, but it will still estimate the occurrence probability of the changepoints over time (i.e., the most likely times at which these changepoints occur). If trendMinOrder=trendMaxOrder=0, no changepoints are allowed in the trend component; then a global polynomial model is used to fit the trend.
- prior$trendMinSepDist: integer (>0). the min separation time between two neighboring trend changepoints.
- prior$trendLeftMargin: integer (>=0); the number of leftmost data points

excluded for trend changepoint detection. That is, when fitting a piecewise polynomial trend model, no changepoints are allowed in the starting window/segment of length `trendLeftMargin`. `trendLeftMargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `trendLeftMargin*deltat`. If missing, `trendLeftMargin` defaults to `trendMinSepDist`.

- `prior$trendRightMargin`: integer (>=0); the number of rightmost data points excluded for trend changepoint detection. That is, when fitting a piecewise polynomial trend model, no changepoints are allowed in the ending window/segment of length `trendRightMargin`. `trendRightMargin` must be an unitless integer–the number of time intervals/data points so that the time window in the original unit is `trendRightMargin*deltat`. If missing, `trendRightMargin` defaults to `trendMinSepDist`.
- `prior$precValue`: numeric (>0); the default value is 10. Useful only if prior$precPriorType='constant'
- `prior$precPriorType`: characters. It takes one of 'constant', 'uniform' (the default), 'componentwise', and 'orderwise'. Below are the differences between them.
  1. `precPriorType='constant'`: the precision parameter used to parameterize the model coefficients is fixed to a constant specified by `prior$precValue`. In other words, `prior$precValue` is a user-defined hyperparameter and the fitting result may be sensitive to the chosen values of `prior$precValue`.
  2. `precPriorType='uniform'`: the precision parameter used to parameterize the model coefficients is a random variable; its initial value is specified by `prior$precValue`. In other words, `precValue` will be inferred by the MCMC, so the fitting result is insensitive to the choice in `prior$precValue`.
  3. `precPriorType='componentwise'`: multiple precision parameters are used to parameterize the model coefficients for individual components (e.g., one for season and another for trend); their initial values is specified by `prior$precValue`. In other words, `precValue` will be inferred by the MCMC, so the fitting result is insensitive to the choice in `prior$precValue`.
  4. `precPriorType='orderwise'`: multiple precision parameters are used to parameterize the model coefficients not just for individual components but also for individual orders of each component; their initial values is specified by `prior$precValue`. In other words, `precValue` will be inferred by the MCMC, so the fitting result is insensitive to the choice in `prior$precValue`.

`mcmc` (optional). a list object consisting of parameters to configure the MCMC inference. These parameter are not part of the Bayesian formulation of the BEAST model but are the settings for the reversible-jump MCMC to generate MCMC chains. Due to the MCMC nature, the longer the simulation chain is, the better the fitting result. Below are possible parameters:

- `mcmc$seed`: integer (>=0); the seed for the random number generator. If `mcmc$seed=0`, an arbitrary seed will be picked up and the fitting result will var across runs. If fixed to the same on-zero integer, the results can be re-produced for different runs. Note that the results may still vary if run on different computers with the same seed because the random generator library depends on CPU's instruction sets.

- `mcmc$samples`: integer (>0); the number of samples collected per MCMC chain.
- `mcmc$chainNumber`: integer (>0); the number of parallel MCMC chains.
- `mcmc$thinningFactor`: integer (>0); a factor to thin chains (e.g., if thinningFactor=5, samples will be taken every 3 iterations).
- `mcmc$burnin`: integer (>0); the number of burn-in samples discarded at the start of each chain.
- `mcmc$maxMoveStepSize`: integer (>0). The RJMCMC sampler employs a move proposal when traversing the model space or proposing new positions of changepoints. 'maxMoveStepSize' is used in the move proposal to specify the max window allowed in jumping from the current changepoint.
- `mcmc$seasonResamplingOrderProb`: a fractional number less than 1.0; the probability of selecting a re-sampling proposal (e.g., resample seasonal harmonic order).
- `mcmc$trendResamplingOrderProb`: a fractional number less than 1.0; the probability of selecting a re-sampling proposal (e.g., resample trend polynomial order)
- `mcmc$credIntervalAlphaLevel`: a fractional number less than 1.0 (default to 0.95); the level of confidence used to compute credible intervals.

`extra` (optional). a list object consisting of flags to control the outputs from the BEAST runs or configure other program setting. Below are possible parameters:

- `extra$quiet`: logical (default to FALSE). If TRUE, no warning messages will be printed out.
- `extra$dumpInputData`: logical (default to FALSE). If TRUE, the input time series will be copied into the output. When the input `Y` is irregular (i.e., `metadata$isRegularOrdered=FALSE`), the dumped copies will be the aggregated regular time series.
- `extra$whichOutputDimIsTime`: integer (<=3). If the input `Y` is a 2D or 3D array (i.e., multiple time series such as stacked images), the `whichOutputDimIsTime` specifies which dimension is the time in the output variables. `whichOutputDimIsTime` defaults to 3 for 3D inputs and is ignored if the input is a vector (i.e., a single time series).
- `extra$ncpStatMethod`: character (deprecated). A string to specify which statistic is used to determine the Number of ChangePoint (ncp) when computing the most likely changepoint locations (e.g., out$trend$cp, and out$season$cp). Three values are possible: 'mode', 'mean', and 'median'; the default is 'mode'. Individual models sampled by BEAST has a varying dimension (e.g., number of changepoints or knots). For example, if mcmc$samples=10, the numbers of changepoints for the 10 sampled models are assumed to be c(0, 2, 4, 1, 1, 2, 7, 6, 6, 1). The mean ncp is 3.1 (rounded to 3), the median is 2.5 (2), and the mode is 1. This argument is deprecated; now all the possible changepoints are outputted, together with several versions of ncp,

including ncp, ncp_median, ncp_mode, and ncp_pct90. A similar parameter ncpStat is added to the plot.beast function to specify which ncp is used when plotting.

- extra$computeCredible: logical (default to TRUE). Credible intervals will be computed and outputted only if set to TRUE.
- extra$fastCIComputation: logical (default to TRUE). If TRUE, a fast method is used to compute credible intervals (CI). Computation of CI is one of the most computational parts and fastCIComputation should be set to TRUE unless more accurate CI estimation is desired.
- extra$computeSeasonOrder: logical (default to TRUE). If TRUE, a posterior estimate of the seasonal harmonic order will be outputted; this flag is only valid if the time series has a seasonal component (i.e., season='harmonic' and prior$seasonMinOrder is not equal to prior$seasonMaxOrder).
- extra$computeTrendOrder: logical (default to TRUE). If TRUE, a posterior estimate of the tend polynomial order will be outputted; this flag is only valid when prior$trendMinOrder is not equal to prior$trendMaxOrder).
- extra$computeTrendOrder: logical (default to TRUE). If TRUE, a posterior estimate of the tend polynomial order will be outputted; this flag is only valid when prior$trendMinOrder is not equal to prior$trendMaxOrder).
- extra$computeSeasonChngpt: logical (default to TRUE). If TRUE, compute the most likely times/positions where changepoints occur in the seasonal component. This flag is not valid if there is a seasonal component in the time series (i.e., season='harmonic' or season='dummy' and prior$seasonMaxKnotNum is non-zero).
- extra$computeTrendChngpt: logical (default to TRUE). If TRUE, compute the most likely times/positions where changepoints occur in the trend component.
- extra$computeSeasonAmp: logical (default to FALSE). If TRUE, compute and output the time-varying amplitude of the seasonality.
- extra$computeTrendSlope: logical (default to FALSE). If TRUE, compute and output the time-varying slope of the estimated trend.
- extra$tallyPosNegSeasonJump: logical (default to FALSE). If TRUE, compute and differentiate seasonal changepoints in terms of the direction of the jumps in the estimated seasonal signal. Those changepoints with a positive jump will be outputted separately from those with a negative jump. A series of output variables (some for positive-jump changepoints, and others for negative-jump changepoints will be dumped).
- extra$tallyPosNegTrendJump: logical (default to FALSE). If TRUE, compute and differentiate trend changepoints in terms of the direction of the jumps in the estimated trend. Those changepoints with a positive jump will be outputted separately from those with a negative jump. A series of output variables (some for positive-jump changepoints, and others for negative-jump changepoints will be dumped).
- extra$tallyIncDecTrendJump: logical (default to FALSE). If TRUE, compute and differentiate trend changepoints in terms of the direction of the jumps in the estimated slope of the trend signal. Those changepoints with

a increase in the slope will be outputted separately from those with a decrease in the slope. A series of output variables (some for increase-jump changepoints, and others for decrease-jump changepoints will be dumped).

- `extra$printProgressBar`: logical (default to FALSE). If TRUE, a progress bar will be displayed to show the status of the running. When running on multiple time series (e.g. stacked image time series), the progress bar will also report an estimate of the remaining time for completion.
- `extra$consoleWidth`: integer (default to 0); the length of chars in each status line when setting printProgressBar=TRUE. If 0, the current width of the console will be used.
- `extra$printOptions`: logical (default to FALSE). If TRUE, the values used in the arguments `metadata`, `prior`, `mcmc`, and `extra` will be printed to the console at the start of the run.
- `extra$numThreadsPerCPU`: integer (default to 2); the number of threads to be scheduled for each CPU core.
- `extra$numParThreads`: integer (default to 0). When handling many time series, BEAST can use multiple concurrent threads. `extra$numParThreads` specifies how many concurrent threads will be used in total. If numParThreads=0, the actual number of threads will be `numThreadsPerCPU * cpuCoreNumber`; that is, each CPU core will generate a number 'numThreadsPerCPU' of threads. On Windows 64, ,BEAST is group-aware and will affine or distribute the threads to all the NUMA node. But currently, up to 256 CPU cores are supported.

`season` characters (default to 'harmonic'); specify if `y` has a periodic component or not. Three strings are possible.

- `'none'`: `y` is trend-only; no periodic components are present in the time series. The args for the seasonal component (i.e.,`sorder.minmax`, `scp.minmax` and `sseg.max`) will be irrelevant and ignored.
- `'harmonic'`: `y` has a periodic/seasonal component. The term `season` is a misnomer, being used here to broadly refer to any periodic variations present in `y`. The periodicity is NOT a model parameter estimated by BEAST but a known constant given by the user through `freq`. By default, the periodic component is modeled as a harmonic curve–a combination of sins and cosines.
- `'dummy'`: the same as `'harmonic'` except that the periodic/seasonal component is modeled as a non-parametric curve. The harmonic order arg `sorder.minmax` is irrelevant and is ignored.
- `'svd'`: (experimental feature) the same as `'harmonic'` except that the periodic/seasonal component is modeled as a linear combination of function bases derived from a Single-value decomposition. The SVD-based basis functions are more parsimonious than the harmonic sin/cos bases in parameterizing the seasonal variations; therefore, more subtle changepoints are likely to be detected.

`method` an string (default to 'bayes'); specify which method is used to formulate model posterior probability.

- `'bayes'`: the full Bayesian formulation as described in Zhao et al. (2019).

- 'bic': approximation of posterior probability using the Bayesian information criterion (bic).
- 'aic': approximation of posterior probability using the Akaike information criterion (aic).
- 'aicc': approximation of posterior probability using the corrected Akaike information criterion (aicc).
- 'hic': approximation of posterior probability using the Hannan-Quinn information criterion (hic)

... additional parameters, not used currently but reserved for future extension

Value

The output is an object of class "beast". It is a list, consisting of the following variables. Exact sizes of the variables depend on the types of the input Y as well as the specified output time dimension extra$whichOutputDimIsTime. In the explanations below, we assume the input Y is a single time series of length N; the dimensions for 2D or 2D inputs may be interpreted accordingly:

time a vector of size 1xN: the times at the N sampled locations. By default, it is simply set to 1:N

data a vector, matrix, or 3D array; this is a copy of the input Y if extra$dumpInputData = TRUE. If extra$dumpInputData=FALSE, it is set to NULL. If the original input Y is irregular, the copy here is the regular version aggregated from the original at the time interval specified by metadata$deltaTime.

marg_lik numeric; the average of the model marginal likelihood; the larger marg_lik, the better the fitting for a given time series.

R2 numeric; the R-square of the model fitting.

RMSE numeric; the RMSE of the model fitting.

sig2 numeric; the estimated variance of the model error.

trend a list object numeric consisting of various outputs related to the estimated trend component:

- ncp: [Number of ChangePoints]. a numeric scalar; the mean number of trend changepoints. Individual models sampled by BEAST has a varying dimension (e.g., number of changepoints or knots), so several alternative statistics (e.g., ncp_mode, ncp_median, and ncp_pct90) are also given to summarize the number of changepoints. For example, if mcmc$samples=10, the numbers of changepoints for the 10 sampled models are assumed to be c(0, 2, 4, 1, 1, 2, 7, 6, 6, 1). The mean ncp is 3.1 (rounded to 3), the median is 2.5 (2), the mode is 1, and the 90th percentile (ncp_pct90) is 6.5.
- ncp_mode: [Number of ChangePoints]. a numeric scalar; the mode for number of changepoints. See the above for explanations.
- ncp_median: [Number of ChangePoints]. a numeric scalar; the median for number of changepoints. See the above for explanations.
- ncp_pct90: [Number of ChangePoints]. a numeric scalar; the 90th percentile for number of changepoints. See the above for explanations.

- `ncpPr`: [Probability of the Number of ChangePoints]. A vector of length `(prior$trendMaxKnotNum+1)`. It gives a probability distribution of having a certain number of trend changepoints over the range of [0,prior$trendMaxKnotNum]; for example, `ncpPr[1]` is the probability of having no trend changepoint; `ncpPr[i]` is the probability of having (i-1) changepoints: Note that it is `ncpPr[i]` not `ncpPr[i-1]` because ncpPr[1] is used for having zero changepoint.
- `cpOccPr`: [ChangePoint OCCurence PRobability]. a vector of length N; it gives a probability distribution of having a changepoint in the trend at each point of time. Plotting `cpOccPr` will depict a continious curve of probability-of-being-changepoint. Of particular note, in the curve, a higher peak indicates a higher chance of being a changepoint only at that particular SINGLE point in time and does not necessarily mean a higher chance of observing a changepoint AROUND that time. For example, a window of cpOccPr values `c(0,0,0.5,0,0)` (i.e., the peak prob is 0.5 and the summed prob is 0.5) is less likely to be a changepoint compared to another window `c(0.1,0.2,0.21,0.2,0.1)` (i.e., the peak prob is 0.21 but the summed prob is 0.71).
- `order`: a vector of length N; the average polynomial order needed to approximate the fitted trend. As an average over many sampled individual piece-wise polynomial trends, `order` is not necessarily an integer.
- `cp`: [Changepoints] a vector of length `tcp.max=tcp.minmax[2]`; the most possible changepoint locations in the trend component. The locations are obtained by first applying a sum-filtering to the `cpOccPr` curve with a filter window size of `tseg.min` and then picking up to a total `prior$MaxKnotNum/tcp.max` of the highest peaks in the filtered curve. NaNs are possible if no enough changepoints are identified. `cp` records all the possible changepoints identified and many of them are bound to be false positives. Do not blindly treat all of them as actual changepoints.
- `cpPr`: [Changepoints PRobability] a vector of length `metadata$trendMaxKnotNum`; the probabilities associated with the changepoints `cp`. Filled with NaNs for the remaining elements if `ncp<trendMaxKnotNum`.
- `cpCI`: [Changepoints Credible Interval] a matrix of dimension `metadata$trendMaxKnotNum x 2`; the credibable intervals for the detected changepoints `cp`.
- `cpAbruptChange`: [Abrupt change at Changepoints] a vector of length `metadata$trendMaxKnotNum` the jumps in the fitted trend curves at the detected changepoints `cp`.
- `Y`: a vector of length N; the estimated trend component. It is the Bayesian model averaging of all the individual sampled trend.
- `SD`: [Standard Deviation] a vector of length N; the estimated standard deviation of the estimated trend component.
- `CI`: [Standard Deviation] a matrix of dimension `N x 2`; the estimated credible interval of the estimated trend. One vector of the matrix is for the upper envelope and another for the lower envelope.
- `slp`: [Slope] a vector of length N; the time-varying slope of the fitted trend component .
- `slpSD`: [Standar Deviation of Slope] a vector of length N; the SD of the slope for the trend component.

- slpSgnPosPr: [PRobability of slope having a positive sign] a vector of length N; the probability of the slope being positive (i.e., increasing trend) for the trend component. For example, if slpSgnPosPr=0.80 at a given point in time, it means that 80% of the individual trend models sampled in the MCMC chain has a positive slope at that point.
- slpSgnZeroPr: [PRobability of slope being zero] a vector of length N; the probability of the slope being zero (i.e., a flat constant line) for the trend component. For example, if slpSgnZeroPr=0.10 at a given point in time, it means that 10% of the individual trend models sampled in the MCMC chain has a zero slope at that point. The probability of slope being negative can be obtained from 1-slpSgnZeroPr-slpSgnPosPr.
- pos_ncp:
- neg_ncp:
- pos_ncpPr:
- neg_ncpPr:
- pos_cpOccPr:
- neg_cpOccPr:
- pos_cp:
- neg_cp:
- pos_cpPr:
- neg_cpPr:
- pos_cpAbruptChange:
- neg_cpAbruptChange:
- pos_cpCI:
- neg_cpCI: The above variables have the same outputs as those variables without the prefix 'pos' and 'neg', except that we differentiate the changepoints with a POStive jump in the trend from those changepoints with a NEGative jump. For example, pos_ncp refers to the average number of trend changepoints that jump up (i.e., positively) in the trend.
- inc_ncp:
- dec_ncp:
- inc_ncpPr:
- dec_ncpPr:
- inc_cpOccPr:
- dec_cpOccPr:
- inc_cp:
- dec_cp:
- inc_cpPr:
- dec_cpPr:
- inc_cpAbruptChange:
- dec_cpAbruptChange:
- inc_cpCI:
- dec_cpCI: The above variables have the same outputs as those variables without the prefix 'inc' and 'dec', except that we differentiate the changepoints at which the trend slope increases from those changepoints at which

the trend slope decreases. For example, if the trend slopes before and after a chngpt is 0.4 and 2.5, then the changepoint is counted toward `inc_ncp`.

`season` a list object numeric consisting of various outputs related to the estimated seasonal/periodic component:

- `ncp`: [Number of ChangePoints]. a numeric scalar; the mean number of seasonal changepoints.
- `ncpPr`: [Probability of the Number of ChangePoints]. A vector of length `(prior$seasonMaxKnotNum+1)`. It gives a probability distribution of having a certain number of seasonal changepoints over the range of [0,prior$seasonMaxKnotNum]; for example, `ncpPr[1]` is the probability of having no seasonal changepoint; `ncpPr[i]` is the probability of having (i-1) changepoints: Note that the index is i rather than (i-1) because ncpPr[1] is used for having zero changepoint.
- `cpOccPr`: [ChangePoint OCCurence PRobability]. a vector of length N; it gives a probability distribution of having a changepoint in the seasonal component at each point of time. Plotting `cpOccPr` will depict a continious curve of probability-of-being-changepoint over the time. Of particular note, in the curve, a higher value at a peak indicates a higher chance of being a changepoint only at that particular SINGLE point in time, and does not necessarily mean a higher chance of observing a changepoint AROUND that time. For example, a window of cpOccPr values `c(0,0,0.5,0,0)` (i.e., the peak prob is 0.5 and the summed prob is 0.5) is less likely to be a changepoint compared to another window values `c(0.1,0.2,0.3,0.2,0.1)` (i.e., the peak prob is 0.3 but the summed prob is 0.8).
- `order`: a vector of length N; the average harmonic order needed to approximate the seasonal component. As an average over many sampled individual piece-wise harmonic curves, `order` is not necessarily an integer.
- `cp`: [Changepoints] a vector of length `metadata$seasonMaxKnotNum`; the most possible changepoint locations in the seasonal component. The locations are obtained by first applying a sum-filtering to the `cpOccPr` curve with a filter window size of `prior$trendMinSeptDist` and then picking up to a total `ncp` of the highest peaks in the filtered curve. If `ncp<seasonMaxKnotNum`, the remaining of the vector is filled with NaNs.
- `cpPr`: [Changepoints PRobability] a vector of length `metadata$seasonMaxKnotNum`; the probabilities associated with the changepoints `cp`. Filled with NaNs for the remaining elements if `ncp<seasonMaxKnotNum`.
- `cpCI`: [Changepoints Credible Interval] a matrix of dimension `metadata$seasonMaxKnotNum x 2`; the credibable intervals for the detected changepoints `cp`.
- `cpAbruptChange`: [Abrupt change at Changepoints] a vector of length `metadata$seasonMaxKnotNu`
the jumps in the fitted seasonal curves at the detected changepoints `cp`.
- `Y`: a vector of length N; the estimated seasonal component. It is the Bayesian model averaging of all the individual sampled seasonal curves.
- `SD`: [Standard Deviation] a vector of length N; the estimated standard deviation of the estimated seasonal component.
- `CI`: [Standard Deviation] a matrix of dimension `N x 2`; the estimated credible interval of the estimated seasonal component. One vector of the matrix is for the upper envelope and another for the lower envelope.

- amp: [AMPlitude] a vector of length N; the time-varying amplitude of the estimated seasonality.
- ampSD: [Standar Deviation of AMPlitude] a vector of length N; , the SD of the amplitude of the seasonality.
- pos_ncp:
- neg_ncp:
- pos_ncpPr:
- neg_ncpPr:
- pos_cpOccPr:
- neg_cpOccPr:
- pos_cp:
- neg_cp:
- pos_cpPr:
- neg_cpPr:
- pos_cpAbruptChange:
- neg_cpAbruptChange:
- pos_cpCI:
- neg_cpCI: The above variables have the same outputs as those variables without the prefix 'pos' and 'neg', except that we differentiate the changepoints with a POStive jump in the trend from those changepoints with a NEGative jump. For example, pos_ncp refers to the average number of trend changepoints that jump up (i.e., positively) in the trend.

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

See Also

beast, beast.irreg, minesweeper, tetris, geeLandsat

Examples

```
#--------------------------------NOTE----------------------------------------------#
```

```
# beast123() is an all-inclusive function that duplicates the functionalities of beast
# and beast.irreg. It can handle a single, multiple, or 3D of stacked time series, being
# either regular or irregular. It allows for customization through four LIST arguments:
#   metadata -- additional info about the input Y
#   prior    -- prior parameters for the beast model
#   mcmc     -- MCMC simulation setting
#   extra   -- misc parameters turning on/off outputs and setting up parallel computations
#
# Despite being essentially the same as beast and beast.irreg, beast123 is provided mainly
# to support concurrent handling of multiple time series (e.g., stacked satellite images)
# via parallel computing: When processing stacked raster layers, DO NOT iterate pixel by pixel
# using beast() or beast.irreg() via an external parallel caller (e.g., doParallel or foreach).
# Instread, please use beast123(), which supports mulithreading internally.


#------------------------------Example 1: one time series with seasonalty-------------#
# Yellowstone is a half-monthly time series of  774 NDVI measurmments at a Yellowstone
# site starting from July 1-15,1981(i.e., start=c(1981,7,7). It has 24 data points per
# year (freq=24).

 library(Rbeast)
 data(Yellowstone)
 plot(Yellowstone)

# Below, the four option args are missing, so defalut values will be used, with some
# warning messages given to altert this. By default, the input Y is assumed to be regular
# with a seasonal component. The default arg values used will be printed out and they can
# serve as a template to customize the parameters.

 o = beast123(Yellowstone)
 plot(o)


#------------------------------Example 2: a trend-only time series-------------------#
# Nile is an annual river flow time series (i.e., no periodic variation). So, season
# is set to 'none' to indicate trend-only analysis. Default values are used for other
# missing options. Unlike the beast() function, beast123 does NOT use the time attributes
# of a 'ts' object. For example, Nile is treated as a pure data number; its (start=1871,
# end=1970, freq=1) attributes are ignored. The default times 1:length(Nile) are used
# instead. The true time info need to be specified by the 'metadata' parameter, as shown
# in the next example.

 o = beast123(Nile,season='none')
 plot(o)


#------------------------------Example 3: call via the full API interface-----------#
# Specify metadata, prior, mcmc, and extra explicitly. Only 'prior' is the true statistical
# model parameters of BEAST; the other three are just options to configure the input/ouput
# or the computation process.

## Not run:
```

```
# metadata is NOT part of BEAST itself, but some extra info to describe the input
# time series Y. Below, the input Y is the 'Yellowstone' ts.

metadata                  = list()
#metadata$isRegularOrdered = TRUE        # This arg not used any longer in this version
metadata$whichDimIsTime   = 1            # Which dim of the input refer to time for
                                         # 2D/3D inputs? Ignored for a single time
                                         # series input.
metadata$startTime        = c(1981,7,7)  # Or startTime=1981.5137
                                         #    startTime=as.Date('1981-7-7')
metadata$deltaTime        = 1/24         # Half-monthly regular ts: 0.5/12=1/24
metadata$period           = 1.0          # The period is 1 year:
                                         # freq x deltaTime = period
                                         # 24    x  1/24    = 1.0
metadata$omissionValue    = NaN          # By default, NaNs are ignored
metadata$maxMissingRateAllowed = 0.7500  # If missingness is higher than .75, the ts
                                         #  is  skipped and not fitted
metadata$deseasonalize    = FALSE        # Do not remove the global seasonal pattern
                                         #  before fitting the beast model
metadata$detrend          = FALSE        # Do not remove the global trend before
                                         # the fitting

# prior is the ONLY true parameters of the beast model,used to specify the priors
# in the Bayesian formulation
prior = list()
prior$seasonMinOrder   = 1         #min harmonic order allowed to fit seasonal cmpnt
prior$seasonMaxOrder   = 5         #max harmonic order allowed to fit seasonal cmpnt
prior$seasonMinKnotNum = 0         #min number of changepnts in seasonal cmpnt
prior$seasonMaxKnotNum = 3         #max number of changepnts in seasonal cmpnt
prior$seasonMinSepDist = 10        #min inter-chngpts separation for seasonal cmpnt
prior$trendMinOrder = 0         #min polynomial order allowed to fit trend cmpnt
prior$trendMaxOrder = 1         #max polynomial order allowed to fit trend cmpnt
prior$trendMinKnotNum  = 0         #min number of changepnts in trend cmpnt
prior$trendMaxKnotNum  = 15        #max number of changepnts in trend cmpnt
prior$trendMinSepDist  = 5         #min inter-chngpts separation for trend cmpnt
prior$precValue        = 10.0      #Initial value of the precision parameter (no
                                   # need to change it unless for precPrioType='const')
prior$precPriorType    = 'uniform' # Possible values: const, uniform, and componentwise

# mcmc is NOT part of the beast model itself, but some parameters to configure the
# MCMC inference.
mcmc = list()
mcmc$seed                      = 9543434# an arbitray seed for random number generator
mcmc$samples                   = 3000   # samples collected per chain
mcmc$thinningFactor            = 3      # take every 3rd sample and discard others
mcmc$burnin                    = 150    # discard the initial 150 samples per chain
mcmc$chainNumber               = 3      # number of chains
mcmc$maxMoveStepSize          = 4      # max random jump step when proposing new chngpts
mcmc$trendResamplingOrderProb  = 0.100  # prob of choosing to resample polynomial order
mcmc$seasonResamplingOrderProb = 0.100  # prob of choosing to resample harmonic order
mcmc$credIntervalAlphaLevel    = 0.950  # the significance level for credible interval
```

```
 # extra is NOT part of the beast model itself, but some parameters to configure the
 # output and computation process
 extra = list()
 extra$dumpInputData        = FALSE #If true, a copy of input time series is outputted
 extra$whichOutputDimIsTime = 1    #For 2D or 3D inputs, which dim of the output refers to
                                    # time? Ignored if the input is a single time series
 extra$computeCredible      = FALSE #If true, compute CI: computing CI is time-intensive.
 extra$fastCIComputation    = TRUE  #If true, a faster way is used to get CI, but it is
                                # still time-intensive. That is why the function beast()
                                    # is slow because it always compute CI.
 extra$computeSeasonOrder   = FALSE #If true, dump the estimated harmonic order over time
 extra$computeTrendOrder    = FALSE #If true, dump the estimated polynomial order over time
 extra$computeSeasonChngpt  = TRUE  #If true, get the most likely locations of s chgnpts
 extra$computeTrendChngpt   = TRUE  #If true, get the most likely locations of t chgnpts
 extra$computeSeasonAmp     = FALSE #If true, get time-varying amplitude of seasonality
 extra$computeTrendSlope    = FALSE #If true, get time-varying slope of trend
 extra$tallyPosNegSeasonJump= FALSE #If true, get those changpts with +/- jumps in season
 extra$tallyPosNegTrendJump = FALSE #If true, get those changpts with +/- jumps in trend
 extra$tallyIncDecTrendJump = FALSE #If true, get those changpts with increasing/
                                    # decreasing trend slopes
 extra$printProgressBar     = TRUE
 extra$printOptions         = TRUE
 extra$quiet                = FALSE # print warning messages, if any
 extra$consoleWidth         = 0     # If 0, the console width is from the current console
 extra$numThreadsPerCPU     = 2     # 'numThreadsPerCPU' and 'numParThreads' are used to
 extra$numParThreads        = 0     # configure multithreading runs; they're used only if
                                    # Y has multiple time series (e.g.,stacked images)

 o = beast123(Yellowstone,metadata,prior,mcmc,extra, season='harmonic')
 plot(o)

## End(Not run)



#------------------------------Example 4: Handle irregular time series-----------------#
#  Handle irregular time series: ohio is a data frame of a Landsat NDVI series observed
#  at unevely-spaced times

## Not run:

 data(ohio)
 str(ohio)

 metadata                  = list()
 metadata$time             = ohio$time # Must supply individual times for irregular inputs
 metadata$deltaTime        = 1/12     # Must supply the desired time interval for aggregation
 metadata$period           = 1.0

 o=beast123(ohio$ndvi, metadata)       # Default values used for those missing parameters

 ########################################################################################
 class(ohio$rdate)                      # Another accepted time format for beast123
```

```
metadata = list()
metadata$deltaTime      = 1/12     # Must supply the desired time interval for aggregation
metadata$time           = ohio$rdate # Must supply individual times for irregular inputs

o=beast123(ohio$ndvi, metadata)       # Default values used for those missing parameters

#####################################################################################
ohio$Y                               # Another accepted time format for beast123
ohio$M
ohio$M

metadata = list()
metadata$deltaTime       = 1/12   # Must supply the desired time interval for aggregation
metadata$time$year        = ohio$Y
metadata$time$month       = ohio$M
metadata$time$day         = ohio$D
o=beast123(ohio$ndvi, metadata)     # Default values used for those missing parameters

#####################################################################################
ohio$Y                               # Another accepted time format for beast123
ohio$doy

metadata = list()
metadata$deltaTime       = 1/12   # Must supply the desired time interval for aggregation
metadata$time$year        = ohio$Y
metadata$time$doy         = ohio$doy
o=beast123(ohio$ndvi, metadata)     # Default values used for those missing parameters

#####################################################################################
ohio$time                            # Another accepted time format for beast123

metadata = list()
metadata$deltaTime      = 1/12    # Must supply the desired time interval for aggregation
metadata$time             = ohio$time # Fractional year

o=beast123(ohio$ndvi, metadata)      # Default values used for those missing parameters

#####################################################################################
ohio$datestr1                        # Another accepted time format for beast123

metadata = list()
metadata$deltaTime        = 1/12        # Must supply the time interval for aggregation
metadata$time$datestr     = ohio$datestr1
metadata$time$strfmt      = '????yyyy?mm?dd'

o=beast123(ohio$ndvi, metadata)        # Default values used for those missing parameters


#####################################################################################
ohio$datestr2                               # Another accepted time format for beast123
metadata = list()
metadata$deltaTime      = 1/12       # Must supply a desired time interval for aggregation
```

```
 metadata$time$datestr     = ohio$datestr2
 metadata$time$strfmt      = '????yyyydoy????'

 o=beast123(ohio$ndvi, metadata)        # Default values used for those missing parameters

 ####################################################################################
 ohio$datestr3                            # Another accepted time format for beast123
 metadata = list()
 metadata$deltaTime      = 1/12      # Must supply the desired time interval for aggregation
 metadata$time$datestr     = ohio$datestr3
 metadata$time$strfmt      = 'Y,,M/D'

 o=beast123(ohio$ndvi, metadata)        # Default values used for those missing parameters

## End(Not run)



#------------------Example 4: Handle multiple time series (i.e., matrix input)-----------#
# Handle multiple time series: 'simdata' is a 2D matrix of dim 300x3; it consits of 3
# time series of length 300 each. For this toy example, I decide to be lazy and use the same
# time series for the three columns.
## Not run:
 data(simdata)                      # dim of simdata: 300 x 3 (time x num_of_time_series)
 dim(simdata)                          # the first dimenion refer to time (i.e, 300)

 metadata                  = list()
 metadata$whichDimIsTime   = 1       # Which dim of the input refer to time for 2D inputs?
                                      # 300 is the ts length, so dim is set to '1' here.
 metadata$period          = 24       # By default, we assume startTime=1 and deltaTime=1

 extra=list()
 extra$whichOutputDimIsTime = 2          # Which dim of the output arrays refers to  time?
 o=beast123(simdata, metadata,extra=extra) # Default values used for those missing parameters

 # The lists of arg parameters can also be directly provided inline within the command
 o=beast123( simdata, metadata=list(whichDimIsTime=1,period=24), extra=list(whichOutput=2) )

 # The field names of the lists can be shortened as long as no ambiguitity is caused.
 o=beast123( simdata, metadata=list(whichDim=1,per=24), extra=list(whichOut=2) )

 #------------------Example 4: Another run by transposing simdata--------------------------#

 simdata1=t(simdata)                  # dim of simdata1: 3 x 300 (num of ts  x time )

 metadata                  = list()
 metadata$whichDimIsTime   = 2       # Which dim of the input refer to time for 2D inputs?
                                      # 300 is the ts length, so dim is set to '2' here.
 metadata$period          = 24       # By default, we assume startTime=1 and deltaTime=1
 o=beast123(simdata1, metadata)       # Default values used for those missing parameters

 o=beast123( simdata1, metadata=list(whichDim=2, per=24) )
```

```
## End(Not run)



#------------------Example 5: Handle stacked time series images (e.g., 3d input)--------#
# Handle 3D stacked images of irregular and unordered time-series: imagestack is a 3D
# array of size 12x9x1066, each pixel being a time series of length 1066
## Not run:
 data(imagestack)
 dim(imagestack$ndvi)               # Dim: 12 x 9 X 1066 (row x col x time)
 imagestack$datestr                 # A character vector of 1066 date strings

 metadata                  = list()
 metadata$whichDimIsTime   = 3      # Which dim of the input refer to time for 3D inputs?
                                    # 1066 is the ts length, so dim is set to '3' here.
                                    # In this example, this arg is not needed because
                                   # the time$datestr can also help to match and pick up
                                    # the right time dimesion of imagestack$ndvi.
 metadata$time$datestr     =  imagestack$datestr
 metadata$time$strfmt      =  'LT05_018032_20080311.yyyy-mm-dd'
 metadata$deltaTime      = 1/12  # Aggregate the irregular ts at a monthly interval:1/12 Yr
 metadata$period           =  1.0   # The period is 1 year: deltaTime*freq=1/12*12=1.0

 extra = list()
 extra$dumpInputData        = TRUE  # Get a copy of aggregated input ts
 extra$numThreadsPerCPU     = 2     # Each cpu core will be assigned 2 threads
 extra$numParThreads     = 0    # If 0, total_num_threads=numThreadsPerCPU*num_of_cpu_core
                                    # if >0, used to specify the total number of threads

 # Default values for missing parameters
 o=beast123(imagestack$ndvi, metadata=metadata,extra=extra)

 print(o,c(5,3))    # print the result for the pixel at Row 5 and Col 3
 plot(o,c(5,3))     # plot the result for the pixel at Row 5 and Col 3
 image(o$trend$ncp) # number of trend changepoints over space

## End(Not run)

#---------Example 6: Handle stacked GeoTiff image files imported with the raster package------#
# Handle 3D stacked images of irregular time-series : 'ndvi.zip' is  a zip file of
# 437 NDIV tiff image files, each having a dim of 12 x 9.
# Code availlable at https://github.com/zhaokg/Rbeast/blob/master/R/beast123_raster_example.txt
```

CNAchrom11 — *DNA copy number alteration data in array-based CGH data for Chromesome 11*

Description

CNAchrom11 is a vector of the log2 intensity ratios for cell line GM03576 for Chromosome 11, obtained from Snijders et al. (2001).

Usage

```
data(CNAchrom11)
```

Source

Snijders et al. (2001), Assembly of microarrays for genome-wide measurement of DNA copy number, Nature Genetics, 29, 263-264 (http://www.nature.com/ng/journal/v29/n3/full/ng754.html).

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

Examples

```
library(Rbeast)
data(CNAchrom11)


o = beast(CNAchrom11, season='none') # no periodic component
plot(o)
```

---

covid19 *Daily confirmed COVID19 cases and deaths in the world*

Description

covid19 is a data frame consisting of daily confirmed COVID19 cases and deaths in the world from Jan 22, 2020 to Dec 16, 2021.

Usage

```
data(covid19)
```

Source

https://ourworldindata.org/grapher/daily-covid-cases-deaths?country=~OWID_WRL (last accessed on Dec 16, 2021)

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

Examples

```
library(Rbeast)
data(covid19)
plot(covid19$date, covid19$newcases, type='l')

## Not run:

# Apply a square root-transformation
newcases = sqrt( covid19$newcases )

# This time series varies periodically every 7 days. 7 days can't be precisely
# represented in the unit of year bcz some years has 365 days and others has 366.
# BEAST can hanlde this in two ways.


#(1) Use the date number as the time unit--the num of days lapsed since 1970-01-01.

 datenum  = as.numeric(covid19$date)
 o        = beast(newcases, start=min(datenum), deltat=1, period=7)
 o$time   = as.Date(o$time, origin='1970-01-01') # Convert from integers to Date.
 plot(o)

#(2) Use strings to explicitly specify deltat and period with a unit.

 startdate = covid19$date[1]
 o         = beast(newcases, start=startdate, deltat='1day', period='7days')
 plot(o)
```

```
## End(Not run)
```

`geeLandsat` *Landsat reflectance and NDVI time series from Google Earth Engine*

Description

Get Landsat reflectance and NDVI time series from Google Earth Engine given longitude and latitude

Usage

```
geeLandsat(lon=NA, lat=NA, radius=100, stat='mean',timeout=700)
```

Arguments

`lon`	numeric within [-180,180]
`lat`	numeric within [-90, 90]
`radius`	a positive number (<=500 meters); the radius of a buffer around the given latitude and longitude for aggregation. If `radius=0`, the single pixel at the lat and lon will be retrieved
`stat`	character; if `radius>0`, used to specify the spatial aggregation method for pixels in the buffer. Possible values are 'mean','min','max', or 'median'.
`timeout`	integer; the seconds elapsed to wait for connection timeout. See the note for an explanation.

Value

a data.frame object consisting of dates, sensor type, reflectances, and NDVI for the requested location. It contains only valid and clear-sky values as obtained by referring to the standard clouds flags.

Note

As a poor man's scheme to interact with Google Earth Engine, `geeLandsat` should be used only for occasional retrieval of Landsat time series at a few sites, NOT for batch downloading for thousands of sites in a R loop. This procedure is provided to get example time series for testing BEAST. Behind the scene, this function calls to a free Python-based server using my own GEE credential. Normally it takes several seconds to retrieve one time series, but as a free cloud service, the Python server only offers 100 seconds of free CPU time per day, with throttling applied. So it may take up to a few mins to get a time series on your end. It may fail due to connection timeout; if so, give it a few tries. If you need to retrieve data for thousands or millions of sites, please contact the author.

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

See Also

beast, beast.irreg, beast123, minesweeper, tetris

Examples

```
 library(Rbeast)
## Not run:
 df = geeLandsat(lon=-80.983877,lat= 40.476882) #if it fails, try a few more times before giving up
 print(df)

## End(Not run)
```

---

googletrend_beach — *A monthly Google Trend time series of the US search interest in the word "beach"*

Description

googletrend_beach is a ts object comprising monthly search interest in "beach" from the United States, as reported from Google Trends. Sudden changes in the search trend are attributed to extreme weather events or the covid19 outbreak

Usage

```
data(googletrend_beach)
```

Source

https://trends.google.com/trends/explore?date=all&geo=US&q=beach

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

Examples

```
library(Rbeast)
data(googletrend_beach) # A monthly ts starting from Jan 2004

o = beast(googletrend_beach )
plot(o)
```

---

imagestack *Decades of Landsat NDVI time series over a small area in Ohio*

Description

`imagestack` is a LIST containing Landsat-derived NDVI image chips at an Ohio site

Usage

```
data(imagestack)
```

Source

Landsat images courtesy of the U.S. Geological Survey

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).

3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

Examples

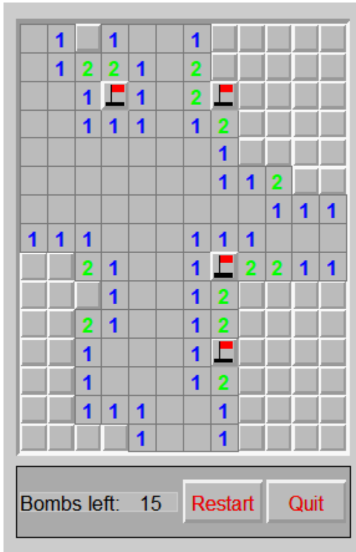
```
data(imagestack)
imagestack$datestr # A string vector containg the observation dates of individual ndvi images
## Not run:
imagestack$ndvi    # NDVI images collected over the past several deccades

## End(Not run)
plot(imagestack$ndvi[3,4,],type='l') # Plot the raw data at a pixel
```

---

minesweeper *The Minesweeper game in R*

Description

A poor man's implementation of the minesweeper game in R. Yes, you are right: it has nothing to do with time series decomposition, changepoint detection, and time series segmentation. Its only remote connection to Rbeast is that this is a practice script I wrote to learn R graphics for implementing Rbeast.



Usage

```
minesweeper(height=15, width=12, prob=0.1)
```

Arguments

`height`	integer; number of rows of the mine grid along the vertical direction.
`width`	integer; number of columns of the mine grid along the horizontal direction.
`prob`	numeric; a fraction between 0 and 1 to specify the probability of mine occurrence in the mine grid.

Value

Instructions:

- LEFT-click to clear a spot.
- RIGHT-click to flag a spot.
- MIDDLE-click(wheel) a cleared and numbered spot to open neighbor spots, if flagged correctly.
- Click Restart for a new game

Note

An interactive graphics window is needed to run this function correctly. So it won't run in RStudio's plot pane. The function will use the x11() or x11(type='Xlib') graphic device to open a pop-up window.

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

See Also

`beast`, `beast.irreg`, `beast123`, `tetris`, `geeLandsat`

Examples

```
 library(Rbeast)

 ## Not run:
 minesweeper()

 # A mine field of size 20x25 with rougly a 15
 minesweeper(20,25,0.15)

## End(Not run)
```

---

ohio *An irregular Landsat NDVI time series at an Ohio site*

Description

`ohio` is a data.frame object comprising decades of Landsat-observed surface reflectances and NDVI at an Ohio site

Usage

```
data(ohio)
```

Source

Landsat images courtesy of the U.S. Geological Survey

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

Examples

```
 library(Rbeast)
 data(ohio) # Landsat surface references and NDVI at a single pixel observed over time
 str(ohio)

## Not run:
 # ohio$ndvi is a single irregular time series
 y = ohio$ndvi
 o = beast.irreg(y, time=ohio$time,deltat=1/12)
 plot(o)
 print(o)

 # ohio also contains irregular time series of individual spectral bands
 # Below, run the multivariate version of the BEAST algorithm to decompose
 # the 5 time series and detect common changepoints altogether

 y = list(ohio$blue, ohio$green, ohio$red, ohio$nir, ohio$swir1);
 o = beast.irreg(y, time=ohio$time,deltat=1/12, freq=12)
 plot(o)
 print(o)

## End(Not run)
```

`plot.beast` *Bayesian changepoint detection and time series decomposition*

Description

Plot the result obtained from the beast function.

Usage

```
## S3 method for class 'beast'
plot(
     x,
     index = 1,
   vars = c('y','s','scp','sorder','t','tcp','torder','slpsgn','o','ocp','error'),
     col         = NULL,
     main        = "BEAST decomposition and changepoint detection",
     xlab        = 'Time',
     ylab        = NULL,
     cex.main    = 1,
     cex.lab     = 1,
     relative.heights = NULL,
     interactive = FALSE,
     ncpStat     = c('median','mode','mean','pct90','max'),
     ...
   )
```

Arguments

`x` a "beast" object returned by `beast`,`beast.irreg`, or `beast123`. It may contain one or many time series.

`index` an integer (default to 1) or a vector of two integers to specify the index of the time series to plot if `x` contains results for multiple time series. `index` is always 1 if `x` has 1 time series. If `x` is returned by `beast123` with a 2D input,`index` should be a single integer. If `x` is from `beast123` applied to 3D arrays of time series (e.g., stacked satellite images), `index` can be a linear index or two subscripts to specify the row and column of the pixel/grid.

`vars` a vector of strings indicating the elements or variables of `x` to plot. Possible vars strings include 'y' (season plus trend), 's' (season component), 't' (trend component), 'o' (outliers), 'scp', 'tcp', 'ocp' (occurrence probability of seasonal/trend/outlier changepoint), 'sorder' (seasonal harmonic order), 'torder' (trend polynomial order), 'samp' (amplitude of seasonality), 'tslp' (slope of trend), 'slpsgn' (probabilities of the slope being positive, zero, and negative) and 'error' (remainder).

`relative.heights` a numeric vector of the same length as that of `vars` to specify the relative heights of subplots of individual variables in `vars`.

`col` a string vector of the same length as that of `vars` to specify the colors of individual subplots associated with `vars`.

`main` a string; the main title.

`xlab` a string: the x axis title.

`ylab` a string vector of the same length as that of `vars` to specify the y axis names of individual subplots associated with `vars`

`cex.main` cex for the main title

`cex.lab`	cex for the axis title
`interactive`	a bool scalar. If TRUE, an interactive GUI is used for examining individual elements of `x`.
`ncpStat`	character. A string to specify which statistic is used for the Number of ChangePoint (ncp). Five values are possible: 'mean', 'mode', 'median','pct90', and 'max'; the default is 'median'. Individual models sampled by BEAST has a varying dimension (e.g., number of changepoints or knots). For example, if mcmc$samples=10, the numbers of changepoints for the 10 sampled models are assumed to be c(0, 2, 4, 1, 1, 2, 7, 6, 6, 1). The mean ncp will be 3.1 (rounded to 3), the median is 2.5 (2), the mode is 1, and the maximum is 7. The 'max' option plots all the changepoints recorded in `out$trend$cp`, `out$season$cp`, or `out$outlier$cp`; many of these changepoints are bound to be false positives, so do not treat all of them as actual changepoints.
`...`	additional parameters to be implemented.

Value

This function creates various plots to demonstrate the results of a beast decomposition. .

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

See Also

`beast`, `beast.irreg`, `beast123`, `plot.beast`,`minesweeper`, `tetris`, `geeLandsat`

Examples

```
 library(Rbeast)
 data(simdata)
## Not run:
 result=beast123(simdata, metadata=list(whichDimIsTime=1))
 plot(result,1)
 plot(result,2)

## End(Not run)
```

print.beast *Bayesian changepoint detection and time series decomposition*

Description

Summarize and print the results obtained from the BEAST time series decomposition and segmentation.

Usage

```
## S3 method for class 'beast'
print(
     x,
     index = 1,
     ...
 )
```

Arguments

x	a "beast" object returned by `beast`, `beast.irreg`, or `beast123`. It may contain one or many time series.
index	an integer (default to 1) or a vector of two integers to specify the index of the time series to print if `x` contains results for multiple time series. If `x` has 1 time series, `index` should be always 1. If `x` is returned by `beast123` applied to a 2D input,`index` should be a single index. If `x` is from `beast123` applied to 3D arrays of time series (e.g., stacked satellite images), `index` can be a linear index or two subscripts to specify the row and column of the desired pixel/grid.
...	additional parameters to be implemented.

Value

Print a summary of changepoints detected for the seasonal or trend component.

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).

3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

See Also

beast, beast.irreg, beast123, minesweeper, tetris, geeLandsat

Examples

```
 library(Rbeast)
 data(simdata)

## Not run:
#out=beast123(simdata) #Error: whichDimIsTime has to be specified to
                       # tell which dim of simdata refers to time.
                       # See below.
 out=beast123(simdata, metadata=list(whichDimIsTime=1))
 print(out, 1)
 print(out, 2)

## End(Not run)
```

---

simdata   *Simulated time series to test BEAST*

Description

`simdata` is a 300 x 3 matrix, consisting three time series of length 300. Currently, the three time series are the same. It is used to illustrate BEAST can handle multiple time series at a single function call. of BEAST.

Usage

```
data(simdata)
```

Source

Rbeast v0.9.2

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).

2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).

3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

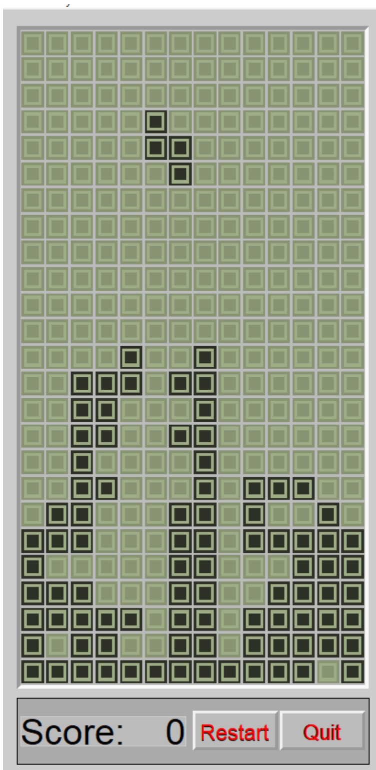
Examples

```
 library(Rbeast)
 data(simdata)
 plot(simdata[,1],type='l')

 ## Not run:
 #out=beast123(simdata) # Error: whichDimIsTime has to be specified. See below
 out=beast123(simdata, metadata=list(whichDimIsTime=1))

 plot(out,1)
 plot(out,2)
 plot(out,3)

## End(Not run)
```

`tetris` *The Tetris game in R*

Description

A poor man's implementation of the Tetris game in R. Yes, you are right again: it has nothing to do with time series decomposition, changepoint detection, and time series segmentation. Its only remote connection to Rbeast is that this is a practice script I wrote to learn R graphics for implementing Rbeast.



Usage

```
tetris(height=25, width=14, speed=0.6)
```

Arguments

`height`	integer; number of rows of the mine grid along the vertical direction.
`width`	integer; number of columns of the mine grid along the horizontal direction.
`speed`	numeric; a time interval between 0.05 and 2 seconds, specifying how fast the tetriminos moves down. The smaller, the faster.

Value

Instructions:

- Left arrow to move left.
- Right arrow to move right.
- Up arrow to rotate.
- Down arrow to speed up.
- Space key to sink to the bottom.

Note

This function works only under the Windows OS not Linux or Mac. An interactive graphics window is needed to run this function correctly. So it won't run in RStudio's plot pane. The function will use the x11() or x11(type='Xlib') graphic device to open a pop-up window.

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

See Also

beast, beast.irreg, beast123, minesweeper, geeLandsat

Examples

```
 library(Rbeast)

 ## Not run:
 tetris()

 # A  field of size 20x25 with blocks moving down every 0.1 sec.
 tetris(20,25,0.1)

## End(Not run)
```

`tsextract` *Bayesian changepoint detection and time series decomposition*

Description

Extract the result of a single time series from an object of class beast

Usage

```
tsextract( x, index = 1 )
```

Arguments

x	a "beast" object returned by beast, beast.irreg, or beast123. It may contain one or many time series.
index	an integer (default to 1) or a vector of two integers to specify the index of the time series to extract if x contains results for multiple time series. If x has 1 time series, index should be always 1. If x is returned by beast123 applied to a 2D input,index should be a single index. If x is from beast123 applied to 3D arrays of time series (e.g., stacked satellite images), index can be a linear index or two subscripts to specify the row and column of the desired pixel/grid.

Value

A LIST object of the result for the chosen time series, which contains the same field as x.

Note

Use this function only to manually and interactively examine individual times series. If the purpose is to loop through x, the use of direct indexing is much faster. For example, if x is a beast object for a 300x200x1000 3D array (row x col x time), use x$trend$Y[20,40,] to get the fitted trend at the pixel of row 20 and col 40.

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

See Also

beast, beast.irreg, beast123, minesweeper, tetris, geeLandsat

Examples

```
library(Rbeast)
data(simdata)


# handle only the 1st ts
out=beast(simdata[,1])


## Not run:
# handle all the ts
out=beast123(simdata, metadata=list(whichDimIsTime=1))

plot(out,1)
plot(out,2)

## End(Not run)
```

`Yellowstone` *30 years' AVHRR NDVI data at a Yellowstone site*

Description

`Yellowstone` is a vector comprising 30 years' AVHRR NDVI data at a Yellowstone site

Usage

```
data(Yellowstone)
```

Source

Rbeast v0.9.2

References

1. Zhao, K., Wulder, M.A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X. and Brown, M., 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. Remote Sensing of Environment, 232, p.111181 (the beast algorithm paper).
2. Zhao, K., Valle, D., Popescu, S., Zhang, X. and Mallick, B., 2013. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. Remote Sensing of Environment, 132, pp.102-119 (the Bayesian MCMC scheme used in beast).
3. Hu, T., Toman, E.M., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K. and Feng, Y., 2021. Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. ISPRS Journal of Photogrammetry and Remote Sensing, 176, pp.250-261(a beast application paper).

Examples

```
library(Rbeast)
data(Yellowstone)
plot(Yellowstone,type='l')

result=beast(Yellowstone)
plot(result)
```

Index