Package 'tspredit'

October 27, 2025

Title Time Series Prediction with Integrated Tuning

Version 1.2.747

Description Time series prediction is a critical task in data analysis, requiring not only the selection of appropriate models, but also suitable data preprocessing and tuning strategies.
TSPredIT (Time Series Prediction with Integrated Tuning) is a framework that provides a seamless integration of data preprocessing, decomposition, model training, hyperparameter optimization, and evaluation.
Unlike other frameworks, TSPredIT emphasizes the co-optimization of both preprocessing and modeling steps, improving predictive performance.
It supports a variety of statistical and machine learning models, filtering techniques, outlier detection, data augmentation, and ensemble strategies.
More information is available in Salles et al. <doi:10.1007/978-3-662-68014-8_2>.

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URL https://cefet-rj-dal.github.io/tspredit/, https://github.com/cefet-rj-dal/tspredit

BugReports https://github.com/cefet-rj-dal/tspredit/issues

Encoding UTF-8

RoxygenNote 7.3.3

Depends R (>= 4.1.0)

Imports stats, DescTools, e1071, elmNNRcpp, FNN, forecast, hht, KFAS, mFilter, nnet, randomForest, wavelets, dplyr, daltoolbox

NeedsCompilation no

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Date/Publication 2025-10-27 06:10:09 UTC

Contents

`adjust_ts_data` *Adjust* `ts_data`

Description

Convert a compatible dataset to a `ts_data` object by setting column names, class, and the `sw` attribute consistently.

Usage

```
adjust_ts_data(data)
```

Arguments

`data`	Matrix or data.frame to adjust.

Value

An adjusted `ts_data`.

do_fit *Fit Time Series Model*

Description

Generic for fitting a time series model. Descendants should implement `do_fit.<class>`.

Usage

```
do_fit(obj, x, y = NULL)
```

Arguments

`obj`	Model object to be fitted.
`x`	Matrix or data.frame with input features.
`y`	Vector or matrix with target values.

Value

A fitted object (same class as `obj`).

do_predict *Predict Time Series Model*

Description

Generic for predicting with a fitted time series model. Descendants should implement `do_predict.<class>`.

Usage

```
do_predict(obj, x)
```

Arguments

`obj`	Fitted model object.
`x`	Matrix or data.frame with input features to predict.

Value

Numeric vector with predicted values.

fertilizers *Fertilizers (Regression)*

Description

List of Brazilian fertilizer consumption series for N, P2O5, K2O. All series are numeric and ordered by time.

- brazil_n: nitrogen consumption from 1961 to 2020.
- brazil_p2o5: phosphate consumption from 1961 to 2020.
- brazil_k2o: potash consumption from 1961 to 2020.

Usage

```
data(fertilizers)
```

Format

list of fertilizers' time series.

Source

This dataset was obtained from the MASS library.

References

International Fertilizer Association (IFA): https://www.fertilizer.org

Examples

```
# Load dataset and preview one of the series (nitrogen)
data(fertilizers)
head(fertilizers$brazil_n)
```

MSE.ts *MSE*

Description

Compute mean squared error (MSE) between actual and predicted values.

Usage

```
MSE.ts(actual, prediction)
```

Arguments

actual	Numeric vector of observed values.
prediction	Numeric vector of predicted values.

Details

MSE = mean((actual - prediction)^2).

Value

Numeric scalar with the MSE.

R2.ts *R2*

Description

Compute coefficient of determination (R-squared).

Usage

```
R2.ts(actual, prediction)
```

Arguments

actual	Numeric vector of observed values.
prediction	Numeric vector of predicted values.

Value

Numeric scalar with R-squared.

---

select_hyper.ts_tune *Select Optimal Hyperparameters for Time Series Models*

Description

Identifies the optimal hyperparameters by minimizing the error from a dataset of hyperparameters. The function selects the hyperparameter configuration that results in the lowest average error. It wraps the dplyr library.

Usage

```
## S3 method for class 'ts_tune'
select_hyper(obj, hyperparameters)
```

Arguments

obj	a ts_tune object containing the model and tuning settings
hyperparameters	hyperparameters dataset

Value

returns the optimized key number of hyperparameters

---

sMAPE.ts *sMAPE*

Description

Compute symmetric mean absolute percent error (sMAPE).

Usage

```
sMAPE.ts(actual, prediction)
```

Arguments

actual	Numeric vector of observed values.
prediction	Numeric vector of predicted values.

Details

sMAPE = mean(|a - p| / ((|a| + |p|)/2)), excluding zero denominators.

Value

Numeric scalar with the sMAPE.

References

- S. Makridakis and M. Hibon (2000). The M3-Competition: results, conclusions and implications. International Journal of Forecasting, 16(4).

tsd *Time series example dataset*

Description

Synthetic dataset based on a sine function.

- x: correspond time from 0 to 10.
- y: dependent variable for time series modeling.

Usage

```
data(tsd)
```

Format

`data.frame`.

Source

This dataset was generated for examples.

Examples

```
# Load dataset and preview the first rows
data(tsd)
head(tsd)
```

ts_arima *ARIMA*

Description

Create a time series prediction object based on the AutoRegressive Integrated Moving Average (ARIMA) family.

This constructor sets up an S3 time series regressor that leverages the `forecast` package to automatically select orders via `auto.arima` and provide one-step and multi-step forecasts.

Usage

```
ts_arima()
```

Details

ARIMA models combine autoregressive (AR), differencing (I), and moving average (MA) components to model temporal dependence in a univariate time series. The `fit()` method uses `forecast::auto.arima()` to select orders using information criteria, and `predict()` supports both a single one-step-ahead over a horizon (rolling) and direct multi-step forecasting.

Assumptions include (after differencing) approximate stationarity and homoskedastic residuals. Always inspect residual diagnostics for adequacy.

Value

A `ts_arima` object (S3), which inherits from `ts_reg`.

References

- G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung (2015). Time Series Analysis: Forecasting and Control. Wiley.
- R. J. Hyndman and Y. Khandakar (2008). Automatic time series forecasting: The forecast package for R. Journal of Statistical Software, 27(3), 1–22. doi:10.18637/jss.v027.i03

Examples

```
# Example: rolling-origin evaluation with multi-step prediction
# Load package and dataset
library(daltoolbox)
data(tsd)

# 1) Wrap the raw vector as `ts_data` without sliding windows
ts <- ts_data(tsd$y, 0)
ts_head(ts, 3)

# 2) Split into train/test using the last 5 observations as test
samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

# 3) Fit ARIMA via auto.arima
model <- ts_arima()
model <- fit(model, x = io_train$input, y = io_train$output)

# 4) Predict 5 steps ahead from the most recent observed point
prediction <- predict(model, x = io_test$input[1,], steps_ahead = 5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

# 5) Evaluate forecast accuracy
ev_test <- evaluate(model, output, prediction)
ev_test
```

`ts_aug_awareness` *Augmentation by Awareness*

Description

Bias the augmentation to emphasize more recent points in each window (recency awareness), increasing their contribution to the augmented sample.

Usage

```
ts_aug_awareness(factor = 1)
```

Arguments

`factor`	Numeric factor controlling the recency weighting.

Value

A `ts_aug_awareness` object.

References

- Q. Wen et al. (2021). Time Series Data Augmentation for Deep Learning: A Survey. IJCAI Workshop on Time Series.

Examples

```
# Recency-aware augmentation over sliding windows
# Load package and example dataset
library(daltoolbox)
data(tsd)

# Convert to 10-lag sliding windows and preview
xw <- ts_data(tsd$y, 10)
ts_head(xw)

# Apply awareness augmentation (bias toward recent rows)
augment <- ts_aug_awareness()
augment <- fit(augment, xw)
xa <- transform(augment, xw)
ts_head(xa)
```

`ts_aug_awaresmooth` *Augmentation by Awareness Smooth*

Description

Recency-aware augmentation that also progressively smooths noise before applying the weighting, producing cleaner augmented samples.

Usage

```
ts_aug_awaresmooth(factor = 1)
```

Arguments

`factor`	Numeric factor controlling the recency weighting.

Value

A `ts_aug_awaresmooth` object.

References

- Q. Wen et al. (2021). Time Series Data Augmentation for Deep Learning: A Survey. IJCAI Workshop on Time Series.

Examples

```
# Recency-aware augmentation with progressive smoothing
# Load package and example dataset
library(daltoolbox)
data(tsd)

# Convert to 10-lag sliding windows and preview
xw <- ts_data(tsd$y, 10)
ts_head(xw)

# Apply awareness+smooth augmentation and inspect result
augment <- ts_aug_awaresmooth()
augment <- fit(augment, xw)
xa <- transform(augment, xw)
ts_head(xa)
```

ts_aug_flip *Augmentation by Flip*

Description

Time series augmentation by mirroring sliding-window observations around their mean to increase diversity and reduce overfitting.

Usage

```
ts_aug_flip()
```

Details

This transformation preserves the window mean while flipping the deviations, effectively generating a symmetric variant of the local pattern.

Value

A `ts_aug_flip` object.

References

- Q. Wen et al. (2021). Time Series Data Augmentation for Deep Learning: A Survey. IJCAI Workshop on Time Series.

Examples

```
# Flip augmentation around the window mean
# Load package and example dataset
library(daltoolbox)
data(tsd)

# Convert to sliding windows and preview
xw <- ts_data(tsd$y, 10)
ts_head(xw)

# Apply flip augmentation and inspect augmented windows
augment <- ts_aug_flip()
augment <- fit(augment, xw)
xa <- transform(augment, xw)
ts_head(xa)
```

ts_aug_jitter *Augmentation by Jitter*

Description

Time series augmentation by adding low-amplitude random noise to each point to increase robustness and reduce overfitting.

Usage

```
ts_aug_jitter()
```

Details

Noise scale is estimated from within-window deviations.

Value

A ts_aug_jitter object.

References

- J. T. Um et al. (2017). Data augmentation of wearable sensor data for Parkinson's disease monitoring using convolutional neural networks.
- Q. Wen et al. (2021). Time Series Data Augmentation for Deep Learning: A Survey. IJCAI Workshop on Time Series.

Examples

```
# Jitter augmentation with noise estimated from windows
# Load package and example dataset
library(daltoolbox)
data(tsd)

# Convert to sliding windows and preview
xw <- ts_data(tsd$y, 10)
ts_head(xw)

# Apply jitter (adds small noise; keeps target column unchanged)
augment <- ts_aug_jitter()
augment <- fit(augment, xw)
xa <- transform(augment, xw)
ts_head(xa)
```

ts_aug_none *No Augmentation*

Description

Identity augmentation that returns the original windows while preserving the augmentation interface and indices.

Usage

```
ts_aug_none()
```

Value

A ts_aug_none object.

Examples

```
# Identity augmentation (no changes to windows)
# Load package and example dataset
library(daltoolbox)
data(tsd)

# Convert to sliding windows and preview
xw <- ts_data(tsd$y, 10)
ts_head(xw)

# No augmentation; returns the same windows with indices preserved
augment <- ts_aug_none()
augment <- fit(augment, xw)
xa <- transform(augment, xw)
ts_head(xa)
```

ts_aug_shrink *Augmentation by Shrink*

Description

Decrease within-window deviation magnitude by a scaling factor to generate lower-variance variants while preserving the mean.

Usage

```
ts_aug_shrink(scale_factor = 0.8)
```

Arguments

scale_factor	Numeric factor used to scale deviations.

Value

A ts_aug_shrink object.

References

- Q. Wen et al. (2021). Time Series Data Augmentation for Deep Learning: A Survey. IJCAI Workshop on Time Series.

Examples

```
# Shrink augmentation reduces within-window deviations
# Load package and example dataset
library(daltoolbox)
data(tsd)

# Convert to sliding windows and preview
xw <- ts_data(tsd$y, 10)
ts_head(xw)

# Apply shrink augmentation and inspect augmented windows
augment <- ts_aug_shrink()
augment <- fit(augment, xw)
xa <- transform(augment, xw)
ts_head(xa)
```

---

ts_aug_stretch *Augmentation by Stretch*

Description

Increase within-window deviation magnitude by a scaling factor to produce higher-variance variants.

Usage

```
ts_aug_stretch(scale_factor = 1.2)
```

Arguments

scale_factor	Numeric factor used to scale deviations.

Value

A ts_aug_stretch object.

References

- Q. Wen et al. (2021). Time Series Data Augmentation for Deep Learning: A Survey. IJCAI Workshop on Time Series.

Examples

```
# Stretch augmentation increases within-window deviations
# Load package and example dataset
library(daltoolbox)
data(tsd)

# Convert to sliding windows and preview
xw <- ts_data(tsd$y, 10)
ts_head(xw)

# Apply stretch augmentation and inspect augmented windows
augment <- ts_aug_stretch()
augment <- fit(augment, xw)
xa <- transform(augment, xw)
ts_head(xa)
```

`ts_aug_wormhole` *Augmentation by Wormhole*

Description

Generate augmented windows by selectively replacing lag terms with older lagged values, creating plausible alternative trajectories.

Usage

```
ts_aug_wormhole()
```

Details

This combinatorial replacement preserves overall scale while introducing temporal permutations of lag content.

Value

A `ts_aug_wormhole` object.

References

- Q. Wen et al. (2021). Time Series Data Augmentation for Deep Learning: A Survey. IJCAI Workshop on Time Series.

Examples

```
# Wormhole augmentation replaces some lags with older values
# Load package and example dataset
library(daltoolbox)
data(tsd)
```

```
# Convert to sliding windows and preview
xw <- ts_data(tsd$y, 10)
ts_head(xw)

# Apply wormhole augmentation and inspect augmented windows
augment <- ts_aug_wormhole()
augment <- fit(augment, xw)
xa <- transform(augment, xw)
ts_head(xa)
```

`ts_data` *ts_data*

Description

Construct a time series data object used throughout the DAL Toolbox.

Accepts either a vector (raw time series) or a matrix/data.frame already organized in sliding windows. Internally, a `ts_data` is stored as a matrix with `sw` lag columns named `t{lag}` (e.g., `t9, t8, ..., t0`). When `sw` is zero or one, the series is stored as a single column (`t0`).

Usage

```
ts_data(y, sw = 1)
```

Arguments

`y`	Numeric vector or matrix-like. Time series values or sliding windows.
`sw`	Integer. Sliding-window size (number of lag columns).

Value

A `ts_data` object (matrix with attributes and column names).

Examples

```
# Example: building sliding windows
data(tsd)
head(tsd)

# 1) Single-column ts_data (no windows)
data <- ts_data(tsd$y)
ts_head(data)

# 2) 10-lag sliding windows (t9 ... t0)
data10 <- ts_data(tsd$y, 10)
ts_head(data10)
```

ts_elm *ELM*

Description

Create a time series prediction object that uses Extreme Learning Machine (ELM) regression.

It wraps the `elmNNRcpp` package to train single-hidden-layer networks with randomly initialized hidden weights and closed-form output weights.

Usage

```
ts_elm(preprocess = NA, input_size = NA, nhid = NA, actfun = "purelin")
```

Arguments

`preprocess`	Normalization preprocessor (e.g., `ts_norm_gminmax()`).
`input_size`	Integer. Number of lagged inputs used by the model.
`nhid`	Integer. Hidden layer size.
`actfun`	Character. One of 'sig', 'radbas', 'tribas', 'relu', 'purelin'.

Details

ELMs are efficient to train and can perform well with appropriate hidden size and activation choice. Consider normalizing inputs and tuning `nhid` and the activation function.

Value

A `ts_elm` object (S3) inheriting from `ts_regsw`.

References

- G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew (2006). Extreme Learning Machine: Theory and Applications. Neurocomputing, 70(1–3), 489–501.

Examples

```
# Example: ELM with sliding-window inputs
# Load package and toy dataset
library(daltoolbox)
data(tsd)

# Create sliding windows of length 10 (t9 ... t0)
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)

# Split last 5 rows as test set
samp <- ts_sample(ts, test_size = 5)
# Project to inputs (X) and outputs (y)
```

```
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

# Define ELM with global min-max normalization and fit
model <- ts_elm(ts_norm_gminmax(), input_size = 4, nhid = 3, actfun = "purelin")
model <- fit(model, x = io_train$input, y = io_train$output)

# Forecast 5 steps ahead starting from the last known window
prediction <- predict(model, x = io_test$input[1,], steps_ahead = 5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

# Evaluate forecast error on the test horizon
ev_test <- evaluate(model, output, prediction)
ev_test
```

`ts_fil_ema` *Exponential Moving Average (EMA)*

Description

Smooth a series by exponentially decaying weights that give more importance to recent observations.

Usage

```
ts_fil_ema(ema = 3)
```

Arguments

`ema`	exponential moving average size

Details

EMA is related to simple exponential smoothing; it reacts faster to level changes than a simple moving average while reducing noise.

Value

A `ts_fil_ema` object.

References

- C. C. Holt (1957). Forecasting trends and seasonals by exponentially weighted moving averages. O.N.R. Research Memorandum.

Examples

```
# Exponential moving average smoothing on a noisy series
# Load package and example data
library(daltoolbox)
data(tsd)

# Inject an outlier to illustrate smoothing effect
tsd$y[9] <- 2 * tsd$y[9]

# Define EMA filter, fit and transform the series
filter <- ts_fil_ema(ema = 3)
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Compare original vs smoothed series
plot_ts_pred(y = tsd$y, yadj = y)
```

---

ts_fil_emd *EMD Filter*

Description

Empirical Mode Decomposition (EMD) filter that decomposes a signal into intrinsic mode functions (IMFs) and reconstructs a smoothed component.

Usage

```
ts_fil_emd(noise = 0.1, trials = 5)
```

Arguments

noise	noise
trials	trials

Value

A ts_fil_emd object.

References

- N. E. Huang et al. (1998). The Empirical Mode Decomposition and the Hilbert Spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society A.

Examples

```
# EMD-based smoothing: remove first IMF as noise
# Load package and example data
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2 * tsd$y[9]  # inject an outlier

# Fit EMD filter and reconstruct without the first (noisiest) IMF
filter <- ts_fil_emd()
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Compare original vs smoothed series
plot_ts_pred(y = tsd$y, yadj = y)
```

---

ts_fil_fft *FFT Filter*

Description

Frequency-domain smoothing using the Fast Fourier Transform (FFT) to attenuate high-frequency components.

Usage

```
ts_fil_fft()
```

Details

The implementation estimates a cutoff based on spectral statistics and reconstructs the series from dominant frequencies.

Value

A `ts_fil_fft` object.

References

- J. W. Cooley and J. W. Tukey (1965). An algorithm for the machine calculation of complex Fourier series. Math. Comput.

Examples

```
# Frequency-domain smoothing via FFT cutoff
# Load package and example data
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2 * tsd$y[9]  # inject an outlier
```

```
# Fit FFT-based filter and reconstruct without high frequencies
filter <- ts_fil_fft()
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Compare original vs frequency-smoothed series
plot_ts_pred(y = tsd$y, yadj = y)
```

`ts_fil_hp` *Hodrick-Prescott Filter*

Description

Decompose a series into trend and cyclical components using the Hodrick–Prescott (HP) filter and optionally blend with the original series.

This filter removes short-term fluctuations by penalizing changes in the growth rate of the trend component.

Usage

```
ts_fil_hp(lambda = 100, preserve = 0.9)
```

Arguments

`lambda`	It is the smoothing parameter of the Hodrick-Prescott filter. Lambda = 100*(frequency)^2 Correspondence between frequency and lambda values annual => frequency = 1 // lambda = 100 quarterly => frequency = 4 // lambda = 1600 monthly => frequency = 12 // lambda = 14400 weekly => frequency = 52 // lambda = 270400 daily (7 days a week) => frequency = 365 // lambda = 13322500 daily (5 days a week) => frequency = 252 // lambda = 6812100
`preserve`	value between 0 and 1. Balance the composition of observations and applied filter. Values close to 1 preserve original values. Values close to 0 adopts HP filter values.

Details

The filter strength is governed by `lambda` = `100 * frequency^2`. Use `preserve` in (0, 1] to convex-combine the raw series and the HP trend.

Value

A `ts_fil_hp` object.

References

- R. J. Hodrick and E. C. Prescott (1997). Postwar U.S. business cycles: An empirical investigation. Journal of Money, Credit and Banking, 29(1).

Examples

```
# time series with noise
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2*tsd$y[9]

# filter
filter <- ts_fil_hp(lambda = 100*(26)^2)  #frequency assumed to be 26
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# plot
plot_ts_pred(y=tsd$y, yadj=y)
```

`ts_fil_kalman` *Kalman Filter*

Description

Estimate a latent trend via a state-space model using the Kalman Filter (KF), wrapping the `KFAS` package.

Usage

```
ts_fil_kalman(H = 0.1, Q = 1)
```

Arguments

`H`	variance or covariance matrix of the measurement noise. This noise pertains to the relationship between the true system state and actual observations. Measurement noise is added to the measurement equation to account for uncertainties or errors associated with real observations. The higher this value, the higher the level of uncertainty in the observations.
`Q`	variance or covariance matrix of the process noise. This noise follows a zero-mean Gaussian distribution. It is added to the equation to account for uncertainties or unmodeled disturbances in the state evolution. The higher this value, the greater the uncertainty in the state transition process.

Value

A `ts_fil_kalman` object.

References

- R. E. Kalman (1960). A new approach to linear filtering and prediction problems. Journal of Basic Engineering, 82(1), 35–45.

Examples

```
# State-space smoothing with Kalman Filter (KF)
# Load package and example data
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2 * tsd$y[9]  # inject an outlier

# Fit KF (H = obs noise, Q = process noise) and transform
filter <- ts_fil_kalman()
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Plot original vs KF-smoothed series
plot_ts_pred(y = tsd$y, yadj = y)
```

---

ts_fil_lowess *LOWESS Smoothing*

Description

Locally Weighted Scatterplot Smoothing (LOWESS) fits local regressions to capture the primary trend while reducing noise and spikes.

Usage

```
ts_fil_lowess(f = 0.2)
```

Arguments

f	smoothing parameter. The larger this value, the smoother the series will be. This provides the proportion of points on the plot that influence the smoothing.

Value

A `ts_fil_lowess` object.

References

- W. S. Cleveland (1979). Robust locally weighted regression and smoothing scatterplots. Journal of the American Statistical Association.

Examples

```
# time series with noise
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2*tsd$y[9]

# filter
```

```
filter <- ts_fil_lowess(f = 0.2)
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# plot
plot_ts_pred(y=tsd$y, yadj=y)
```

`ts_fil_ma` *Moving Average (MA)*

Description

Smooth out fluctuations and reduce noise by averaging over a fixed-size rolling window.

Usage

```
ts_fil_ma(ma = 3)
```

Arguments

`ma`	moving average size

Details

Larger windows produce smoother series but may lag turning points.

Value

A `ts_fil_ma` object.

Examples

```
# time series with noise
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2*tsd$y[9]

# filter
filter <- ts_fil_ma(3)
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# plot
plot_ts_pred(y=tsd$y, yadj=y)
```

ts_fil_none *No Filter*

Description

Identity filter that returns the original series unchanged.

Usage

```
ts_fil_none()
```

Value

A ts_fil_none object.

Examples

```
# Identity filter (returns original series)
# Load package and example series
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2 * tsd$y[9]  # inject an outlier for comparison

# Fit identity filter and transform (no change expected)
filter <- ts_fil_none()
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Plot original vs (identical) filtered series
plot_ts_pred(y = tsd$y, yadj = y)
```

ts_fil_qes *Quadratic Exponential Smoothing*

Description

Double/triple exponential smoothing capturing level, trend, and optionally seasonality components.

Usage

```
ts_fil_qes(gamma = FALSE)
```

Arguments

gamma	If TRUE, enables the gamma seasonality component.

Value

A ts_fil_qes object.

References

- P. R. Winters (1960). Forecasting sales by exponentially weighted moving averages. Management Science.

Examples

```
# time series with noise
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2*tsd$y[9]

# filter
filter <- ts_fil_qes()
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# plot
plot_ts_pred(y=tsd$y, yadj=y)
```

---

ts_fil_recursive *Recursive Filter*

Description

Apply recursive linear filtering (ARMA-style recursion) to a univariate series or each column of a multivariate series. Useful for smoothing and mitigating autocorrelation.

Usage

```
ts_fil_recursive(filter)
```

Arguments

filter	smoothing parameter. The larger the value, the greater the smoothing. The smaller the value, the less smoothing, and the resulting series shape is more similar to the original series.

Value

A ts_fil_recursive object.

Examples

```
# time series with noise
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2*tsd$y[9]

# filter
filter <- ts_fil_recursive(filter =  0.05)
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# plot
plot_ts_pred(y=tsd$y, yadj=y)
```

`ts_fil_remd` *Robust EMD Filter*

Description

Ensemble/robust EMD-based denoising using CEEMD to separate noise-dominated IMFs and reconstruct the signal.

Usage

```
ts_fil_remd(noise = 0.1, trials = 5)
```

Arguments

`noise`	noise
`trials`	trials

Value

A `ts_fil_remd` object.

References

- Z. Wu and N. E. Huang (2009). Ensemble Empirical Mode Decomposition: a noise-assisted data analysis method. Advances in Adaptive Data Analysis.

Examples

```
# time series with noise
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2*tsd$y[9]

# filter
filter <- ts_fil_remd()
```

```
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# plot
plot_ts_pred(y=tsd$y, yadj=y)
```

`ts_fil_seas_adj` *Seasonal Adjustment*

Description

Remove the seasonal component from a time series while preserving level and trend, using a state-space/BATS approach.

Usage

```
ts_fil_seas_adj(frequency = NULL)
```

Arguments

`frequency`	Frequency of the time series. It is an optional parameter. It can be configured when the frequency of the time series is known.

Value

A `ts_fil_seas_adj` object.

References

- R. J. Hyndman and G. Athanasopoulos (2021). Forecasting: Principles and Practice (3rd ed). OTexts. (BATS/seasonal adjustment)

Examples

```
# Seasonal adjustment using BATS at known frequency
# Load package and example data
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2 * tsd$y[9]  # inject an outlier (illustrative)

# Fit seasonal adjustment (set frequency if known) and transform
filter <- ts_fil_seas_adj(frequency = 26)
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Plot original vs seasonally adjusted series
plot_ts_pred(y = tsd$y, yadj = y)
```

`ts_fil_ses` *Simple Exponential Smoothing*

Description

Exponential smoothing focused on the level component, with optional extensions to trend/seasonality via Holt–Winters variants.

Usage

```
ts_fil_ses(gamma = FALSE)
```

Arguments

`gamma`	If TRUE, enables the gamma seasonality component.

Value

A `ts_fil_ses` object.

References

- R. G. Brown (1959). Statistical Forecasting for Inventory Control.

Examples

```
# time series with noise
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2*tsd$y[9]

# filter
filter <- ts_fil_ses()
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# plot
plot_ts_pred(y=tsd$y, yadj=y)
```

ts_fil_smooth *Time Series Smooth*

Description

Remove or reduce randomness (noise) using a robust smoothing strategy that first mitigates outliers and then smooths residual variation.

Usage

```
ts_fil_smooth()
```

Value

A ts_fil_smooth object.

Examples

```
# Robust smoothing with iterative outlier mitigation
# Load package and example data
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2 * tsd$y[9]  # inject an outlier

# Fit smoother and transform to reduce spikes/noise
filter <- ts_fil_smooth()
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Compare original vs smoothed series
plot_ts_pred(y = tsd$y, yadj = y)
```

ts_fil_spline *Smoothing Splines*

Description

Fit a cubic smoothing spline to a time series for smooth trend extraction with a tunable roughness penalty.

Usage

```
ts_fil_spline(spar = NULL)
```

Arguments

spar	smoothing parameter. When spar is specified, the coefficient of the integral of the squared second derivative in the fitting criterion (penalized log-likelihood) is a monotone function of spar.

Value

A ts_fil_spline object.

References

- P. Craven and G. Wahba (1978). Smoothing noisy data with spline functions. Numerische Mathematik.

Examples

```
# Smoothing splines with adjustable roughness penalty
# Load package and example data
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2 * tsd$y[9]  # inject an outlier

# Fit spline smoother (spar controls smoothness) and transform
filter <- ts_fil_spline(spar = 0.5)
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Compare original vs smoothed series
plot_ts_pred(y = tsd$y, yadj = y)
```

---

ts_fil_wavelet *Wavelet Filter*

Description

Denoise a series using discrete wavelet transforms and selected wavelet families.

Usage

```
ts_fil_wavelet(filter = "haar")
```

Arguments

filter	Available wavelet filters: 'haar', 'd4', 'la8', 'bl14', 'c6'.

Value

A ts_fil_wavelet object.

References

- S. Mallat (1989). A Theory for Multiresolution Signal Decomposition: The Wavelet Representation. IEEE Transactions on Pattern Analysis and Machine Intelligence.

Examples

```
# Denoising with discrete wavelets (optionally selecting best filter)
# Load package and example data
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2 * tsd$y[9]  # inject an outlier

# Fit wavelet filter ("haar" by default; can pass a list to select best)
filter <- ts_fil_wavelet()
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Compare original vs wavelet-denoised series
plot_ts_pred(y = tsd$y, yadj = y)
```

---

ts_fil_winsor *Winsorization of Time Series*

Description

Apply Winsorization to limit extreme values by replacing them with nearer order statistics, reducing the influence of outliers.

Usage

```
ts_fil_winsor()
```

Value

A `ts_fil_winsor` object.

References

- J. W. Tukey (1962). The future of data analysis. Annals of Mathematical Statistics. (Winsorization discussed in robust summaries.)

Examples

```
# Winsorization: cap extreme values to reduce outlier impact
# Load package and example data
library(daltoolbox)
data(tsd)
tsd$y[9] <- 2 * tsd$y[9]  # inject an outlier
```

```
# Fit Winsor filter and transform series
filter <- ts_fil_winsor()
filter <- fit(filter, tsd$y)
y <- transform(filter, tsd$y)

# Plot original vs Winsorized series
plot_ts_pred(y = tsd$y, yadj = y)
```

---

ts_head *Extract the First Observations from a* ts_data *Object*

Description

Return the first n observations from a ts_data.

Usage

```
ts_head(x, n = 6L, ...)
```

Arguments

x	ts_data object
n	number of rows to return
...	optional arguments

Value

The first n observations of a ts_data (as a matrix/data.frame).

Examples

```
data(tsd)
data10 <- ts_data(tsd$y, 10)
ts_head(data10)
```

---

ts_integtune *Time Series Integrated Tune*

Description

Integrated tuning over input sizes, preprocessing, augmentation, and model hyperparameters for time series.

Usage

```
ts_integtune(
  input_size,
  base_model,
  folds = 10,
  ranges = NULL,
  preprocess = list(ts_norm_gminmax()),
  augment = list(ts_aug_none())
)
```

Arguments

input_size	Integer vector. Candidate input window sizes.
base_model	Base model object for tuning.
folds	Integer. Number of cross-validation folds.
ranges	Named list of hyperparameter ranges to explore.
preprocess	List of preprocessing objects to compare.
augment	List of augmentation objects to apply during training.

Value

A ts_integtune object.

References

Salles, R., Pacitti, E., Bezerra, E., Marques, C., Pacheco, C., Oliveira, C., Porto, F., Ogasawara, E. (2023). TSPredIT: Integrated Tuning of Data Preprocessing and Time Series Prediction Models. Lecture Notes in Computer Science.

Examples

```
# Integrated search over input size, preprocessing and model hyperparameters
library(daltoolbox)
data(tsd)

# Build windows and split into train/test, then project to (X, y)
ts <- ts_data(tsd$y, 10)
samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

# Configure integrated tuning: ranges for input_size, ELM (nhid, actfun), and preprocessors
tune <- ts_integtune(
  input_size = 3:5,
  base_model = ts_elm(),
  ranges = list(nhid = 1:5, actfun = c('purelin')),
  preprocess = list(ts_norm_gminmax())
)
```

```
# Run search; augmentation (if provided) is applied during training internally
model <- fit(tune, x = io_train$input, y = io_train$output)

# Forecast and evaluate on the held-out window
prediction <- predict(model, x = io_test$input[1,], steps_ahead = 5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

`ts_knn` *KNN Time Series Prediction*

Description

Create a prediction object that uses the K-Nearest Neighbors regression for time series via sliding windows.

Usage

```
ts_knn(preprocess = NA, input_size = NA, k = NA)
```

Arguments

`preprocess`	Normalization preprocessor (e.g., `ts_norm_gminmax()`).
`input_size`	Integer. Number of lagged inputs.
`k`	Integer. Number of neighbors.

Details

KNN regression predicts a value as the average (or weighted average) of the outputs of the k most similar windows in the training set. Similarity is computed in the feature space induced by lagged inputs. Consider normalization for distance-based methods.

Value

A `ts_knn` object (S3) inheriting from `ts_regsw`.

References

- T. M. Cover and P. E. Hart (1967). Nearest neighbor pattern classification. IEEE Transactions on Information Theory, 13(1), 21–27.

Examples

```
# Example: distance-based regression on sliding windows
# Load tools and example series
library(daltoolbox)
data(tsd)

# Build 10-lag windows and preview a few rows
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)

# Split end of series as test and project (X, y)
samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

# Define KNN regressor and fit (distance-based; normalization recommended)
model <- ts_knn(ts_norm_gminmax(), input_size = 4, k = 3)
model <- fit(model, x = io_train$input, y = io_train$output)

# Predict multiple steps ahead and evaluate
prediction <- predict(model, x = io_test$input[1,], steps_ahead = 5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

---

ts_mlp *MLP*

Description

Create a time series prediction object based on a Multilayer Perceptron (MLP) regressor.

It wraps the `nnet` package to train a single-hidden-layer neural network on sliding-window inputs. Use `ts_regsw` utilities to project inputs/outputs.

Usage

```
ts_mlp(preprocess = NA, input_size = NA, size = NA, decay = 0.01, maxit = 1000)
```

Arguments

`preprocess`	Normalization preprocessor (e.g., `ts_norm_gminmax()`).
`input_size`	Integer. Number of lagged inputs used by the model.
`size`	Integer. Number of hidden neurons.
`decay`	Numeric. L2 weight decay (regularization) parameter.
`maxit`	Integer. Maximum number of training iterations.

Details

The MLP is a universal function approximator capable of learning non-linear mappings from lagged inputs to next-step values. For stability, consider normalizing inputs (e.g., `ts_norm_gminmax()`). Hidden size and weight decay control capacity and regularization respectively.

Value

A `ts_mlp` object (S3) inheriting from `ts_regsw`.

References

- D. E. Rumelhart, G. E. Hinton, and R. J. Williams (1986). Learning representations by back-propagating errors. Nature 323, 533–536.
- W. N. Venables and B. D. Ripley (2002). Modern Applied Statistics with S. Fourth Edition. Springer. (for the `nnet` package)

Examples

```
# Example: MLP on sliding windows with min-max normalization
# Load package and dataset
library(daltoolbox)
data(tsd)
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)

samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

# Prepare projection (X, y)
samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

# Define and fit the MLP
model <- ts_mlp(ts_norm_gminmax(), input_size = 4, size = 4, decay = 0)
model <- fit(model, x=io_train$input, y=io_train$output)

# Predict 5 steps ahead
prediction <- predict(model, x = io_test$input[1,], steps_ahead = 5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

# Evaluate
ev_test <- evaluate(model, output, prediction)
ev_test
```

ts_norm_an *Adaptive Normalization*

Description

Transform data to a common scale while adapting to changes in distribution over time (optionally over a trailing window).

Usage

```
ts_norm_an(outliers = outliers_boxplot(), nw = 0)
```

Arguments

outliers	Indicate outliers transformation class. NULL can avoid outliers removal.
nw	integer: window size.

Value

A ts_norm_an object.

References

Ogasawara, E., Martinez, L. C., De Oliveira, D., Zimbrão, G., Pappa, G. L., Mattoso, M. (2010). Adaptive Normalization: A novel data normalization approach for non-stationary time series. Proceedings of the International Joint Conference on Neural Networks (IJCNN). doi:10.1109/IJCNN.2010.5596746

Examples

```
# time series to normalize
library(daltoolbox)
data(tsd)

# convert to sliding windows
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# normalization
preproc <- ts_norm_an()
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,10])
```

ts_norm_diff *First Differences*

Description

Transform a series by first differences to remove level and highlight changes; normalization is then applied to the differenced series.

Usage

```
ts_norm_diff(outliers = outliers_boxplot())
```

Arguments

outliers	Indicate outliers transformation class. NULL can avoid outliers removal.

Value

A ts_norm_diff object.

References

Salles, R., Assis, L., Guedes, G., Bezerra, E., Porto, F., Ogasawara, E. (2017). A framework for benchmarking machine learning methods using linear models for univariate time series prediction. Proceedings of the International Joint Conference on Neural Networks (IJCNN). doi:10.1109/IJCNN.2017.7966139

Examples

```
# Differencing + global min-max normalization
# Load package and example data
library(daltoolbox)
data(tsd)

# Convert to sliding windows and preview raw last column
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# Fit differencing preprocessor and transform; note one fewer lag column
preproc <- ts_norm_diff()
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,9])
```

ts_norm_ean *Adaptive Normalization with EMA*

Description

Normalize a time series using exponentially weighted statistics that adapt to distributional changes, optionally after outlier mitigation.

Usage

```
ts_norm_ean(outliers = outliers_boxplot(), nw = 0)
```

Arguments

outliers	Indicate outliers transformation class. NULL can avoid outliers removal.
nw	windows size

Value

A ts_norm_ean object.

References

Ogasawara, E., Martinez, L. C., De Oliveira, D., Zimbrão, G., Pappa, G. L., Mattoso, M. (2010). Adaptive Normalization: A novel data normalization approach for non-stationary time series. Proceedings of the International Joint Conference on Neural Networks (IJCNN). doi:10.1109/IJCNN.2010.5596746

Examples

```
# time series to normalize
library(daltoolbox)
data(tsd)

# convert to sliding windows
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# normalization
preproc <- ts_norm_ean()
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,10])
```

ts_norm_gminmax *Global Min–Max Normalization*

Description

Rescale values so the global minimum maps to 0 and the global maximum maps to 1 over the training set.

Usage

```
ts_norm_gminmax(outliers = outliers_boxplot())
```

Arguments

outliers	Indicate outliers transformation class. NULL can avoid outliers removal.

Details

The same scaling is applied to inputs and inverted on predictions via `inverse_transform`.

Value

A `ts_norm_gminmax` object.

References

Ogasawara, E., Murta, L., Zimbrão, G., Mattoso, M. (2009). Neural networks cartridges for data mining on time series. Proceedings of the International Joint Conference on Neural Networks (IJCNN). doi:10.1109/IJCNN.2009.5178615

Examples

```
# Global min-max normalization across the full training set
# Load package and example data
library(daltoolbox)
data(tsd)

# Build 10-lag windows and preview raw scale
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# Fit global min-max and transform; inspect post-scale values
preproc <- ts_norm_gminmax()
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,10])
```

ts_norm_none *No Normalization*

Description

Identity transform that leaves data unchanged but aligns with the pre/post-processing interface.

Usage

```
ts_norm_none()
```

Value

A ts_norm_none object.

Examples

```
# Identity normalization (no scaling applied)
# Load package and example data
library(daltoolbox)
data(tsd)

# Convert to sliding windows
xw <- ts_data(tsd$y, 10)

# No data normalization — transform returns inputs unchanged
normalize <- ts_norm_none()
normalize <- fit(normalize, xw)
xa <- transform(normalize, xw)
ts_head(xa)
```

ts_norm_swminmax *Sliding-Window Min–Max Normalization*

Description

Create an object for normalizing each window by its own min and max, preserving local contrast while standardizing scales.

Usage

```
ts_norm_swminmax(outliers = outliers_boxplot())
```

Arguments

outliers	Indicate outliers transformation class. NULL can avoid outliers removal.

Value

A ts_norm_swminmax object.

References

Ogasawara, E., Murta, L., Zimbrão, G., Mattoso, M. (2009). Neural networks cartridges for data mining on time series. Proceedings of the International Joint Conference on Neural Networks (IJCNN). doi:10.1109/IJCNN.2009.5178615

Examples

```
# Per-window min-max normalization for sliding windows
# Load package and example data
library(daltoolbox)
data(tsd)

# Build 10-lag windows and preview raw scale
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# Fit per-window min-max and transform; inspect post-scale values
preproc <- ts_norm_swminmax()
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,10])
```

---

ts_projection *Time Series Projection*

Description

Split a ts_data (sliding windows) into input features and output targets for modeling.

Usage

```
ts_projection(ts)
```

Arguments

ts	Matrix or data.frame containing a ts_data representation.

Details

For a multi-column ts_data, returns all but the last column as inputs and the last column as the output. For a single-row matrix, returns ts_data-wrapped inputs/outputs preserving names and window size.

Value

A ts_projection object with two elements: $input and $output.

Examples

```
# Setting up a ts_data and projecting (X, y)
# Load example dataset and create windows
data(tsd)
ts <- ts_data(tsd$y, 10)

io <- ts_projection(ts)

# Input data (features)
ts_head(io$input)

# Output data (target)
ts_head(io$output)
```

---

ts_reg *TSReg*

Description

Base class for time series regression models that operate directly on time series (non-sliding-window specialization).

Usage

```
ts_reg()
```

Details

This class is intended to be subclassed by modeling backends that do not require the sliding-window interface. Methods such as fit(), predict(), and evaluate() dispatch on this class.

Value

A ts_reg object (S3) to be extended by concrete models.

Examples

```
# Abstract base class — instantiate concrete subclasses instead
# Examples: ts_mlp(), ts_rf(), ts_svm(), ts_arima()
```

ts_regsw *TSRegSW*

Description

Base class for time series regression models built on sliding-window representations.

Usage

```
ts_regsw(preprocess = NA, input_size = NA)
```

Arguments

preprocess	Normalization preprocessor (e.g., ts_norm_gminmax()).
input_size	Integer. Number of lagged inputs per example.

Details

This class provides helpers to map ts_data matrices into the input window expected by ML backends and to apply pre/post processing (e.g., normalization) consistently during fit and predict.

Value

A ts_regsw object (S3) to be extended by concrete models.

Examples

```
# Abstract base class for sliding-window regressors
# Use concrete subclasses such as ts_mlp(), ts_rf(), ts_svm(), ts_elm()
```

ts_rf *Random Forest*

Description

Create a time series prediction object that uses Random Forest regression on sliding-window inputs.

It wraps the randomForest package to fit an ensemble of decision trees.

Usage

```
ts_rf(preprocess = NA, input_size = NA, nodesize = 1, ntree = 10, mtry = NULL)
```

Arguments

preprocess	Normalization preprocessor (e.g., ts_norm_gminmax()).
input_size	Integer. Number of lagged inputs used by the model.
nodesize	Integer. Minimum terminal node size.
ntree	Integer. Number of trees in the forest.
mtry	Integer. Number of variables randomly sampled at each split.

Details

Random Forests reduce variance by averaging many decorrelated trees. For tabular sliding-window features, they can capture nonlinearities and interactions without heavy feature engineering. Consider normalizing inputs for comparability across windows and tuning mtry, ntree, and nodesize.

Value

A ts_rf object (S3) inheriting from ts_regsw.

References

- L. Breiman (2001). Random forests. Machine Learning, 45(1), 5–32.

Examples

```
# Example: sliding-window Random Forest
# Load tools and data
library(daltoolbox)
data(tsd)

# Turn series into 10-lag windows and preview
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)

# Train/test split and (X, y) projection
samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

# Define Random Forest and fit (tune ntree/mtry/nodesize as needed)
model <- ts_rf(ts_norm_gminmax(), input_size = 4, nodesize = 3, ntree = 50)
model <- fit(model, x = io_train$input, y = io_train$output)

# Forecast multiple steps and assess error
prediction <- predict(model, x = io_test$input[1,], steps_ahead = 5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

`ts_sample` *Time Series Sample*

Description

Split a `ts_data` into train and test sets.

Extracts `test_size` rows from the end (minus an optional `offset`) as the test set. The remaining initial rows form the training set. The `offset` is useful to reproduce experiments with different forecast origins.

Usage

```
ts_sample(ts, test_size = 1, offset = 0)
```

Arguments

`ts`	A `ts_data` matrix.
`test_size`	Integer. Number of rows in the test split (default = 1).
`offset`	Integer. Offset from the end before the test split (default = 0).

Value

A list with `$train` and `$test` (both `ts_data`).

Examples

```
# Setting up a ts_data and making a temporal split
# Load example dataset and build windows
data(tsd)
ts <- ts_data(tsd$y, 10)

# Separating into train and test
test_size <- 3
samp <- ts_sample(ts, test_size)

# First five rows from training data
ts_head(samp$train, 5)

# Last five rows from training data
ts_head(samp$train[-c(1:(nrow(samp$train)-5)),])

# Testing data
ts_head(samp$test)
```

`ts_svm` *SVM*

Description

Create a time series prediction object that uses Support Vector Regression (SVR) on sliding-window inputs.

It wraps the `e1071` package to fit epsilon-insensitive regression with linear, radial, polynomial, or sigmoid kernels.

Usage

```
ts_svm(
  preprocess = NA,
  input_size = NA,
  kernel = "radial",
  epsilon = 0,
  cost = 10
)
```

Arguments

`preprocess`	Normalization preprocessor (e.g., `ts_norm_gminmax()`).
`input_size`	Integer. Number of lagged inputs used by the model.
`kernel`	Character. One of 'linear', 'radial', 'polynomial', 'sigmoid'.
`epsilon`	Numeric. Epsilon-insensitive loss width.
`cost`	Numeric. Regularization parameter controlling margin violations.

Details

SVR aims to find a function with at most epsilon deviation from each training point while being as flat as possible. The `cost` parameter controls the trade-off between margin width and violations; `epsilon` controls the insensitivity tube width. RBF kernels often work well for nonlinear series; tune `cost`, `epsilon`, and kernel hyperparameters.

Value

A `ts_svm` object (S3) inheriting from `ts_regsw`.

References

- C. Cortes and V. Vapnik (1995). Support-Vector Networks. Machine Learning, 20, 273–297.

Examples

```
# Example: SVR with min-max normalization
# Load package and dataset
library(daltoolbox)
data(tsd)

# Create sliding windows and preview
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)

# Temporal split and (X, y) projection
samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

# Define SVM regressor and fit to training data
model <- ts_svm(ts_norm_gminmax(), input_size = 4)
model <- fit(model, x = io_train$input, y = io_train$output)

# Multi-step forecast and evaluation
prediction <- predict(model, x = io_test$input[1,], steps_ahead = 5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

---

ts_tune *Time Series Tune*

Description

Create a `ts_tune` object for hyperparameter tuning of a time series model.

Sets up a cross-validated search over hyperparameter ranges and input sizes for a base model. Results include the evaluated configurations and the selected best configuration.

Usage

```
ts_tune(input_size, base_model, folds = 10, ranges = NULL)
```

Arguments

`input_size`	Integer vector. Candidate input window sizes.
`base_model`	Base model object to tune (e.g., `ts_mlp()`).
`folds`	Integer. Number of cross-validation folds.
`ranges`	Named list of hyperparameter ranges to explore.

Value

A ts_tune object.

References

- R. Kohavi (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. IJCAI.
- Salles, R., Pacitti, E., Bezerra, E., Marques, C., Pacheco, C., Oliveira, C., Porto, F., Ogasawara, E. (2023). TSPredIT: Integrated Tuning of Data Preprocessing and Time Series Prediction Models. Lecture Notes in Computer Science.

Examples

```
# Example: grid search over input_size and ELM hyperparameters
# Load library and example data
library(daltoolbox)
data(tsd)

# Prepare 10-lag windows and split into train/test
ts <- ts_data(tsd$y, 10)
ts_head(ts, 3)
samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

# Define tuning: vary input_size and ELM hyperparameters (nhid, actfun)
tune <- ts_tune(
  input_size = 3:5,
  base_model = ts_elm(ts_norm_gminmax()),
  ranges = list(nhid = 1:5, actfun = c('purelin'))
)

# Run CV-based search and get the best fitted model
model <- fit(tune, x = io_train$input, y = io_train$output)

# Forecast and evaluate on the held-out horizon
prediction <- predict(model, x = io_test$input[1,], steps_ahead = 5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

[.ts_data *Subset Extraction for Time Series Data*

Description

Extracts a subset of a time series object based on specified rows and columns. The function allows for flexible indexing and subsetting of time series data.

Usage

```
## S3 method for class 'ts_data'
x[i, j, ...]
```

Arguments

x	ts_data object
i	row i
j	column j
...	optional arguments

Value

A new ts_data object with preserved metadata and column names.

Examples

```
data(tsd)
data10 <- ts_data(tsd$y, 10)
ts_head(data10)
#single line
data10[12,]

#range of lines
data10[12:13,]

#single column
data10[,1]

#range of columns
data10[,1:2]

#range of rows and columns
data10[12:13,1:2]

#single line and a range of columns
data10[12,1:2]

#range of lines and a single column
data10[12:13,1]

#single observation
data10[12,1]
```

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