Package 'TSPred'

July 21, 2025

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Type Package
Title Functions for Benchmarking Time Series Prediction
Version 5.1.1
Date 2025-06-10
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Description Functions for defining and conducting a time series prediction process includ- ing pre(post)processing, decomposition, modelling, prediction and accuracy assessment. The gen- erated models and its yielded prediction errors can be used for benchmarking other time se- ries prediction methods and for creating a demand for the refinement of such meth- ods. For this purpose, benchmark data from prediction competitions may be used.
Depends R (>= 3.5.0)
Imports forecast, KFAS, stats, MuMIn, wavelets, ModelMetrics, RSNNS, Rlibeemd, e1071, elmNNRcpp, nnet, randomForest, magrittr, plyr, methods, dplyr, keras, tfdatasets
License GPL (>= 2)
<pre>BugReports https://github.com/RebeccaSalles/TSPred/issues</pre>
URL https://github.com/RebeccaSalles/TSPred/wiki
RoxygenNote 7.3.2
LazyData true
Encoding UTF-8
NeedsCompilation no
Repository CRAN

Date/Publication 2025-06-10 20:50:05 UTC

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TSPred-package

Functions for Benchmarking Time Series Prediction

Description

Functions for time series pre(post)processing, decomposition, modelling, prediction and accuracy assessment. The generated models and its yielded prediction errors can be used for benchmarking other time series prediction methods and for creating a demand for the refinement of such methods. For this purpose, benchmark data from prediction competitions may be used.

Author(s)

Rebecca Pontes Salles

Maintainer: rebeccapsalles@acm.org

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Description

The an() function normalizes data of the provided time series to bring values into the range [0,1]. The function applies the method of Adaptive Normalization designed for non-stationary heteroscedastic (with non-uniform volatility) time series. an.rev() reverses the normalization.

Usage

```
an(data, max = NULL, min = NULL, byRow = TRUE, outlier.rm = TRUE, alpha = 1.5)
an.rev(data, max, min, an)
```

Arguments

data	A numeric matrix with sliding windows of time series data as returned by sw.
max	A numeric vector indicating the maximal values of each row (sliding window) in data. If NULL it is automatically computed.
min	A numeric vector indicating the minimum values of each row (sliding window) in data. If NULL it is automatically computed.
byRow	If TRUE, the normalization is performed by rows (sliding windows), the default.
outlier.rm	If TRUE, outlier values are removed from the data during the normalization process, the default.
alpha	The multiplier for the interquartile range used as base for outlier removal. The default is set to 1.5 . The value 3.0 is also commonly used to remove only the extreme outliers.
an	The mean of each data window computed by an() and returned as attribute.

Value

data normalized between 0 and 1. max and min are returned as attributes, as well as the mean values of each row (sliding window) in data (an).

Author(s)

Rebecca Pontes Salles

References

E. Ogasawara, L. C. Martinez, D. De Oliveira, G. Zimbrao, G. L. Pappa, and M. Mattoso, 2010, Adaptive Normalization: A novel data normalization approach for non-stationary time series, Proceedings of the International Joint Conference on Neural Networks.

an

ARIMA

See Also

Other normalization methods: minmax()

Examples

```
data(CATS)
swin <- sw(CATS[,1],5)
d <- an(swin, outlier.rm=FALSE)
x <- an.rev(d, max=attributes(d)$max, min=attributes(d)$min, an=attributes(d)$an)
all(round(x,4)==round(swin,4))</pre>
```

ARIMA

Time series prediction models

Description

Constructors for the modeling class representing a time series modeling and prediction method based on a particular model.

Usage

```
ARIMA(train_par = list(), pred_par = list(level = c(80, 95)))
ETS(train_par = list(), pred_par = list(level = c(80, 95)))
HW(train_par = list(), pred_par = list(level = c(80, 95)))
TF(train_par = list(), pred_par = list(level = c(80, 95)))
NNET(
  size = 5,
  train_par = NULL,
  pred_par = list(level = c(80, 95)),
  sw = SW(window_len = size + 1),
 proc = list(MM = MinMax())
)
RFrst(
  ntree = 500,
  train_par = NULL,
  pred_par = list(level = c(80, 95)),
  sw = SW(window_len = 6),
 proc = list(MM = MinMax())
)
RBF(
```

```
size = 5,
  train_par = NULL,
  pred_par = list(level = c(80, 95)),
  sw = SW(window_len = size + 1),
  proc = list(MM = MinMax())
)
SVM(
  train_par = NULL,
  pred_par = list(level = c(80, 95)),
  sw = SW(window_len = 6),
  proc = list(MM = MinMax())
)
MLP(
  size = 5,
  train_par = NULL,
  pred_par = list(level = c(80, 95)),
  sw = SW(window_len = size + 1),
  proc = list(MM = MinMax())
)
ELM(
  train_par = list(),
  pred_par = list(),
  sw = SW(window_len = 6),
  proc = list(MM = MinMax())
)
Tensor_CNN(
  train_par = NULL,
  pred_par = list(level = c(80, 95)),
  sw = SW(window_len = 6),
  proc = list(MM = MinMax())
)
Tensor_LSTM(
  train_par = NULL,
  pred_par = list(batch_size = 1, level = c(80, 95)),
  sw = SW(window_len = 6),
  proc = list(MM = MinMax())
)
```

Arguments

train_par	List of named parameters required by train_func.
pred_par	List of named parameters required by pred_func.
size	See mlp

```
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```

ARIMA

SW	A SW object regarding sliding windows processing.
proc	A list of processing objects regarding any pre(post)processing needed during training or prediction.
ntree	See randomForest

Value

An object of class modeling.

Linear models

ARIMA: ARIMA model. train_func set as auto.arima and pred_func set as forecast.

ETS: Exponential Smoothing State Space model. train_func set as ets and pred_func set as forecast.

HW: Holt-Winter's Exponential Smoothing model. train_func set as hw and pred_func set as forecast.

TF: Theta Forecasting model. train_func set as thetaf and pred_func set as forecast.

Machine learning models

NNET: Artificial Neural Network model. train_func set as nnet and pred_func set as predict.

RFrst: Random Forest model. train_func set as randomForest and pred_func set as predict.

RBF: Radial Basis Function (RBF) Network model. train_func set as rbf and pred_func set as predict.

SVM: Support Vector Machine model. train_func set as tune.svm and pred_func set as predict.

MLP: Multi-Layer Perceptron (MLP) Network model. train_func set as mlp and pred_func set as predict.

ELM: Extreme Learning Machine (ELM) model. train_func set as elm_train and pred_func set as elm_predict.

Tensor_CNN: Convolutional Neural Network - TensorFlow. train_func based on functions from tensorflow and keras, and pred_func set as predict.

Tensor_LSTM: Long Short Term Memory Neural Networks - TensorFlow. train_func based on functions from tensorflow and keras, and pred_func set as predict.

Author(s)

Rebecca Pontes Salles

See Also

Other constructors: LT(), MSE_eval(), evaluating(), modeling(), processing(), tspred()

arimainterp

Description

The function predicts nonconsecutive blocks of N unknown values of a single time series using the arimapred function and an interpolation approach.

Usage

```
arimainterp(
  TimeSeries,
  n.ahead,
  extrap = TRUE,
  xreg = NULL,
  newxreg = NULL,
  se.fit = FALSE
)
```

Arguments

TimeSeries	A matrix, or data frame which contains a set of time series used for fitting ARIMA models. Each column corresponds to one time series. Each time series in TimeSeries is assumed to be a sequence of known values of the single time series that intercalates blocks of unknown values. The time series values in column 1 are lagged values of the ones in column 2, and the values in these two columns are assumed to be intercalated by the first block of N unknown values to be predicted. This is also valid for columns 2 and 3, and so forth.
n.ahead	A numeric value (N) with the number of consecutive unknown values of each block which is to be predicted of TimeSeries, that is, the length of the blocks of N unknown values.
extrap	A Boolean parameter which defines whether one of the blocks of N unknown values to be predicted follows the last sequence of known values in TimeSeries. If extrap is TRUE, the last block of N unknown values will be extrapolated from the last time series in TimeSeries.
xreg	A list of vectors, matrices, data frames or times series of external regressors used for fitting the ARIMA models. The first component of the list contains external regressors for the first time series in TimeSeries and therefore must have the same number of rows as this respective time series. This is also valid for the second component, and so forth. Ignored if NULL.
newxreg	A list of vectors, matrices, data frames or times series with further values of $xreg$ to be used for prediction of the blocks of N unknown values. Each component of the list must have at least n.ahead rows. Ignored if NULL.
se.fit	If se.fit is TRUE, the standard errors of the predictions are returned.

arimaparameters

Details

In order to avoid error accumulation, when possible, the function provides the separate prediction of each half of the blocks of unknown values using their past and future known values, respectively. If extrap is TRUE, this strategy is not possible for the last of the blocks of unknown values, for whose prediction the function uses only its past values. By default the function omits any missing values found in TimeSeries.

Value

A vector of time series of predictions, or if se.fit is TRUE, a vector of lists, each one with the components pred, the predictions, and se, the estimated standard errors. Both components are time series. See the predict.Arima function in the stats package and the function arimapred.

Author(s)

Rebecca Pontes Salles

References

H. Cheng, P.-N. Tan, J. Gao, and J. Scripps, 2006, "Multistep-Ahead Time Series Prediction", In: W.-K. Ng, M. Kitsuregawa, J. Li, and K. Chang, eds., Advances in Knowledge Discovery and Data Mining, Springer Berlin Heidelberg, p. 765-774.

See Also

arimapred, marimapred

Examples

```
data(CATS)
arimainterp(CATS[,c(2:3)],n.ahead=20,extrap=TRUE)
```

arimaparameters Get ARIMA model parameters

Description

The function returns the parameters of a fitted ARIMA model, including non-seasonal and seasonal orders and drift.

Usage

arimaparameters(fit)

Arguments

fit

An object of class "Arima" containing a fitted ARIMA model.

Details

The fit object could possibly be the result of auto.arima or Arima of the forecast package, or arima of the stats package.

Value

A list giving the number of AR, MA, seasonal AR and seasonal MA coefficients, plus the period and the number of non-seasonal and seasonal differences of the provided ARIMA model. The value of the fitted drift constant is also presented.

Author(s)

Rebecca Pontes Salles

References

R.J. Hyndman and G. Athanasopoulos, 2013, Forecasting: principles and practice. OTexts.

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

fittestArima, arimapred

Examples

```
data(SantaFe.A)
arimaparameters(forecast::auto.arima(SantaFe.A[,1]))
```

arimapred

Automatic ARIMA fitting and prediction

Description

The function predicts and returns the next n consecutive values of a time series using an automatically fitted ARIMA model. It may also plot the predicted values against the actual ones using the function plotarimapred.

arimapred

Usage

```
arimapred(
  timeseries,
  timeseries.cont = NULL,
  n.ahead = NULL,
  na.action = stats::na.omit,
  xreg = NULL,
  newxreg = NULL,
  se.fit = FALSE,
  plot = FALSE,
  range.p = 0.2,
  ylab = NULL,
  xlab = NULL,
  main = NULL
)
```

Arguments

timeseries	A vector or univariate time series which contains the values used for fitting an ARIMA model.
timeseries.con	t
	A vector or univariate time series containing a continuation for timeseries with actual values. Ignored if NULL.
n.ahead	Number of consecutive values of the time series, which are to be predicted. If n.ahead is NULL, the number of consecutive values to be predicted is assumed to be equal to the length of timeseries.cont. Required when timeseries.cont is NULL.
na.action	A function for treating missing values in timeseries and timeseries.cont. The default function is na.omit, which omits any missing values found in timeseries or timeseries.cont.
xreg	A vector, matrix, data frame or times series of external regressors used for fitting the ARIMA model. It must have the same number of rows as timeseries. Ignored if NULL.
newxreg	A vector, matrix, data frame or times series with new values of xreg to be used for prediction. Must have at least n.ahead rows or the number of rows in timeseries.cont. Ignored if NULL.
se.fit	If se.fit is TRUE, the standard errors of the predictions are returned.
plot	If plot is TRUE, the function will generate a graphic of the predicted values against the actual ones in timeseries.cont.
range.p	A percentage which defines how much the range of the graphic's y-axis will be increased from the minimum limits imposed by data.
ylab	A title for the graphic's y-axis. Ignored if NULL.
xlab	A title for the graphic's x-axis. Ignored if NULL.
main	An overall title for the graphic. Ignored if NULL.

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Details

The ARIMA model used for time series prediction is automatically fitted by the auto.arima function in the forecast package. In order to avoid drift errors, the function introduces an auxiliary regressor whose values are a sequence of consecutive integer numbers starting from 1. The fitted ARIMA model is used for prediction by the predict.Arima function in the stats package. For more details, see the auto.arima function in the forecast package and the predict.Arima function in the stats package.

Value

A time series of predictions, or if se.fit is TRUE, a list with the components pred, the predictions, and se, the estimated standard errors. Both components are time series. See the predict.Arima function in the stats package.

Author(s)

Rebecca Pontes Salles

References

R.J. Hyndman and G. Athanasopoulos, 2013, Forecasting: principles and practice. OTexts.

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

auto.arima, predict.Arima, plotarimapred, marimapred

Examples

```
data(SantaFe.A,SantaFe.A.cont)
arimapred(SantaFe.A[,1],SantaFe.A.cont[,1])
arimapred(SantaFe.A[,1],n.ahead=100)
```

BCT

Box Cox Transformation

Description

The BCT() function returns a transformation of the provided time series using a Box-Cox transformation. BCT.rev() reverses the transformation. Wrapper functions for BoxCox and InvBoxCox of the forecast package, respectively.

Usage

BCT(x, lambda = NULL, ...)

Arguments

x	A numeric vector or univariate time series of class ts.
lambda	Box-Cox transformation parameter. If NULL, lambda is selected using BoxCox.lambda of the forecast package.
	Additional arguments passed to the BoxCox.lambda function for BCT(), and to the InvBoxCox function for BCT.rev().

Details

If lambda is not 0, the Box-Cox transformation is given by

$$f_{\lambda}(x) = \frac{x^{\lambda} - 1}{\lambda}$$

If $\lambda = 0$, the Box-Cox transformation is given by

$$f_0(x) = \log(x)$$

Value

•

A vector of the same length as x containing the transformed values.

Author(s)

Rebecca Pontes Salles

References

Box, G. E. P. and Cox, D. R. (1964) An analysis of transformations. JRSS B 26 211-246.

See Also

DIF, detrend, MAS, LT, PCT

Examples

data(CATS)
BCT(CATS[,1])

benchmark

Description

benchmark is a generic function for benchmarking results based on particular metrics. The function invokes particular methods which depend on the class of the first argument.

Usage

```
benchmark(obj, ...)
```

S3 method for class 'tspred' benchmark(obj, bmrk_objs, rank.by = c("MSE"), ...)

Arguments

obj	An object of class tspred defining a particular time series prediction process.
	Ignored
bmrk_objs	A list of objects of class tspred to be compared against obj.
rank.by	A vector of the given names of the metrics that should base the ranking.

Details

The function benchmark.tspred benchmarks a time series prediction process defined by a tspred object based on a particular metric. The metrics resulting from its execution are compared against the ones produced by other time series prediction processes (defined in a list of tspred objects).

Value

A list containing:

rank

A data frame with the ranking of metrics computed for the benchmarked tspred objects. ranked_tspred_objs A list of the benchmarked tspred objects ordered according to the produced rank.

Author(s)

Rebecca Pontes Salles

See Also

[tspred()] for defining a particular time series prediction process.

benchmark

Examples

```
#Obtaining objects of the processing class
proc1 <- subsetting(test_len=20)</pre>
proc2 <- BoxCoxT(lambda=NULL)</pre>
proc3 <- WT(level=1, filter="bl14")</pre>
#Obtaining objects of the modeling class
modl1 <- ARIMA()</pre>
#Obtaining objects of the evaluating class
eval1 <- MSE_eval()</pre>
eval2 <- MAPE_eval()</pre>
#Defining a time series prediction process
tspred_1 <- tspred(subsetting=proc1,</pre>
                     processing=list(BCT=proc2,
                                      WT=proc3),
                     modeling=modl1,
                     evaluating=list(MSE=eval1,
                                      MAPE=eval2)
                    )
summary(tspred_1)
#Obtaining objects of the processing class
proc4 <- SW(window_len = 6)</pre>
proc5 <- MinMax()</pre>
#Obtaining objects of the modeling class
modl2 <- NNET(size=5,sw=proc4,proc=list(MM=proc5))</pre>
#Defining a time series prediction process
tspred_2 <- tspred(subsetting=proc1,</pre>
                     processing=list(BCT=proc2,
                                      WT=proc3),
                     modeling=modl2,
                     evaluating=list(MSE=eval1,
                                      MAPE=eval2)
                    )
summary(tspred_2)
data("CATS")
data <- CATS[3]</pre>
tspred_1_run <- workflow(tspred_1,data=data,prep_test=TRUE,onestep=TRUE)</pre>
tspred_2_run <- workflow(tspred_2,data=data,prep_test=TRUE,onestep=TRUE)</pre>
```

```
b <- benchmark(tspred_1_run,list(tspred_2_run),rank.by=c("MSE"))</pre>
```

Description

A univariate artificial time series presenting 5 non-consecutive blocks of 20 unknown points.

Usage

CATS

Format

A data frame with 980 observations on the following 5 variables.

V1 a numeric vector containing the known points 1-980 of the CATS time series.

V2 a numeric vector containing the known points 1001-1980 of the CATS time series.

V3 a numeric vector containing the known points 2001-2980 of the CATS time series.

V4 a numeric vector containing the known points 3001-3980 of the CATS time series.

V5 a numeric vector containing the known points 4001-4980 of the CATS time series.

Details

The CATS Competition presented an artificial time series with 5,000 points, among which 100 are unknown. The competition proposed that the competitors predicted the 100 unknown values from the given time series, which are grouped into five non-consecutive blocks of 20 successive values (CATS.cont). The unknown points of the series are the 981-1000, 1981-2000, 2981-3000, 3981-4000 and 4981-5000. The performance evaluation done by the CATS Competition was based on the MSEs computed on the 100 unknown values (E1) and on the 80 first unknown values (E2). The E2 error was considered relevant because some of the proposed methods used interpolation techniques, which cannot be applied in the case of the fifth set of unknown points.

References

A. Lendasse, E. Oja, O. Simula, M. Verleysen, and others, 2004, Time Series Prediction Competition: The CATS Benchmark, In: IJCNN'2004-International Joint Conference on Neural Networks

A. Lendasse, E. Oja, O. Simula, and M. Verleysen, 2007, Time series prediction competition: The CATS benchmark, Neurocomputing, v. 70, n. 13-15 (Aug.), p. 2325-2329.

See Also

CATS.cont

CATS.cont

Examples

```
data(CATS)
str(CATS)
plot(ts(CATS["V5"]))
```

CATS.cont

Continuation dataset of the time series of the CATS Competition

Description

A dataset of providing the 5 blocks of 20 unknown points of the univariate time series in CATS

Usage

CATS.cont

Format

A data frame with 20 observations on the following 5 variables.

V1 a numeric vector containing the unknown points 981-1000 of the CATS time series in CATS

- V2 a numeric vector containing the unknown points 1981-2000 of the CATS time series in CATS
- V3 a numeric vector containing the unknown points 2981-3000 of the CATS time series in CATS
- V4 a numeric vector containing the unknown points 3981-4000 of the CATS time series in CATS

V5 a numeric vector containing the unknown points 4981-5000 of the CATS time series in CATS

Details

Contains the 100 unknown observations which were to be predicted of the CATS time series in (CATS) as demanded by the CATS Competition.

Source

A. Lendasse, E. Oja, O. Simula, M. Verleysen, and others, 2004, Time Series Prediction Competition: The CATS Benchmark, In: IJCNN'2004-International Joint Conference on Neural Networks

References

A. Lendasse, E. Oja, O. Simula, and M. Verleysen, 2007, Time series prediction competition: The CATS benchmark, Neurocomputing, v. 70, n. 13-15 (Aug.), p. 2325-2329.

See Also

CATS

detrend

Examples

```
data(CATS.cont)
str(CATS.cont)
plot(ts(CATS.cont["V5"]))
```

detrend

Detrending Transformation

Description

The detrend() function performs a detrending transformation and removes a trend from the provided time series. detrend.rev() reverses the transformation.

Usage

detrend(x, trend)

Arguments

х	A numeric vector or univariate time series of class ts.
trend	A numeric vector or univariate time series containing the trend to be removed
	Generally, the fitted values of a model object.

Value

A vector of the same length as x containing the residuals of x after trend removal.

Author(s)

Rebecca Pontes Salles

References

R. H. Shumway, D. S. Stoffer, Time Series Analysis and Its Applications: With R Examples, Springer, New York, NY, 4 edition, 2017.

See Also

DIF, BCT, MAS, LT, PCT

Examples

```
data(CATS,CATS.cont)
fpoly <- fittestPolyR(CATS[,1],h=20)
trend <- fitted(fpoly$model)
residuals <- detrend(CATS[,1],trend)</pre>
```

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Description

The Diff() function returns a simple or seasonal differencing transformation of the provided time series. Diff.rev() reverses the transformation. Wrapper functions for diff and diffinv of the stats package, respectively.

Usage

```
Diff(
    x,
    lag = ifelse(type == "simple", 1, stats::frequency(x)),
    differences = NULL,
    type = c("simple", "seasonal"),
    ...
)
Diff.rev(
    x,
    lag = ifelse(type == "simple", 1, stats::frequency(x)),
    differences = 1,
    xi,
    type = c("simple", "seasonal"),
    addinit = TRUE
)
```

Arguments

x	A numeric vector or univariate time series containing the values to be differ- enced.
lag	Integer indicating the lag parameter. Default set to 1 if type = "simple", or frequency(x) if type = "seasonal".
differences	Integer representing the order of the difference. If NULL, the order of the difference is automatically selected using ndiffs (if type = "simple") or nsdiffs (if type = "seasonal") from the forecast package.
type	Character string. Indicates if the function should perform simple or seasonal differencing.
	Additional arguments passed to ndiffs (if type = "simple") or nsdiffs (if type = "seasonal") from the forecast package.
xi	Numeric vector or time series containing the initial values for the integrals. If missing, zeros are used.
addinit	If FALSE, the reverse transformed time series does not contain x1. Default set to TRUE.

Diff

Value

x if differences is automatically selected, and is not set as greater than 0. Same as diff otherwise.

Author(s)

Rebecca Pontes Salles

References

R.J. Hyndman and G. Athanasopoulos, 2013, Forecasting: principles and practice. OTexts.

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

```
Other transformation methods: LogT(), WaveletT(), emd(), mas(), mlm_io(), outliers_bp(),
pct(), train_test_subset()
```

Examples

```
data(CATS)
d <- Diff(CATS[,1], differences = 1)
x <- Diff.rev(as.vector(d), differences = attributes(d)$differences, xi = attributes(d)$xi)
all(round(x,4)==round(CATS[,1],4))
```

 emd

Automatic empirical mode decomposition

Description

The function automatically applies an empirical mode decomposition to a provided univariate time series. Wrapper function for emd of the Rlibeemd package. It also allows the automatic selection of meaningful IMFs using fittestEMD. emd.rev() reverses the transformation.

Usage

```
emd(
    x,
    num_imfs = 0,
    S_number = 4L,
    num_siftings = 50L,
    meaningfulImfs = NULL,
    h = 1,
    ...
)
emd.rev(pred)
```

emd

Arguments

х	A numeric vector or univariate time series to be decomposed.
num_imfs	Number of Intrinsic Mode Functions (IMFs) to compute. See emd.
S_number,num_si	ftings See emd.
meaningfulImfs	Vector indicating the indices of the meaningful IMFs according to the possible intervals i:num_imfs for i=1,, (num_imfs-1), where num_imfs is the number of IMFs in a decomposition. If meaningfulImfs = NULL (default), the function returns all IMF's produced by emd as meaningful. If meaningfulImfs = 0 the function automatically selects the meaningful IMFs of a decomposition using fittestEMD.
h	See fittestEMD. Passed to fittestEMD if meaningfulImfs = 0.
	Additional arguments passed to fittestEMD.
pred	A list containing IMFs produced by empirical mode decomposition.

Value

A list containing the meaningful IMFs of the empirical mode decomposition of x. A vector indicating the indices of the meaningful IMFs and the number of IMFs produced are passed as attributes named "meaningfulImfs" and "num_imfs", respectively.

Author(s)

Rebecca Pontes Salles

References

Kim, D., Paek, S. H., & Oh, H. S. (2008). A Hilbert-Huang transform approach for predicting cyber-attacks. Journal of the Korean Statistical Society, 37(3), 277-283.

See Also

fittestEMD, fittestWavelet

Other transformation methods: Diff(), LogT(), WaveletT(), mas(), mlm_io(), outliers_bp(),
pct(), train_test_subset()

Examples

```
data(CATS)
e <- emd(CATS[,1])
x <- emd.rev(e)
all(round(x,4)==round(CATS[,1],4))</pre>
```

Description

The EUNITE Competition main dataset composed of a set of univariate time series of half-an-hour electrical loads measured between 1997 and 1998.

Usage

EUNITE.Loads

Format

A data frame with 730 observations on the following 48 variables.

X00.30 a numeric vector with loads measured in the period 00:00-00:30 of 1997-1998. X01.00 a numeric vector with loads measured in the period 00:30-01:00 of 1997-1998. X01.30 a numeric vector with loads measured in the period 01:00-01:30 of 1997-1998. X02.00 a numeric vector with loads measured in the period 01:30-02:00 of 1997-1998. X02.30 a numeric vector with loads measured in the period 02:00-02:30 of 1997-1998. X03.00 a numeric vector with loads measured in the period 02:30-03:00 of 1997-1998. X03.30 a numeric vector with loads measured in the period 03:00-03:30 of 1997-1998. X04.00 a numeric vector with loads measured in the period 03:30-04:00 of 1997-1998. X04.30 a numeric vector with loads measured in the period 04:00-04:30 of 1997-1998. X05.00 a numeric vector with loads measured in the period 04:30-05:00 of 1997-1998. X05.30 a numeric vector with loads measured in the period 05:00-05:30 of 1997-1998. X06.00 a numeric vector with loads measured in the period 05:30-06:00 of 1997-1998. X06.30 a numeric vector with loads measured in the period 06:00-06:30 of 1997-1998. X07.00 a numeric vector with loads measured in the period 06:30-07:00 of 1997-1998. X07.30 a numeric vector with loads measured in the period 07:00-07:30 of 1997-1998. X08.00 a numeric vector with loads measured in the period 07:30-08:00 of 1997-1998. X08.30 a numeric vector with loads measured in the period 08:00-08:30 of 1997-1998. X09.00 a numeric vector with loads measured in the period 08:30-09:00 of 1997-1998. X09.30 a numeric vector with loads measured in the period 09:00-09:30 of 1997-1998. X10.00 a numeric vector with loads measured in the period 09:30-10:00 of 1997-1998. X10.30 a numeric vector with loads measured in the period 10:00-10:30 of 1997-1998. X11.00 a numeric vector with loads measured in the period 10:30-11:00 of 1997-1998. **X11.30** a numeric vector with loads measured in the period 11:00-11:30 of 1997-1998. X12.00 a numeric vector with loads measured in the period 11:30-12:00 of 1997-1998.

X12.30 a numeric vector with loads measured in the period 12:00-12:30 of 1997-1998.
X13.00 a numeric vector with loads measured in the period 12:30-13:00 of 1997-1998.
X13.30 a numeric vector with loads measured in the period 13:00-13:30 of 1997-1998.
X14.00 a numeric vector with loads measured in the period 13:30-14:00 of 1997-1998.
X14.30 a numeric vector with loads measured in the period 14:00-14:30 of 1997-1998.
X15.00 a numeric vector with loads measured in the period 14:30-15:00 of 1997-1998.
X15.30 a numeric vector with loads measured in the period 15:00-15:30 of 1997-1998.
X16.00 a numeric vector with loads measured in the period 15:30-16:00 of 1997-1998.
X16.30 a numeric vector with loads measured in the period 16:00-16:30 of 1997-1998.
X17.00 a numeric vector with loads measured in the period 16:30-17:00 of 1997-1998.
X17.30 a numeric vector with loads measured in the period 17:00-17:30 of 1997-1998.
X18.00 a numeric vector with loads measured in the period 17:30-18:00 of 1997-1998.
X18.30 a numeric vector with loads measured in the period 18:00-18:30 of 1997-1998.
X19.00 a numeric vector with loads measured in the period 18:30-19:00 of 1997-1998.
X19.30 a numeric vector with loads measured in the period 19:00-19:30 of 1997-1998.
X20.00 a numeric vector with loads measured in the period 19:30-20:00 of 1997-1998.
X20.30 a numeric vector with loads measured in the period 20:00-20:30 of 1997-1998.
X21.00 a numeric vector with loads measured in the period 20:30-21:00 of 1997-1998.
X21.30 a numeric vector with loads measured in the period 21:00-21:30 of 1997-1998.
X22.00 a numeric vector with loads measured in the period 21:30-22:00 of 1997-1998.
X22.30 a numeric vector with loads measured in the period 22:00-22:30 of 1997-1998.
X23.00 a numeric vector with loads measured in the period 22:30-23:00 of 1997-1998.
X23.30 a numeric vector with loads measured in the period 23:00-23:30 of 1997-1998.
X24.00 a numeric vector with loads measured in the period 23:30-24:00 of 1997-1998.

Details

The EUNITE Competition proposed the prediction of maximum daily electrical loads based on half-an-hour loads and average daily temperatures of 1997-1998 (EUNITE.Temp). The holidays with respect to this period were also provided (EUNITE.Reg) and the use of data on average daily temperatures of 1995-1996 was allowed. The dataset present considerable seasonality due to properties of electrical load demand, climate influence and holiday effects, among other reasons. Competitors were asked to predict the 31 values corresponding to the daily maximum electrical loads of January 1999 (EUNITE.Loads.cont). The performance evaluation done by the EUNITE Competition was based on the MAPE error and on the MAXIMAL error of prediction found by the competitors.

Source

EUNITE 1999, Electricity Load Forecast using Intelligent Adaptive Technology: The EUNITE Network Competition. URL: http://www.eunite.org/knowledge/Competitions/1st_competition/ 1st_competition.htm.

References

B.-J. Chen, M.-W. Chang, and C.-J. Lin, 2004, Load forecasting using support vector Machines: a study on EUNITE competition 2001, IEEE Transactions on Power Systems, v. 19, n. 4 (Nov.), p. 1821-1830.

See Also

EUNITE.Loads.cont, EUNITE.Reg, EUNITE.Temp

Examples

```
data(EUNITE.Loads)
str(EUNITE.Loads)
plot(ts(EUNITE.Loads["X24.00"]))
```

EUNITE.Loads.cont	Continuation dataset of the electrical loads of the EUNITE Competi-
	tion

Description

A dataset of univariate time series providing 31 points beyond the end of the time series in EUNITE. Loads containing half-an-hour electrical loads measured in January 1999.

Usage

EUNITE.Loads.cont

Format

A data frame with 31 observations on the following 48 variables.

- **X00.30** a numeric vector containing further observations of X00.30 in EUNITE.Loads relative to January 1999.
- **X01.00** a numeric vector containing further observations of X01.00 in EUNITE.Loads relative to January 1999.
- **X01.30** a numeric vector containing further observations of X01.30 in EUNITE.Loads relative to January 1999.
- **X02.00** a numeric vector containing further observations of X02.00 in EUNITE.Loads relative to January 1999.
- **X02.30** a numeric vector containing further observations of X02.30 in EUNITE.Loads relative to January 1999.
- **X03.00** a numeric vector containing further observations of X03.00 in EUNITE.Loads relative to January 1999.

- **X03.30** a numeric vector containing further observations of X03.30 in EUNITE.Loads relative to January 1999.
- **X04.00** a numeric vector containing further observations of X04.00 in EUNITE.Loads relative to January 1999.
- **X04.30** a numeric vector containing further observations of X04.30 in EUNITE.Loads relative to January 1999.
- **X05.00** a numeric vector containing further observations of X05.00 in EUNITE.Loads relative to January 1999.
- **X05.30** a numeric vector containing further observations of X05.30 in EUNITE.Loads relative to January 1999.
- **X06.00** a numeric vector containing further observations of X06.00 in EUNITE.Loads relative to January 1999.
- **X06.30** a numeric vector containing further observations of X06.30 in EUNITE.Loads relative to January 1999.
- **X07.00** a numeric vector containing further observations of X07.00 in EUNITE.Loads relative to January 1999.
- **X07.30** a numeric vector containing further observations of X07.30 in EUNITE.Loads relative to January 1999.
- **X08.00** a numeric vector containing further observations of X08.00 in EUNITE.Loads relative to January 1999.
- **X08.30** a numeric vector containing further observations of X08.30 in EUNITE.Loads relative to January 1999.
- **X09.00** a numeric vector containing further observations of X09.00 in EUNITE.Loads relative to January 1999.
- **X09.30** a numeric vector containing further observations of X09.30 in EUNITE.Loads relative to January 1999.
- **X10.00** a numeric vector containing further observations of X10.00 in EUNITE.Loads relative to January 1999.
- **X10.30** a numeric vector containing further observations of X10.30 in EUNITE.Loads relative to January 1999.
- **X11.00** a numeric vector containing further observations of X11.00 in EUNITE.Loads relative to January 1999.
- **X11.30** a numeric vector containing further observations of X11.30 in EUNITE.Loads relative to January 1999.
- **X12.00** a numeric vector containing further observations of X12.00 in EUNITE.Loads relative to January 1999.
- **X12.30** a numeric vector containing further observations of X12.30 in EUNITE.Loads relative to January 1999.
- **X13.00** a numeric vector containing further observations of X13.00 in EUNITE.Loads relative to January 1999.
- **X13.30** a numeric vector containing further observations of X13.30 in EUNITE.Loads relative to January 1999.

- **X14.00** a numeric vector containing further observations of X14.00 in EUNITE.Loads relative to January 1999.
- **X14.30** a numeric vector containing further observations of X14.30 in EUNITE.Loads relative to January 1999.
- **X15.00** a numeric vector containing further observations of X15.00 in EUNITE.Loads relative to January 1999.
- **X15.30** a numeric vector containing further observations of X15.30 in EUNITE.Loads relative to January 1999.
- **X16.00** a numeric vector containing further observations of X16.00 in EUNITE.Loads relative to January 1999.
- **X16.30** a numeric vector containing further observations of X16.30 in EUNITE.Loads relative to January 1999.
- **X17.00** a numeric vector containing further observations of X17.00 in EUNITE.Loads relative to January 1999.
- **X17.30** a numeric vector containing further observations of X17.30 in EUNITE.Loads relative to January 1999.
- **X18.00** a numeric vector containing further observations of X18.00 in EUNITE.Loads relative to January 1999.
- **X18.30** a numeric vector containing further observations of X18.30 in EUNITE.Loads relative to January 1999.
- **X19.00** a numeric vector containing further observations of X19.00 in EUNITE.Loads relative to January 1999.
- **X19.30** a numeric vector containing further observations of X19.30 in EUNITE.Loads relative to January 1999.
- **X20.00** a numeric vector containing further observations of X20.00 in EUNITE.Loads relative to January 1999.
- **X20.30** a numeric vector containing further observations of X20.30 in EUNITE.Loads relative to January 1999.
- **X21.00** a numeric vector containing further observations of X21.00 in EUNITE.Loads relative to January 1999.
- **X21.30** a numeric vector containing further observations of X21.30 in EUNITE.Loads relative to January 1999.
- **X22.00** a numeric vector containing further observations of X22.00 in EUNITE.Loads relative to January 1999.
- **X22.30** a numeric vector containing further observations of X22.30 in EUNITE.Loads relative to January 1999.
- **X23.00** a numeric vector containing further observations of X23.00 in EUNITE.Loads relative to January 1999.
- **X23.30** a numeric vector containing further observations of X23.30 in EUNITE.Loads relative to January 1999.
- **X24.00** a numeric vector containing further observations of X24.00 in EUNITE.Loads relative to January 1999.

EUNITE.Reg

Details

Contains the 31 values corresponding to the daily maximum electrical loads of January 1999 which were to be predicted of EUNITE.Loads as demanded by the EUNITE Competition.

Source

EUNITE 1999, Electricity Load Forecast using Intelligent Adaptive Technology: The EUNITE Network Competition. URL: http://www.eunite.org/knowledge/Competitions/1st_competition/ 1st_competition.htm.

References

B.-J. Chen, M.-W. Chang, and C.-J. Lin, 2004, Load forecasting using support vector Machines: a study on EUNITE competition 2001, IEEE Transactions on Power Systems, v. 19, n. 4 (Nov.), p. 1821-1830.

See Also

EUNITE.Loads, EUNITE.Reg, EUNITE.Temp

Examples

```
data(EUNITE.Loads.cont)
str(EUNITE.Loads.cont)
plot(ts(EUNITE.Loads.cont["X24.00"]))
```

EUNITE.Reg

Electrical loads regressors of the EUNITE Competition

Description

The EUNITE Competition dataset containing a set of variables serving as regressors for the electrical loads measured between 1997 and 1998 in EUNITE.Loads.

Usage

EUNITE.Reg

Format

A data frame with 730 observations on the following 2 variables.

- **Holiday** a numeric vector containing daily data on the holidays for the time period 1997-1998. Composed of binary values where 1 represents a holiday and 0 a common day.
- **Weekday** a numeric vector containing daily data on the weekdays for the time period 1997-1998. Composed of integer values where 1 represents a Sunday, 2 a Monday, 3 a Tuesday, 4 a Wednesday, 5 a Thursday, 6 a Friday and 7 a Saturday.

Details

The EUNITE Competition proposed the prediction of maximum daily electrical loads based on half-an-hour loads (EUNITE.Loads) and average daily temperatures of 1997-1998 (EUNITE.Temp). Competitors were asked to predict the 31 values corresponding to the daily maximum electrical loads of January 1999 (EUNITE.Loads.cont). For the posed prediction problem, it is useful to consider as regressors the holidays and the weekdays with respect to this period in EUNITE.Reg, which are expected to have a considerable impact on the electrical consumption.

Source

EUNITE 1999, Electricity Load Forecast using Intelligent Adaptive Technology: The EUNITE Network Competition. URL: http://www.eunite.org/knowledge/Competitions/1st_competition/ 1st_competition.htm.

References

B.-J. Chen, M.-W. Chang, and C.-J. Lin, 2004, Load forecasting using support vector Machines: a study on EUNITE competition 2001, IEEE Transactions on Power Systems, v. 19, n. 4 (Nov.), p. 1821-1830.

See Also

EUNITE.Reg.cont, EUNITE.Loads, EUNITE.Temp

Examples

data(EUNITE.Reg)
str(EUNITE.Reg)

EUNITE.Reg.cont

Continuation dataset of the electrical loads regressors of the EUNITE Competition

Description

A dataset of regressor variables for electrical loads measured in January 1999, providing 31 points beyond the end of the data in EUNITE.Reg.

Usage

EUNITE.Reg.cont

Format

A data frame with 31 observations on the following 2 variables.

- **Holiday** a numeric vector containing further data of the variable Holiday in EUNITE.Reg relative to January 1999.
- **Weekday** a numeric vector containing further data of the variable Weekday in EUNITE. Reg relative to January 1999.

Details

Contains the 31 values of the regressors used for the prediction of the daily maximum electrical loads of January 1999 from EUNITE.Loads as demanded by the EUNITE Competition.

Source

EUNITE 1999, Electricity Load Forecast using Intelligent Adaptive Technology: The EUNITE Network Competition. URL: http://www.eunite.org/knowledge/Competitions/1st_competition/ 1st_competition.htm.

References

B.-J. Chen, M.-W. Chang, and C.-J. Lin, 2004, Load forecasting using support vector Machines: a study on EUNITE competition 2001, IEEE Transactions on Power Systems, v. 19, n. 4 (Nov.), p. 1821-1830.

See Also

EUNITE.Reg, EUNITE.Loads, EUNITE.Temp

Examples

```
data(EUNITE.Reg.cont)
str(EUNITE.Reg.cont)
```

EUNITE.Temp

Temperatures of the EUNITE Competition

Description

The EUNITE Competition dataset composed of a univariate time series of average daily temperatures measured between 1995 and 1998.

Usage

EUNITE.Temp

Format

A data frame with 1461 observations on the following variable.

Temperature a numeric vector with average daily temperatures measured in the period 1995-1998.

Details

The EUNITE Competition proposed the prediction of maximum daily electrical loads based on half-an-hour loads (EUNITE.Loads) and average daily temperatures of 1997-1998, where the latter is used as a regressor. Competitors were asked to predict the 31 values corresponding to the daily maximum electrical loads of January 1999 (EUNITE.Loads.cont). For the posed prediction problem, the average daily temperatures of January 1999 must also be predicted and for that, the use of data on average daily temperatures of 1995-1996 was allowed.

Source

EUNITE 1999, Electricity Load Forecast using Intelligent Adaptive Technology: The EUNITE Network Competition. URL: http://www.eunite.org/knowledge/Competitions/1st_competition/ 1st_competition.htm.

References

B.-J. Chen, M.-W. Chang, and C.-J. Lin, 2004, Load forecasting using support vector Machines: a study on EUNITE competition 2001, IEEE Transactions on Power Systems, v. 19, n. 4 (Nov.), p. 1821-1830.

See Also

EUNITE.Temp.cont, EUNITE.Loads, EUNITE.Reg

Examples

```
data(EUNITE.Temp)
str(EUNITE.Temp)
plot(ts(EUNITE.Temp))
```

EUNITE.Temp.cont Continuation dataset of the temperatures of the EUNITE Competition

Description

A dataset with a univariate time series providing 31 points beyond the end of the time series in EUNITE.Temp containing average daily temperatures measured in January 1999.

Usage

EUNITE.Temp.cont

evaluate

Format

A data frame with 31 observations on the following variable.

Temperature a numeric vector containing further observations of Temperature in EUNITE.Temp relative to January 1999.

Details

Contains the 31 values corresponding to the average daily temperatures of January 1999 which were to be predicted of EUNITE. Temp as demanded by the EUNITE Competition.

Source

EUNITE 1999, Electricity Load Forecast using Intelligent Adaptive Technology: The EUNITE Network Competition. URL: http://www.eunite.org/knowledge/Competitions/1st_competition/ 1st_competition.htm.

References

B.-J. Chen, M.-W. Chang, and C.-J. Lin, 2004, Load forecasting using support vector Machines: a study on EUNITE competition 2001, IEEE Transactions on Power Systems, v. 19, n. 4 (Nov.), p. 1821-1830.

See Also

EUNITE.Temp, EUNITE.Loads, EUNITE.Reg

Examples

```
data(EUNITE.Temp.cont)
str(EUNITE.Temp.cont)
plot(ts(EUNITE.Temp.cont))
```

evaluate

Evaluating prediction/modeling quality

Description

evaluate is a generic function for evaluating the quality of time series prediction or modeling fitness based on a particular metric defined in an evaluating object. The function invokes particular *methods* which depend on the class of the first argument.

Usage

```
evaluate(obj, ...)
## S3 method for class 'evaluating'
evaluate(obj, test, pred, ...)
## S3 method for class 'fitness'
evaluate(obj, mdl, test = NULL, pred = NULL, ...)
## S3 method for class 'error'
evaluate(obj, mdl = NULL, test = NULL, pred = NULL, ..., fitness = FALSE)
```

Arguments

obj	An object of class evaluating defining a particular metric.
	Other parameters passed to eval_func of obj.
test	A vector or univariate time series containing actual values for a time series that are to be compared against pred.
pred	A vector or univariate time series containing time series predictions that are to be compared against the values in test.
mdl	A time series model object for which fitness is to be evaluated.
fitness	Should the function compute the fitness quality? If TRUE the function uses mdl to compute fitness error, otherwise, it uses test and pred to compute prediction error.
	For evaluate.fitness, test and pred are ignored and can be set to NULL. For evaluate.error, mdl is ignored if fitness is FALSE, otherwise, test and pred are ignored and can be set to NULL.

Value

A list containing obj and the computed metric values.

Author(s)

Rebecca Pontes Salles

See Also

Other evaluate: evaluate.tspred()

Examples

```
data(CATS,CATS.cont)
mdl <- forecast::auto.arima(CATS[,1])
pred <- forecast::forecast(mdl, h=length(CATS.cont[,1]))
evaluate(MSE_eval(), test=CATS.cont[,1], pred=pred$mean)
evaluate(MSE_eval(), mdl, fitness=TRUE)</pre>
```

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evaluate.tspred

evaluate(AIC_eval(), mdl)

evaluate.tspred Evaluate method for tspred objects

Description

Evaluates the modeling fitness and quality of time series prediction of the trained models and predicted time series data contained in a tspred class object, respectively, based on a particular metric. Each metric is defined by an evaluating object in the list contained in the tspred class object.

Usage

S3 method for class 'tspred'
evaluate(obj, fitness = TRUE, ...)

Arguments

obj	An object of class tspred defining a particular time series prediction process.
fitness	Should the function compute fitness quality metrics?
	Other parameters passed to the method evaluate of the evaluating objects from obj.

Details

The function evaluate.tspred calls the method evaluate on each evaluating object contained in obj. It uses each trained model, the testing set and the time series predictions contained in obj to compute the metrics. Finally, the produced quality metrics are introduced in the structure of the tspred class object in obj.

Value

An object of class tspred with updated structure containing computed quality metric values.

Author(s)

Rebecca Pontes Salles

See Also

[tspred()] for defining a particular time series prediction process, and [MSE_eval()] for defining a time series prediction/modeling quality metric.

Other evaluate: evaluate()

Examples

data(CATS)

```
#Obtaining objects of the processing class
proc1 <- subsetting(test_len=20)</pre>
proc2 <- BoxCoxT(lambda=NULL)</pre>
proc3 <- WT(level=1, filter="bl14")</pre>
#Obtaining objects of the modeling class
modl1 <- ARIMA()</pre>
#Obtaining objects of the evaluating class
eval1 <- MSE_eval()</pre>
#Defining a time series prediction process
tspred_1 <- tspred(subsetting=proc1,</pre>
                     processing=list(BCT=proc2,
                                       WT=proc3),
                     modeling=modl1,
                     evaluating=list(MSE=eval1)
)
summary(tspred_1)
tspred_1 <- subset(tspred_1, data=CATS[3])</pre>
tspred_1 <- preprocess(tspred_1,prep_test=FALSE)</pre>
tspred_1 <- train(tspred_1)</pre>
tspred_1 <- predict(tspred_1, onestep=TRUE)</pre>
tspred_1 <- postprocess(tspred_1)</pre>
tspred_1 <- evaluate(tspred_1)</pre>
```

evaluating

Prediction/modeling quality evaluation

Description

Constructor for the evaluating class representing a time series prediction or modeling fitness quality evaluation based on a particular metric. The evaluating class has two specialized subclasses fitness and error reagarding fitness criteria and prediction/modeling error metrics, respectively.

Usage

```
evaluating(eval_func, eval_par = NULL, ..., subclass = NULL)
fitness(eval_func, eval_par = NULL, ..., subclass = NULL)
error(eval_func, eval_par = NULL, ..., subclass = NULL)
```

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fittestArima

Arguments

eval_func	A function for computing a particular metric.
eval_par	List of named parameters required by eval_func.
	Other parameters to be encapsulated in the class object.
subclass	Name of new specialized subclass object created in case it is provided.

Value

An object of class evaluating. A list usually containing at least the following elements:

func	A function for computing a particular metric.
par	Particular parameters required by func.

Author(s)

Rebecca Pontes Salles

See Also

Other constructors: ARIMA(), LT(), MSE_eval(), modeling(), processing(), tspred()

Examples

f <- fitness(eval_func=stats::AIC, method="Akaike's Information Criterion", subclass="AIC")
summary(f)</pre>

fittestArima

Automatic ARIMA fitting, prediction and accuracy evaluation

Description

The function predicts and returns the next n consecutive values of a univariate time series using an automatically best fitted ARIMA model. It also evaluates the fitness of the produced model, using AICc, AIC, BIC and logLik criteria, and its prediction accuracy, using the MSE, NMSE, MAPE, sMAPE and maximal error accuracy measures.

Usage

```
fittestArima(
  timeseries,
  timeseries.test = NULL,
  h = NULL,
  na.action = stats::na.omit,
  level = c(80, 95),
  ...
)
```

Arguments

timeseries	A vector or univariate time series which contains the values used for fitting an ARIMA model.
timeseries.tes	t
	A vector or univariate time series containing a continuation for timeseries with actual values. It is used as a testing set and base for calculation of prediction error measures. Ignored if NULL.
h	Number of consecutive values of the time series to be predicted. If h is NULL, the number of consecutive values to be predicted is assumed to be equal to the length of timeseries.test. Required when timeseries.test is NULL.
na.action	A function for treating missing values in timeseries and timeseries.test. The default function is na.omit, which omits any missing values found in timeseries or timeseries.test.
level	Confidence level for prediction intervals.
	Additional arguments passed to the auto.arima modelling function.

Details

The ARIMA model is automatically fitted by the auto.arima function and it is used for prediction by the forecast function both in the forecast package.

The fitness criteria AICc, AIC (AIC), BIC (BIC) and log-likelihood (logLik) are extracted from the fitted ARIMA model. Also, the prediction accuracy of the model is computed by means of MSE (MSE), NMSE (NMSE), MAPE (MAPE), sMAPE (sMAPE) and maximal error (MAXError) measures.

Value

A list with components:

model	A list of class "ARIMA" containing the best fitted ARIMA model. See th auto.arima function in the forecast package.	ne
parameters	A list containing the parameters of the best fitted ARIMA model. See the arimaparameters function.	ne
AICc	Numeric value of the computed AICc criterion of the fitted model.	
AIC	Numeric value of the computed AIC criterion of the fitted model.	
BIC	Numeric value of the computed BIC criterion of the fitted model.	

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fittestArima

logLik	Numeric value of the computed log-likelihood of the fitted model.
pred	A list with the components mean, lower and upper, containing the predictions and the lower and upper limits for prediction intervals, respectively. All compo- nents are time series. See the forecast function in the forecast package.
MSE	Numeric value of the resulting MSE error of prediction.
NMSE	Numeric value of the resulting NMSE error of prediction.
MAPE	Numeric value of the resulting MAPE error of prediction.
sMAPE	Numeric value of the resulting sMAPE error of prediction.
MaxError	Numeric value of the maximal error of prediction.

Author(s)

Rebecca Pontes Salles

References

R.J. Hyndman and G. Athanasopoulos, 2013, Forecasting: principles and practice. OTexts.

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

fittestArimaKF, fittestLM, marimapred

Examples

```
data(CATS,CATS.cont)
fArima <- fittestArima(CATS[,1],CATS.cont[,1])</pre>
#predicted values
pred <- fArima$pred$mean</pre>
#model information
cbind(AICc=fArima$AICc, AIC=fArima$AIC, BIC=fArima$BIC,
logLik=fArima$logLik, MSE=fArima$MSE, NMSE=fArima$NMSE,
MAPE=fArima$MSE, sMAPE=fArima$MSE, MaxError=fArima$MaxError)
#plotting the time series data
plot(c(CATS[,1],CATS.cont[,1]),type='o',lwd=2,xlim=c(960,1000),ylim=c(0,200),
xlab="Time",ylab="ARIMA")
#plotting the predicted values
lines(ts(pred,start=981),lwd=2,col='blue')
#plotting prediction intervals
lines(ts(fArima$pred$upper[,2],start=981),lwd=2,col='light blue')
lines(ts(fArima$pred$lower[,2],start=981),lwd=2,col='light blue')
```

```
fittestArimaKF
```

Description

The function predicts and returns the next n consecutive values of a univariate time series using the best evaluated ARIMA model automatically fitted with Kalman filter. It also evaluates the fitness of the produced model, using AICc, AIC, BIC and logLik criteria, and its prediction accuracy, using the MSE, NMSE, MAPE, sMAPE and maximal error accuracy measures.

Usage

```
fittestArimaKF(
  timeseries,
  timeseries.test = NULL,
  h = NULL,
  na.action = stats::na.omit,
  level = 0.9,
  filtered = TRUE,
  initQ = NULL,
  rank.by = c("MSE", "NMSE", "MAPE", "SMAPE", "MaxError", "AIC", "AICc", "BIC", "logLik",
      "errors", "fitness"),
    ...
)
```

Arguments

timeseries	A vector or univariate time series which contains the values used for fitting an ARIMA model with Kalman filter.
timeseries.test	
	A vector or univariate time series containing a continuation for timeseries with actual values. It is used as a testing set and base for calculation of prediction error measures. Ignored if NULL.
h	Number of consecutive values of the time series to be predicted. If h is NULL, the number of consecutive values to be predicted is assumed to be equal to the length of timeseries.test. Required when timeseries.test is NULL.
na.action	A function for treating missing values in timeseries and timeseries.test. The default function is na.omit, which omits any missing values found in timeseries or timeseries.test.
level	Confidence level for prediction intervals. See the ${\tt predict.SSModel}$ function in the KFAS package.
filtered	If filtered is TRUE, Kalman filtered time series observations are used for prediction, otherwise, Kalman smoothed observations are used for prediction.
initQ	Numeric argument regarding the initial value for the covariance of disturbances parameter to be optimized over. The initial value to be optimized is set to

	and the examples in KFAS. If NULL, initQ is automatically set. See 'Details'.
rank.by	Character string. Criteria used for ranking candidate models generated using different options of values for initQ. Only used if initQ is NULL. Ignored otherwise. See 'Details'.
	Additional arguments passed to the auto.arima modelling function.

·· · · · · · ·

Details

A best ARIMA model is automatically fitted by the auto.arima function in the forecast package. The coefficients of this model are then used as initial parameters for optimization of a state space model (SSModel) using the Kalman filter and functions of the KFAS package (see SSMarima and artransform).

If initQ is NULL, it is automatically set as either log(var(timeseries)) or 0. For that, a set of candidate ARIMA state space models is generated by different initial parameterization of initQ during the model optimization process. The value option which generates the best ranked candidate ARIMA model according to the criteria in rank.by is selected.

The ranking criteria in rank.by may be set as a prediction error measure (such as MSE, NMSE, MAPE, sMAPE or MAXError), or as a fitness criteria (such as AIC, AICc, BIC or logLik). In the former case, the candidate models are used for time series prediction and the error measures are calculated by means of a cross-validation process. In the latter case, the candidate models are fitted and fitness criteria are calculated based on all observations in timeseries.

If rank.by is set as "errors" or "fitness", the candidate models are ranked by all the mentioned prediction error measures or fitness criteria, respectively. The wheight of the ranking criteria is equally distributed. In this case, a rank.position.sum criterion is produced for ranking the candidate models. The rank.position.sum criterion is calculated as the sum of the rank positions of a model (1 = 1st position = better ranked model, 2 = 2nd position, etc.) on each calculated ranking criteria.

Value

A list with components:

model	An object of class "SSModel" containing the best evaluated ARIMA model fit- ted with Kalman Filter.
initQ	The initQ argument provided (or automatically selected) for optimization of the best evaluated ARIMA model fitted with Kalman Filter.
AICc	Numeric value of the computed AICc criterion of the best evaluated model.
AIC	Numeric value of the computed AIC criterion of the best evaluated model.
BIC	Numeric value of the computed BIC criterion of the best evaluated model.
logLik	Numeric value of the computed log-likelihood of the best evaluated model.
pred	A list with the components mean, lower and upper, containing the predictions of the best evaluated model and the lower and upper limits for prediction intervals, respectively. All components are time series. See predict.SSModel.
MSE	$Numeric \ value \ of \ the \ resulting \ MSE \ error \ of \ prediction. \ Require \ \texttt{timeseries.test}.$

NMSE	Numeric value of the resulting NMSE error of prediction. Require timeseries.test.
MAPE	Numeric value of the resulting MAPE error of prediction. Require timeseries.test.
sMAPE	$Numeric\ value\ of\ the\ resulting\ sMAPE\ error\ of\ prediction.\ Require\ timeseries.test.$
MaxError	Numeric value of the maximal error of prediction. Require timeseries.test.
rank.val	Data.frame with the fitness or prediction accuracy criteria computed for all can- didate ARIMA with Kalman filter models ranked by rank.by. It has the at- tribute "ranked.models", which is a list of objects of class "SSModel" con- taining all the candidate ARIMA models fitted with Kalman Filter, also ranked by rank.by. Only provided if initQ was automatically selected.
rank.by	Ranking criteria used for ranking candidate models and producing rank.val.

Author(s)

Rebecca Pontes Salles

References

R.J. Hyndman and G. Athanasopoulos, 2013, Forecasting: principles and practice. OTexts.

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

fittestArima, fittestLM, marimapred

Examples

```
data(CATS,CATS.cont)
fArimaKF <- fittestArimaKF(CATS[,2],CATS.cont[,2])</pre>
#predicted values
pred <- fArimaKF$pred</pre>
#extracting Kalman filtered and smoothed time series from the best fitted model
fs <- KFAS::KFS(fArimaKF$model,filtering=c("state","mean"),smoothing=c("state","mean"))</pre>
f <- fitted(fs, filtered = TRUE) #Kalman filtered time series</pre>
s <- fitted(fs) #Kalman smoothed time series</pre>
#plotting the time series data
plot(c(CATS[,2],CATS.cont[,2]),type='o',lwd=2,xlim=c(960,1000),ylim=c(200,600),
xlab="Time",ylab="ARIMAKF")
#plotting the Kalman filtered time series
lines(f,col='red',lty=2,lwd=2)
#plotting the Kalman smoothed time series
lines(s,col='green',lty=2,lwd=2)
#plotting predicted values
lines(ts(pred$mean,start=981),lwd=2,col='blue')
#plotting prediction intervals
lines(ts(pred$upper,start=981),lwd=2,col='light blue')
lines(ts(pred$lower,start=981),lwd=2,col='light blue')
```

fittestEMD

Automatic prediction with empirical mode decomposition

Description

The function automatically applies an empirical mode decomposition to a provided univariate time series. The resulting components of the decomposed series are used as base for predicting and returning the next n consecutive values of the provided univariate time series using also automatically fitted models. It also evaluates fitness and prediction accuracy of the produced models.

Usage

```
fittestEMD(
  timeseries,
  timeseries.test = NULL,
  h = NULL,
  num_imfs = 0,
  S_number = 4L,
  num_siftings = 50L,
  level = 0.95,
  na.action = stats::na.omit,
  model = c("ets", "arima"),
  rank.by = c("MSE", "NMSE", "MAPE", "SMAPE", "MaxError", "errors")
)
```

Arguments

timeseries timeseries.test	A vector or univariate time series.	
	A vector or univariate time series containing a continuation for timeseries with actual values. It is used as a testing set and base for calculation of prediction error measures. Ignored if NULL.	
h	Number of consecutive values of the time series to be predicted. If h is NULL, the number of consecutive values to be predicted is assumed to be equal to the length of timeseries.test. Required when timeseries.test is NULL.	
num_imfs	Number of Intrinsic Mode Functions (IMFs) to compute. See emd.	
S_number, num_siftings		
	See emd.	
level	Confidence level for prediction intervals. See predict.lm and predict.	
na.action	A function for treating missing values in timeseries and timeseries.test. The default function is na.omit, which omits any missing values found in timeseries or timeseries.test.	

fittestEMD

model	Character string. Indicates which model is to be used for fitting and prediction of the components of the decomposed series.
rank.by	Character string. Criteria used for ranking candidate decompositions/models/predictions generated during parameter selection. See 'Details'.

Details

The function produces an empirical mode decomposition of timeseries. See the emd function. The Intrinsic Mode Functions (IMFs) and residue series resulting from the decomposition are separately used as base for model fitting and prediction. The set of predictions for all IMFs and residue series are then reversed transformed in order to produce the next h consecutive values of the provided univariate time series in timeseries. See the emd.rev function.

The function automatically selects the meaningful IMFs of a decomposition. For that, the function produces models for different selections of meaningful IMFs according to the possible intervals $i:num_imfs$ for $i=1, ..., (num_imfs-1)$, where num_imfs is the number of IMFs in a decomposition. The options of meaningful IMFs of a decomposition which generate the best ranked model fitness/predictions according to the criteria in rank.by are selected.

The ranking criteria in rank.by may be set as a prediction error measure (such as MSE, NMSE, MAPE, sMAPE or MAXError), or as a fitness criteria (such as AIC, AICc, BIC or logLik). In the former case, the candidate empirical mode decompositions are used for time series prediction and the error measures are calculated by means of a cross-validation process. In the latter case, the component series of the candidate decompositions are modeled and model fitness criteria are calculated based on all observations in timeseries. In particular, the fitness criteria calculated for ranking the candidate decompositions correspond to the models produced for the IMFs.

If rank.by is set as "errors" or "fitness", the candidate decompositions are ranked by all the mentioned prediction error measures or fitness criteria, respectively. The wheight of the ranking criteria is equally distributed. In this case, a rank.position.sum criterion is produced for ranking the candidate decompositions. The rank.position.sum criterion is calculated as the sum of the rank positions of a decomposition (1 = 1st position = better ranked model, 2 = 2nd position, etc.) on each calculated ranking criteria.

Value

A list with components:

emd	Same as emd. Contains the empirical mode decomposition of timeseries.
meaningfulImfs	Character string indicating the automatically selected meaningful IMFs of the decomposition.
pred	A list with the components mean, lower and upper, containing the predictions based on the best evaluated decomposition and the lower and upper limits for prediction intervals, respectively. All components are time series.
MSE	Numeric value of the resulting MSE error of prediction. Require timeseries.test.
NMSE	$Numeric \ value \ of \ the \ resulting \ NMSE \ error \ of \ prediction. \ Require \ timeseries. \ test.$
MAPE	$Numeric \ value \ of \ the \ resulting \ MAPE \ error \ of \ prediction. \ Require \ timeseries. \ test.$
SMAPE	$Numeric \ value \ of \ the \ resulting \ sMAPE \ error \ of \ prediction. \ Require \ \texttt{timeseries.test}.$
MaxError	Numeric value of the maximal error of prediction. Require timeseries.test.

fittestLM

Author(s)

Rebecca Pontes Salles

References

Kim, D., Paek, S. H., & Oh, H. S. (2008). A Hilbert-Huang transform approach for predicting cyber-attacks. Journal of the Korean Statistical Society, 37(3), 277-283.

See Also

fittestWavelet, fittestMAS

Examples

data(CATS)

femd <- fittestEMD(CATS[,1],h=20)</pre>

fittestLM

Automatically finding fittest linear model for prediction

Description

The function automatically evaluates and returns the fittest linear model among ARIMA and polynomial regression, with and without Kalman filtering, for prediction of a given univariate time series. Wrapper for the fittestArima, fittestArimaKF, fittestPolyR and fittestPolyRKF functions for automatic time series prediction, whose results are also returned.

Usage

```
fittestLM(
  timeseries,
  timeseries.test = NULL,
  h = NULL,
  level = 0.95,
  na.action = stats::na.omit,
  filtered = TRUE,
  order = NULL,
  minorder = 0,
  maxorder = 5,
  raw = FALSE,
```

fittestLM

```
initQ = NULL,
rank.by = c("MSE", "NMSE", "MAPE", "SMAPE", "MaxError", "AIC", "AICC", "BIC", "logLik",
    "errors", "fitness"),
...
)
```

Arguments

timeseries	A vector or univariate time series which contains the values used for fitting the models.
timeseries.tes	t
	A vector or univariate time series containing a continuation for timeseries with actual values. It is used as a testing set and base for calculation of prediction error measures. Ignored if NULL.
h	Number of consecutive values of the time series to be predicted. If h is NULL, the number of consecutive values to be predicted is assumed to be equal to the length of timeseries.test. Required when timeseries.test is NULL.
level	Confidence level for prediction intervals.
na.action	A function for treating missing values in timeseries and timeseries.test. The default function is na.omit, which omits any missing values found in timeseries or timeseries.test.
filtered	See fittestArimaKF and fittestPolyRKF.
order	See fittestPolyR and fittestPolyRKF.
minorder	See fittestPolyR and fittestPolyRKF.
maxorder	See fittestPolyR and fittestPolyRKF.
raw	See fittestPolyR.
initQ	See fittestArimaKF and fittestPolyRKF.
rank.by	Character string. Criteria used for ranking candidate models. See 'Details'.
	See fittestArima and fittestArimaKF.

Details

The results of the best evaluated models returned by fittestArima, fittestArimaKF, fittestPolyR and fittestPolyRKF are ranked and the fittest linear model for prediction of the given univariate time series is selected based on the criteria in rank.by.

The ranking criteria in rank.by may be set as a prediction error measure (such as MSE, NMSE, MAPE, sMAPE or MAXError), or as a fitness criteria (such as AIC, AICc, BIC or logLik). See fittestArima, fittestArimaKF, fittestPolyR or fittestPolyRKF.

If rank.by is set as "errors" or "fitness", the candidate models are ranked by all the mentioned prediction error measures or fitness criteria, respectively. The wheight of the ranking criteria is equally distributed. In this case, a rank.position.sum criterion is produced for ranking the candidate models. The rank.position.sum criterion is calculated as the sum of the rank positions of a model (1 = 1st position = better ranked model, 2 = 2nd position, etc.) on each calculated ranking criteria.

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fittestMAS

Value

A list with components:

model	An object containing the fittest evaluated linear model. The class of the model object is dependent on the results of the evaluation (ranking). See fittestArima, fittestArimaKF, fittestPolyR and fittestPolyRKF.
rank	Data.frame with the fitness and/or prediction accuracy criteria computed for all models considered, ranked by rank.by.
ranked.results	A list of lists containing the ranked results of the functions fittestArima, fittestArimaKF, fittestPolyR and fittestPolyRKF. Also ranked by rank.by

Author(s)

Rebecca Pontes Salles

See Also

fittestArima, fittestArimaKF, fittestPolyR, fittestPolyRKF

Examples

```
data(CATS,CATS.cont)
fittest <- fittestLM(CATS[,1],CATS.cont[,1])</pre>
```

#fittest model information
fittest\$rank[1,]

#predictions of the fittest model
fittest\$ranked.results[[1]]\$pred

fittestMAS

Automatic prediction with moving average smoothing

Description

The function uses an automatically produced moving average smoother as base for predicting and returning the next n consecutive values of the provided univariate time series using an also automatically fitted model (ets/stlf or arima). It also evaluates the fitness and prediction accuracy of the produced model.

Usage

```
fittestMAS(
  timeseries,
  timeseries.test = NULL,
  h = NULL,
  order = NULL,
  minorder = 1,
  maxorder = min(36, length(ts(na.action(timeseries)))/2),
  model = c("ets", "arima"),
  level = 0.95,
  na.action = stats::na.omit,
  rank.by = c("MSE", "NMSE", "MAPE", "SMAPE", "MaxError", "AIC", "AICc", "BIC", "logLik",
        "errors", "fitness"),
    ...
)
```

Arguments

timeseries timeseries.tes	A vector or univariate time series.
	A vector or univariate time series containing a continuation for timeseries with actual values. It is used as a testing set and base for calculation of prediction error measures. Ignored if NULL.
h	Number of consecutive values of the time series to be predicted. If h is NULL, the number of consecutive values to be predicted is assumed to be equal to the length of timeseries.test. Required when timeseries.test is NULL.
order	A numeric integer value corresponding to the order of moving average smoother to be produced. If NULL, the order of the moving average smoother returned by the function is automatically selected within the interval minorder:maxorder. See 'Details'.
minorder	A numeric integer value corresponding to the minimum order of candidate mov- ing average smoothers to be produced and evaluated. Ignored if order is pro- vided. See 'Details'.
maxorder	A numeric integer value corresponding to the maximal order of candidate mov- ing average smoothers to be produced and evaluated. Ignored if order is pro- vided. See 'Details'.
model	Character string. Indicates which model is to be used for fitting and prediction of the moving average smoothed series.
level	Confidence level for prediction intervals. See the forecast function of the forecast package.
na.action	A function for treating missing values in timeseries and timeseries.test. The default function is na.omit, which omits any missing values found in timeseries or timeseries.test.
rank.by	Character string. Criteria used for ranking candidate models generated. See 'Details'.
	Additional arguments passed to the modeling functions.

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fittestMAS

Details

The function produces a moving average smoother of timeseries with order order and uses it as base for model fitting and prediction. If model="arima", an arima model is used and automatically fitted using the auto.arima function. If model="ets", the function fits an [forecast]ets model (if timeseries is non-seasonal or the seasonal period is 12 or less) or stlf model (if the seasonal period is 13 or more).

For producing the prediction of the next h consecutive values of the provided univariate time series, the function mas.rev is used.

If order is NULL, it is automatically selected. For that, a set with candidate models constructed for moving average smoothers of orders from minorder to maxorder is generated. The default value of maxorder is set based on code from the sma function of smooth package. The value option of order which generate the best ranked candidate model according to the criteria in rank.by is selected.

The ranking criteria in rank.by may be set as a prediction error measure (such as MSE, NMSE, MAPE, sMAPE or MAXError), or as a fitness criteria (such as AIC, AICc, BIC or logLik). In the former case, the candidate models are used for time series prediction and the error measures are calculated by means of a cross-validation process. In the latter case, the candidate models are fitted and fitness criteria are calculated based on all observations in timeseries.

If rank.by is set as "errors" or "fitness", the candidate models are ranked by all the mentioned prediction error measures or fitness criteria, respectively. The wheight of the ranking criteria is equally distributed. In this case, a rank.position.sum criterion is produced for ranking the candidate models. The rank.position.sum criterion is calculated as the sum of the rank positions of a model (1 = 1st position = better ranked model, 2 = 2nd position, etc.) on each calculated ranking criteria.

Value

A list with components:

model	A list containing information about the best evaluated model.
order	The order of moving average smoother provided or automatically selected.
ma	The simple moving average smoother of order order of the provided time series.
AICc	Numeric value of the computed AICc criterion of the best evaluated model.
AIC	Numeric value of the computed AIC criterion of the best evaluated model.
BIC	Numeric value of the computed BIC criterion of the best evaluated model.
logLik	Numeric value of the computed log-likelihood of the best evaluated model.
pred	A list with the components mean, lower and upper, containing the predictions of the best evaluated model and the lower and upper limits for prediction intervals, respectively. All components are time series. See the forecast function in the forecast package.
MSE	Numeric value of the resulting MSE error of prediction. Require timeseries.test.
NMSE	Numeric value of the resulting NMSE error of prediction. Require timeseries.test.
MAPE	Numeric value of the resulting MAPE error of prediction. Require timeseries.test.
sMAPE	$Numeric\ value\ of\ the\ resulting\ sMAPE\ error\ of\ prediction.\ Require\ \verbtimeseries.test.$
MaxError	Numeric value of the maximal error of prediction. Require timeseries.test.

rank.val	Data.frame with the fitness or prediction accuracy criteria computed for all can-
	didate models ranked by rank.by. It has the attribute "ranked.models", which
	is a list of objects containing all the candidate models, also ranked by rank.by.
rank.by	Ranking criteria used for ranking candidate models and producing rank.val.

Author(s)

Rebecca Pontes Salles

References

R.J. Hyndman and G. Athanasopoulos, 2013, Forecasting: principles and practice. OTexts.

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

fittestEMD, fittestWavelet

Examples

data(CATS)

fMAS <- fittestMAS(CATS[,1],h=20,model="arima")</pre>

#automatically selected order of moving average
mas.order <- fMAS\$order</pre>

fittestPolyR

Automatic fitting and prediction of polynomial regression

Description

The function predicts and returns the next n consecutive values of a univariate time series using the best evaluated automatically fitted polynomial regression model. It also evaluates the fitness of the produced model, using AICc, AIC, BIC and logLik criteria, and its prediction accuracy, using the MSE, NMSE, MAPE, sMAPE and maximal error accuracy measures.

Usage

```
fittestPolyR(
  timeseries,
  timeseries.test = NULL,
  h = NULL,
  order = NULL,
  minorder = 0,
```

fittestPolyR

```
maxorder = 5,
raw = FALSE,
na.action = stats::na.omit,
level = 0.95,
rank.by = c("MSE", "NMSE", "MAPE", "SMAPE", "MaxError", "AIC", "AICC", "BIC", "logLik",
        "errors", "fitness")
)
```

Arguments

timeseries	A vector or univariate time series which contains the values used for fitting a polynomial regression model.
timeseries.tes	t
	A vector or univariate time series containing a continuation for timeseries with actual values. It is used as a testing set and base for calculation of prediction error measures. Ignored if NULL.
h	Number of consecutive values of the time series to be predicted. If h is NULL, the number of consecutive values to be predicted is assumed to be equal to the length of timeseries.test. Required when timeseries.test is NULL.
order	A numeric integer value corresponding to the order of polynomial regression to be fitted. If NULL, the order of the polynomial regression returned by the function is automatically selected within the interval minorder:maxorder. See 'Details'.
minorder	A numeric integer value corresponding to the minimum order of candidate poly- nomial regression to be fitted and evaluated. Ignored if order is provided. See 'Details'.
maxorder	A numeric integer value corresponding to the maximal order of candidate poly- nomial regression to be fitted and evaluated. Ignored if order is provided. See 'Details'.
raw	If TRUE, use raw and not orthogonal polynomials. Orthogonal polynomials help avoid correlation between variables. Default is FALSE. See poly of the stats package.
na.action	A function for treating missing values in timeseries and timeseries.test. The default function is na.omit, which omits any missing values found in timeseries or timeseries.test.
level	Confidence level for prediction intervals. See the predict.lm function in the stats package.
rank.by	Character string. Criteria used for ranking candidate models generated. See 'Details'.

Details

A set with candidate polynomial regression models of order order is generated with help from the dredge function from the MuMIn package. The candidate models are ranked according to the criteria in rank.by and the best ranked model is returned by the function.

If order is NULL, it is automatically selected. For that, the candidate polynomial regression models generated receive orders from minorder to maxorder. The value option of order which generate the best ranked candidate polynomial regression model acoording to the criteria in rank.by is selected.

The ranking criteria in rank.by may be set as a prediction error measure (such as MSE, NMSE, MAPE, sMAPE or MAXError), or as a fitness criteria (such as AIC, AICc, BIC or logLik). In the former case, the candidate models are used for time series prediction and the error measures are calculated by means of a cross-validation process. In the latter case, the candidate models are fitted and fitness criteria are calculated based on all observations in timeseries.

If rank.by is set as "errors" or "fitness", the candidate models are ranked by all the mentioned prediction error measures or fitness criteria, respectively. The wheight of the ranking criteria is equally distributed. In this case, a rank.position.sum criterion is produced for ranking the candidate models. The rank.position.sum criterion is calculated as the sum of the rank positions of a model (1 = 1st position = better ranked model, 2 = 2nd position, etc.) on each calculated ranking criteria.

Value

A list with components:

model	An object of class "stats::lm" containing the best evaluated polynomial regres- sion model.
order	The order argument provided (or automatically selected) for the best evaluated polynomial regression model.
AICc	Numeric value of the computed AICc criterion of the best evaluated model.
AIC	Numeric value of the computed AIC criterion of the best evaluated model.
BIC	Numeric value of the computed BIC criterion of the best evaluated model.
logLik	Numeric value of the computed log-likelihood of the best evaluated model.
pred	A list with the components mean, lower and upper, containing the predictions of the best evaluated model and the lower and upper limits for prediction intervals, respectively. All components are time series. See predict.lm.
MSE	Numeric value of the resulting MSE error of prediction. Require timeseries.test.
NMSE	Numeric value of the resulting NMSE error of prediction. Require timeseries.test.
MAPE	Numeric value of the resulting MAPE error of prediction. Require timeseries.test.
sMAPE	Numeric value of the resulting sMAPE error of prediction. Require timeseries.test.
MaxError	Numeric value of the maximal error of prediction. Require timeseries.test.
rank.val	Data.frame with the coefficients and the fitness or prediction accuracy criteria computed for all candidate polynomial regression models ranked by rank.by. It has the attribute "model.calls", which is a list of objects of class "expression" containing the calls of all the candidate polynomial regression models, also ranked by rank.by.
rank.by	Ranking criteria used for ranking candidate models and producing rank.val.

Author(s)

Rebecca Pontes Salles

fittestPolyRKF

References

R.J. Hyndman and G. Athanasopoulos, 2013, Forecasting: principles and practice. OTexts.

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

fittestPolyRKF, fittestLM

Examples

```
data(CATS,CATS.cont)
fPolyR <- fittestPolyR(CATS[,3],CATS.cont[,3])
#predicted values
pred <- fPolyR$pred

#plotting the time series data
plot(c(CATS[,3],CATS.cont[,3]),type='o',lwd=2,xlim=c(960,1000),ylim=c(-100,300),
xlab="Time",ylab="PR")
#plotting predicted values
lines(ts(pred$mean,start=981),lwd=2,col='blue')
#plotting prediction intervals
lines(ts(pred$lower,start=981),lwd=2,col='light blue')
lines(ts(pred$upper,start=981),lwd=2,col='light blue')</pre>
```

fittestPolyRKF	Automatic fitting and prediction of polynomial regression with Kalman
	filter

Description

The function predicts and returns the next n consecutive values of a univariate time series using the best evaluated polynomial regression model automatically fitted with Kalman filter. It also evaluates the fitness of the produced model, using AICc, AIC, BIC and logLik criteria, and its prediction accuracy, using the MSE, NMSE, MAPE, sMAPE and maximal error accuracy measures.

Usage

```
fittestPolyRKF(
   timeseries,
   timeseries.test = NULL,
   h = NULL,
   na.action = stats::na.omit,
   level = 0.9,
   order = NULL,
   minorder = 0,
   maxorder = 5,
```

```
initQ = NULL,
filtered = TRUE,
rank.by = c("MSE", "NMSE", "MAPE", "SMAPE", "MaxError", "AIC", "AICC", "BIC", "logLik",
    "errors", "fitness")
)
```

Arguments

timeseries	A vector or univariate time series which contains the values used for fitting a polynomial regression model with Kalman filter. ~~Describe timeseries here~~
timeseries.tes	t
	A vector or univariate time series containing a continuation for timeseries with actual values. It is used as a testing set and base for calculation of prediction error measures. Ignored if NULL.
h	Number of consecutive values of the time series to be predicted. If h is NULL, the number of consecutive values to be predicted is assumed to be equal to the length of timeseries.test. Required when timeseries.test is NULL.
na.action	A function for treating missing values in timeseries and timeseries.test. The default function is na.omit, which omits any missing values found in timeseries or timeseries.test.
level	Confidence level for prediction intervals. See the predict.SSModel function in the KFAS package. ~~Describe na.action here~~
order	A numeric integer value corresponding to the order of polynomial regression to be fitted. If NULL, the order of the polynomial regression returned by the function is automatically selected within the interval minorder:maxorder. See 'Details'.
minorder	A numeric integer value corresponding to the minimum order of candidate poly- nomial regression to be fitted and evaluated. Ignored if order is provided. See 'Details'.
maxorder	A numeric integer value corresponding to the maximal order of candidate poly- nomial regression to be fitted and evaluated. Ignored if order is provided. See 'Details'.
initQ	Numeric argument regarding the initial values for the covariance of disturbances parameter to be optimized over. The initial values to be optimized are set to rep(initQ,(order+1)). See the Q argument of the SSModel function in the KFAS package and the examples in KFAS. If NULL, initQ is automatically set. See 'Details'.
filtered	If filtered is TRUE, Kalman filtered time series observations are used for pre- diction, otherwise, Kalman smoothed observations are used for prediction.
rank.by	Character string. Criteria used for ranking candidate models generated using different options of values for order and/or initQ. Ignored if both order and initQ are provided. See 'Details'.

Details

The polynomial regression model produced and returned by the function is generated and represented as state space model (SSModel) based on code from the dlmodeler package. See dlmodeler.polynomial. The model is optimized using the Kalman filter and functions of the KFAS package (see fitSSM).

fittestPolyRKF

If order is NULL, it is automatically selected. For that, a set of candidate polynomial regression state space models of orders from minorder to maxorder is generated and evaluated. Also, if initQ is NULL, it is automatically set as either log(stats::var(timeseries)) or 0. For that, candidate models receive different initial parameterization of initQ during the model optimization process. The value options of order and/or initQ which generate the best ranked candidate polynomial regression model acoording to the criteria in rank.by are selected.

The ranking criteria in rank.by may be set as a prediction error measure (such as MSE, NMSE, MAPE, sMAPE or MAXError), or as a fitness criteria (such as AIC, AICc, BIC or logLik). In the former case, the candidate models are used for time series prediction and the error measures are calculated by means of a cross-validation process. In the latter case, the candidate models are fitted and fitness criteria are calculated based on all observations in timeseries.

If rank.by is set as "errors" or "fitness", the candidate models are ranked by all the mentioned prediction error measures or fitness criteria, respectively. The wheight of the ranking criteria is equally distributed. In this case, a rank.position.sum criterion is produced for ranking the candidate models. The rank.position.sum criterion is calculated as the sum of the rank positions of a model (1 = 1st position = better ranked model, 2 = 2nd position, etc.) on each calculated ranking criteria.

Value

A list with components:

model	An object of class "SSModel" containing the best evaluated polynomial regres- sion model fitted with Kalman Filter.
order	The order argument provided (or automatically selected) for the best evaluated polynomial regression model fitted with Kalman Filter.
initQ	The initQ argument provided (or automatically selected) for optimization of the best evaluated polynomial regression model fitted with Kalman Filter.
AICc	Numeric value of the computed AICc criterion of the best evaluated model.
AIC	Numeric value of the computed AIC criterion of the best evaluated model.
BIC	Numeric value of the computed BIC criterion of the best evaluated model.
logLik	Numeric value of the computed log-likelihood of the best evaluated model.
pred	A list with the components mean, lower and upper, containing the predictions of the best evaluated model and the lower and upper limits for prediction intervals, respectively. All components are time series. See predict.SSModel.
MSE	Numeric value of the resulting MSE error of prediction. Require timeseries.test.
NMSE	Numeric value of the resulting NMSE error of prediction. Require timeseries.test.
MAPE	Numeric value of the resulting MAPE error of prediction. Require timeseries.test.
sMAPE	Numeric value of the resulting sMAPE error of prediction. Require timeseries.test.
MaxError	Numeric value of the maximal error of prediction. Require timeseries.test.
rank.val	Data.frame with the fitness or prediction accuracy criteria computed for all can- didate polynomial regression with Kalman filter models ranked by rank.by. It has the attribute "ranked.models", which is a list of objects of class "SS- Model" containing all the candidate polynomial regression models fitted with Kalman Filter, also ranked by rank.by. Only provided if order or initQ were automatically selected.

rank.by Ranking criteria used for ranking candidate models and producing rank.val.

Author(s)

Rebecca Pontes Salles

References

R.J. Hyndman and G. Athanasopoulos, 2013, Forecasting: principles and practice. OTexts.

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

fittestPolyR, fittestLM ~

Examples

```
data(CATS,CATS.cont)
fPolyRKF <- fittestPolyRKF(CATS[,1],CATS.cont[,1])
#predicted values
pred <- fPolyRKF$pred</pre>
```

```
#extracting Kalman filtered and smoothed time series from the best fitted model
fs <- KFAS::KFS(fPolyRKF$model,filtering=c("state","mean"),smoothing=c("state","mean"))</pre>
f <- fitted(fs, filtered = TRUE) #Kalman filtered time series</pre>
s <- fitted(fs) #Kalman smoothed time series
#plotting the time series data
plot(c(CATS[,1],CATS.cont[,1]),type='o',lwd=2,xlim=c(960,1000),ylim=c(0,200),
xlab="Time",ylab="PRKF")
#plotting the Kalman filtered time series
lines(f,col='red',lty=2,lwd=2)
#plotting the Kalman smoothed time series
lines(s,col='green',lty=2,lwd=2)
#plotting predicted values
lines(ts(pred$mean,start=981),lwd=2,col='blue')
#plotting prediction intervals
lines(ts(pred$lower,start=981),lwd=2,col='light blue')
lines(ts(pred$upper,start=981),lwd=2,col='light blue')
```

fittestWavelet

fittestWavelet

Description

The function automatically applies a maximal overlap discrete wavelet transform to a provided univariate time series. The resulting components of the decomposed series are used as base for predicting and returning the next n consecutive values of the provided univariate time series using also automatically fitted models (ets or arima). It also evaluates fitness and prediction accuracy of the produced models.

Usage

```
fittestWavelet(
  timeseries,
  timeseries.test = NULL,
  h = 1,
  filters = c("haar", "d4", "la8", "bl14", "c6"),
  n.levels = NULL,
  maxlevel = NULL,
  boundary = "periodic",
  model = c("ets", "arima"),
  conf.level = 0.95,
  na.action = stats::na.omit,
  rank.by = c("MSE", "NMSE", "MAPE", "SMAPE", "MaxError", "AIC", "AICC", "BIC", "logLik",
        "errors", "fitness"),
    ...
)
```

Arguments

timeseries	A vector or univariate time series.
timeseries.test	
	A vector or univariate time series containing a continuation for timeseries with actual values. It is used as a testing set and base for calculation of prediction error measures. Ignored if NULL.
h	Number of consecutive values of the time series to be predicted. If h is NULL, the number of consecutive values to be predicted is assumed to be equal to the length of timeseries.test. Required when timeseries.test is NULL.
filters	A vector containing character strings indicating which wavelet filter to use in the decomposition. If length(filters)>1, the wavelet transform filter used for generating the return of the function is automatically selected. If NULL, all supported filters are considered for automatic selection. See 'Details'. For more details on all the supported filters and corresponding character strings see wt.filter.
n.levels	An integer specifying the level of the decomposition. If NULL, the level of the wavelet decomposition returned by the function is automatically selected within the interval 1:maxlevel. See 'Details'.
maxlevel	A numeric integer value corresponding to the maximal level of candidate wavelet decompositions to be produced and evaluated. If NULL, maxlevel is set as $floor(log(((nobs-1)/(L-1))+1)/log(2)))$, where nobs=length(timeseries)

	and L is the length of the wavelet and scaling filters. See modwt and wt.filter. Ignored if n.levels is provided. See 'Details'.
boundary	Character string. Indicates which boundary method to use. See modwt.
model	Character string. Indicates which model is to be used for fitting and prediction of the components of the decomposed series.
conf.level	Confidence level for prediction intervals. See the forecast function of the forecast package. ~~Describe na.action here~~
na.action	A function for treating missing values in timeseries and timeseries.test. The default function is na.omit, which omits any missing values found in timeseries or timeseries.test.
rank.by	Character string. Criteria used for ranking candidate decompositions/models/predictions generated during parameter selection. See 'Details'.
	Additional arguments passed to the modeling functions. ~~Describe na.action here~~

Details

The function produces a maximal overlap discrete wavelet transform of timeseries. It performs a time series decomposition of level n.levels using the wavelet filter filters. See the modwt function. Each component series resulting from the decomposition (n.levels wavelet coefficients series and n.levels scaling coefficients series) is separately used as base for model fitting and prediction. If model="arima", arima models are used and automatically fitted using the auto.arima function. If model="ets", the function fits [forecast]ets models. The set of predictions for all component series are then reversed transformed in order to produce the next h consecutive values of the provided univariate time series in timeseries. See the imodwt function.

If length(filters)>1 or filters=NULL, it is automatically selected. For that, a set of candidate wavelet decompositions with different options of filters is generated and used for model fitting and prediction. Also, if n.levels is NULL, it is automatically set as a value within the interval 1:maxlevel (if maxlevel is not provided, it is calculated according to the wavelet filter based on code from modwt). For that, candidate decompositions are specified with different levels. The options of filter and/or level of decomposition which generate the best ranked model fitness/predictions according to the criteria in rank.by are selected.

The ranking criteria in rank.by may be set as a prediction error measure (such as MSE, NMSE, MAPE, sMAPE or MAXError), or as a fitness criteria (such as AIC, AICc, BIC or logLik). In the former case, the candidate wavelet decompositions are used for time series prediction and the error measures are calculated by means of a cross-validation process. In the latter case, the component series of the candidate decompositions are modeled and model fitness criteria are calculated based on all observations in timeseries. In particular, the fitness criteria calculated for ranking the candidate decomposition correspond to the model produced for the n.levelsth scaling coefficients series as it can be considered the main component of a decomposition of level n.levels (Conejo,2005).

If rank.by is set as "errors" or "fitness", the candidate decompositions are ranked by all the mentioned prediction error measures or fitness criteria, respectively. The wheight of the ranking criteria is equally distributed. In this case, a rank.position.sum criterion is produced for ranking the candidate decompositions. The rank.position.sum criterion is calculated as the sum of the rank positions of a decomposition (1 = 1st position = better ranked model, 2 = 2nd position, etc.) on each calculated ranking criteria.

fittestWavelet

Value

A list with components:

WT	An object of class modwt containing the wavelet transformed/decomposed time series.
level	The level of wavelet decomposition provided or automatically selected.
filter	A character string indicating the (provided or automatically selected) wavelet filter used in the decomposition.
AICc	Numeric value of the computed AICc criterion of the fitted model for the levelth scaling coefficients series.
AIC	Numeric value of the computed AIC criterion of the fitted model for the levelth scaling coefficients series.
BIC	Numeric value of the computed BIC criterion of the fitted model for the levelth scaling coefficients series.
logLik	Numeric value of the computed log-likelihood of the fitted model for the levelth scaling coefficients series.
pred	A list with the components mean, lower and upper, containing the predictions based on the best evaluated decomposition and the lower and upper limits for prediction intervals, respectively. All components are time series. See the forecast function in the forecast package.
MSE	Numeric value of the resulting MSE error of prediction. Require timeseries.test.
NMSE	Numeric value of the resulting NMSE error of prediction. Require timeseries.test.
MAPE	Numeric value of the resulting MAPE error of prediction. Require timeseries.test.
sMAPE	Numeric value of the resulting sMAPE error of prediction. Require timeseries.test.
MaxError	Numeric value of the maximal error of prediction. Require timeseries.test.
rank.val	Data.frame with the fitness or prediction accuracy criteria computed based on all candidate decompositions ranked by rank.by. It has the attribute "ranked.wt", which is a list of modwt objects containing all the candidate decompositions, also ranked by rank.by. Only provided if filters or n.levels were automatically selected.
rank.by	Ranking criteria used for ranking candidate decompositions and producing rank.val.

Author(s)

Rebecca Pontes Salles

References

A. J. Conejo, M. A. Plazas, R. Espinola, A. B. Molina, Day-ahead electricity price forecasting using the wavelet transform and ARIMA models, IEEE Transactions on Power Systems 20 (2005) 1035-1042.

T. Joo, S. Kim, Time series forecasting based on wavelet filtering, Expert Systems with Applications 42 (2015) 3868-3874.

C. Stolojescu, I. Railean, S. M. P. Lenca, A. Isar, A wavelet based prediction method for time series. In Proceedings of the 2010 International Conference Stochastic Modeling Techniques and Data Analysis, Chania, Greece (pp. 8-11) (2010).

See Also

fittestEMD, fittestMAS ~

Examples

data(CATS)

fW <- fittestWavelet(CATS[,1],h=20,model="arima")</pre>

#plot wavelet transform/decomposition
plot(fW\$WT)

ipeadata_d

The Ipea Most Requested Dataset (daily)

Description

The Institute of Applied Economic Research of Brazil (Ipea) (Ipea, 2017) is a public institution of Brazil that provides support to the federal government with regard to public policies: fiscal, social, and economic. Ipea provides public datasets derived from real economic and financial data of the world.

Usage

ipeadata_d

Format

The ipeadata_d dataset contains 12 time series of 901 to 8154 observations. The 12 time series are provided as the following variables of a data frame.

GM366_IBVSP366 Stock Index: Sao Paulo Stock Exchange - closed - BM&FBovespa.

GM366_ERC366 Exchange rate - R\$ / US\$ - commercial - purchase - mean - R\$ - Bacen Outras/SGS.

GM366_EREURO366 Euro area - exchange rate - euro / US\$ - mean - Euro - Bacen Outras/SGS.

GM366_ERPV366 Exchange rate - R\$ / US\$ - parallel - selling - mean - R\$ - Economic value.

GM366_ERV366 Exchange rate - R\$ / US\$ - commercial - selling - mean - R\$ - Bacen Out-ras/SGS.

GM366_TJOVER366 Interest Rate: Over / Selic - (% p.a.) - Bacen Outras/SGS.

GM366_TJTR366 Interest rate - TR - (% p.m.) - Bacen Outras/SGS.

SECEX366_MVTOT366 Imports - weekly mean - US\$ - MDIC/Secex.

SECEX366_XVTOT366 Exports - weekly mean - US\$ - MDIC/Secex.

JPM366_EMBI366 EMBI + Risco-Brasil - JP Morgan.

BM366_TJOVER366 Interest rate - Selic - fixed by Copom - (% p.a.) - Bacen/Boletim/M. Finan..

GM366_TJOVERV366 Interest Rate: Over / Selic - Ipea.

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ipeadata_m

Details

The ipeadata_d dataset is provided by Ipea. It comprehends the most requested time series collected in daily rates. The ipeadata_d dataset comprehend observations of exchange rates (R\$/US\$), exports/imports prices, interest rates, and more, measured from 1962 to September of 2017.

The data had missing data removed by the function na.omit.

ipeadata_d.cont provide 30 points beyond the end of the time series in ipeadata_d. Intended for use as testing set.

Source

Ipea, Ipeadata. Macroeconomic and regional data, Technical Report, http://www.ipeadata.gov. br, 2017. The "Most request series" section and filtered by "Frequency" equal to "Daily".

References

Ipea, Ipeadata. Macroeconomic and regional data, Technical Report, http://www.ipeadata.gov. br, 2017.

See Also

ipeadata_m~

Examples

```
data(ipeadata_d)
str(ipeadata_d)
plot(ts(ipeadata_d[1]))
```

ipeadata_m

The Ipea Most Requested Dataset (monthly)

Description

The Institute of Applied Economic Research of Brazil (Ipea) (Ipea, 2017) is a public institution of Brazil that provides support to the federal government with regard to public policies: fiscal, social, and economic. Ipea provides public datasets derived from real economic and financial data of the world.

Usage

ipeadata_m

Format

The ipeadata_m dataset contains 23 time series of 156 to 1019 observations. The 23 time series are provided as the following variables of a data frame.

- BM12_ERC12 Exchange rate Brazilian real (R\$) / US dollar (US\$) purchase average R\$ Bacen / Boletim / BP.
- BM12_ERV12 Exchange rate Brazilian real (R\$) / US dollar (US\$) selling average R\$ Bacen / Boletim / BP.
- **IGP12_IGPDI12** IGP-DI general price index domestic supply (aug 1994 = 100) FGV/Conj. Econ. - IGP.
- FUNCEX12_MDPT12 Imports prices index (average 2006 = 100) Funcex.
- FUNCEX12_XPT12 Exports prices index (average 2006 = 100) Funcex.
- PRECOS12_INPC12 INPC national consumer price index (dec 1993 = 100) IBGE/SNIPC.
- **PRECOS12_INPCBR12** INPC national consumer price index growth rate (% p.m.) IBGE/SNIPC.
- **PRECOS12_IPCA12** IPCA extended consumer price index (dec 1993 = 100) IBGE/SNIPC.

SEADE12_TDAGSP12 Unemployment rate - open - RMSP - (%) - Seade/PED.

SEADE12_TDOTSP12 Unemployment rate - hidden - RMSP - (%) - Seade/PED.

- SEADE12_TDOPSP12 Unemployment rate hidden precarious RMSP (%) Seade/PED.
- GAC12_SALMINRE12 Real minimum wage R\$ Ipea.
- **IGP12_IGPM12** IGP-M general price index at market prices (aug 1994 = 100) FGV/Conj. Econ. - IGP.
- PRECOS12_IPCAG12 IPCA extended consumer price index growth rate (% p.m.) IBGE/SNIPC.
- **IGP12_IGPDIG12** IGP-DI general price index domestic supply growth rate (% p.m.) FGV/Conj. Econ. IGP.
- **IGP12_IGPMG12** IGP-M general price index at market prices growth rate (% p.m.) FGV/Conj. Econ. IGP.
- **IGP12_IGPOGG12** IGP-OG general price index overall supply growth rate (% p.m.) FGV/Conj. Econ. IGP.
- **PRECOS12_IPCA15G12** IPCA 15 extended consumer price index growth rate (% p.m.) IBGE/SNIPC.
- [BM12_PIB12 GDP R\$ Bacen / Boletim / Ativ. Ec..
- MTE12_SALMIN12 Minimum wage R\$ MTE.
- BM12_TJOVER12 Interest rate Overnight/Selic (% p.m.) Bacen/Boletim/M. Finan..
- SEADE12_TDTGSP12 Unemployment rate Sao Paulo (%) Seade/PED.
- **PMEN12_TD12** Unemployment rate reference: 30 days RMs (%) IBGE/PME obs: PME closed in 2016-mar.

LogT

Details

The ipeadata_m dataset is provided by Ipea. It comprehends the most requested time series collected in monthly rates. The ipeadata_m dataset comprehend observations of exchange rates (R\$/US\$), exports/imports prices, interest rates, minimum wage, unemployment rate, and more, measured from 1930 to September of 2017.

The data had missing data removed by the function na.omit.

ipeadata_m.cont provide 12 points beyond the end of the time series in ipeadata_m. Intended for use as testing set.

Source

Ipea, Ipeadata. Macroeconomic and regional data, Technical Report, http://www.ipeadata.gov. br, 2017. The "Most request series" section and filtered by "Frequency" equal to "Monthly".

References

Ipea, Ipeadata. Macroeconomic and regional data, Technical Report, http://www.ipeadata.gov. br, 2017.

See Also

ipeadata_d ~

Examples

```
data(ipeadata_m)
str(ipeadata_m)
plot(ts(ipeadata_m[1]))
```

LogT

Logarithmic Transformation

Description

The LogT() function returns a logarithmic transformation of the provided time series. A natural log is returned by default. LogT.rev() reverses the transformation.

Usage

LogT(x, base = exp(1))
LogT.rev(x, base = exp(1))

Arguments

x	A numeric vector or univariate time series of class ts.
base	A numeric value corresponding to the base with respect to which logarithms are computed. Default: exp(1).

Value

A vector of the same length as x containing the transformed values.

Author(s)

Rebecca Pontes Salles

References

R. H. Shumway, D. S. Stoffer, Time Series Analysis and Its Applications: With R Examples, Springer, New York, NY, 4 edition, 2017.

See Also

Other transformation methods: Diff(), WaveletT(), emd(), mas(), mlm_io(), outliers_bp(),
pct(), train_test_subset()

Examples

data(NN5.A)
LogT(NN5.A[,10])

LT

Time series transformation methods

Description

Constructors for the processing class representing a time series processing method based on a particular time series transformation.

Usage

```
LT(base = exp(1))
BoxCoxT(lambda = NULL, prep_par = NULL, postp_par = NULL, ...)
WT(
    level = NULL,
    filter = NULL,
    boundary = "periodic",
```

```
prep_par = NULL,
 postp_par = NULL,
  . . .
)
subsetting(train_perc = 0.8, test_len = NULL)
SW(window_len = NULL)
NAS(na.action = stats::na.omit, prep_par = NULL)
MinMax(min = NULL, max = NULL, byRow = TRUE)
AN(min = NULL, max = NULL, byRow = TRUE, outlier.rm = TRUE, alpha = 1.5)
DIFF(
  lag = NULL,
 differences = NULL,
 type = "simple",
 postp_par = list(addinit = FALSE)
)
MAS(order = NULL, prep_par = NULL, postp_par = list(addinit = FALSE))
PCT(postp_par = NULL)
EMD(num_imfs = 0, meaningfulImfs = NULL, prep_par = NULL)
```

Arguments

base	LogT
lambda	See BCT
prep_par	List of named parameters required by prep_func.
postp_par	List of named parameters required by postp_func.
	Other parameters to be encapsulated in the class object.
level	See WaveletT
filter	See WaveletT
boundary	See WaveletT
train_perc	See train_test_subset
test_len	See train_test_subset
window_len	See sw
na.action	Function for handling missing values in time series data
min	See an
max	See an
byRow	See an

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```
outlier.rmSee analphaSee anlagSee DiffdifferencesSee DifftypeSee DifforderSee masnum_imfsSee emdmeaningfulImfsSee emd
```

Value

An object of class processing.

Mapping-based nonstationary transformation methods

LT: Logarithmic transform. prep_func set as LogT and postp_func set as LogT.rev. BoxCoxT: Box-Cox transform. prep_func set as BCT and postp_func set as BCT.rev. DIFF: Differencing. prep_func set as Diff and postp_func set as Diff.rev. MAS: Moving average smoothing. prep_func set as mas and postp_func set as mas.rev. PCT: Percentage change transform. prep_func set as pct and postp_func set as pct.rev.

Splitting-based nonstationary transformation methods

WT: Wavelet transform. prep_func set as WaveletT and postp_func set as WaveletT.rev. EMD: Empirical mode decomposition. prep_func set as emd and postp_func set as emd.rev.

Data subsetting methods

subsetting: Subsetting data into training and testing sets. prep_func set as train_test_subset and postp_func set to NULL.

SW: Sliding windows. prep_func set as sw and postp_func set to NULL.

Methods for handling missing values

NAS: Missing values treatment. prep_func set as parameter na.action and postp_func set to NULL.

Normalization methods

MinMax: MinMax normalization. prep_func set as minmax and postp_func set to minmax.rev. AN: Adaptive normalization. prep_func set as an and postp_func set to an.rev.

Author(s)

Rebecca Pontes Salles

MAPE

References

R. Salles, K. Belloze, F. Porto, P.H. Gonzalez, and E. Ogasawara. Nonstationary time series transformation methods: An experimental review. Knowledge-Based Systems, 164:274-291, 2019.

See Also

Other constructors: ARIMA(), MSE_eval(), evaluating(), modeling(), processing(), tspred()

MAPE

MAPE error of prediction

Description

The function calculates the MAPE error between actual and predicted values.

Usage

MAPE(actual, prediction)

Arguments

actual	A vector or univariate time series containing actual values for a time series that are to be compared against its respective predictions.
prediction	A vector or univariate time series containing time series predictions that are to be compared against the values in actual.

Value

A numeric value of the MAPE error of prediction.

Author(s)

Rebecca Pontes Salles

References

Z. Chen and Y. Yang, 2004, Assessing forecast accuracy measures, Preprint Series, n. 2004-2010, p. 2004-10.

See Also

sMAPE, MSE, NMSE, MAXError

Examples

```
data(SantaFe.A,SantaFe.A.cont)
pred <- marimapred(SantaFe.A,n.ahead=100)
MAPE(SantaFe.A.cont[,1], pred)</pre>
```

marimapar

Description

The function returns the parameters of a set of automatically fitted ARIMA models, including nonseasonal and seasonal orders and drift. Based on multiple application of the arimapar function.

Usage

```
marimapar(timeseries, na.action = stats::na.omit, xreg = NULL)
```

Arguments

timeseries	A vector, matrix, or data frame which contains a set of time series used for fitting ARIMA models. Each column corresponds to one time series.
na.action	A function for treating missing values in timeseries. The default function is na.omit, which omits any missing values found in timeseries.
xreg	A vector, matrix, data frame or times series of external regressors used for fitting all the ARIMA models. It must have the same number of rows as TimeSeries. Ignored if NULL.

Details

See the arimapar function.

Value

A list of numeric vectors, each one giving the number of AR, MA, seasonal AR and seasonal MA coefficients, plus the period and the number of non-seasonal and seasonal differences of the automatically fitted ARIMA models. It is also presented the value of the fitted drift constants.

References

See the arimapar function.

See Also

arimapar, arimapred, marimapred

marimapred

Description

The function predicts and returns the next n consecutive values of a set of time series using automatically fitted ARIMA models. Based on multiple application of the arimapred function.

Usage

```
marimapred(
  TimeSeries,
  TimeSeriesCont = NULL,
  n.ahead = NULL,
  na.action = stats::na.omit,
  xreg = NULL,
  newxreg = NULL,
  se.fit = FALSE,
  plot = FALSE,
  range.p = 0.2,
  ylab = NULL,
  xlab = NULL,
  main = NULL
)
```

Arguments

TimeSeries	A vector, matrix, or data frame which contains a set of time series used for fitting ARIMA models. Each column corresponds to one time series.
TimeSeriesCont	A vector, matrix, or data frame containing continuation points for TimeSeries with actual values. Each column corresponds to one time series. Ignored if NULL.
n.ahead	A numeric vector (or a single numeric value) with the number of consecutive values which are to be predicted of each respective time series in TimeSeries. If n. ahead is NULL, the number of values to be predicted of each time series in TimeSeries is assumed to be equal to the number of rows in each respective time series in TimeSeriesCont. Required when TimeSeriesCont is NULL.
na.action	A function for treating missing values in TimeSeries and TimeSeriesCont. The default function is na.omit, which omits any missing values found in TimeSeries or TimeSeriesCont.
xreg	A list of vectors, matrices, data frames or times series of external regressors used for fitting the ARIMA models. The first component of the list contains external regressors for the first time series in TimeSeries and therefore must have the same number of rows as this respective time series. This is also valid for the second component, and so forth. Ignored if NULL.

newxreg	A list of vectors, matrices, data frames or times series with new values of xreg to be used for prediction. The first component of the list must have at least the same number of rows as the respective first value in n.ahead or, if n.ahead is NULL, the number of continuation points in the respective first time series in TimeSeriesCont. This is also valid for the second component, and so forth. Ignored if NULL.
se.fit	If se.fit is TRUE, the standard errors of the predictions are returned.
plot	A Boolean parameter which defines whether the function arimapred will gen- erate a graphic. If plot is TRUE, graphics will be generated for each time series in TimeSeries.
range.p	A percentage which defines how much the range of the graphics' y-axis will be increased from the minimum limits imposed by data.
ylab	A title for the graphics' y-axis. Ignored if NULL. ~~Describe ylab here~~
xlab	A title for the graphics' x-axis. Ignored if NULL. ~~Describe xlab here~~
main	An overall title for the graphics. Ignored if NULL. ~~Describe main here~~

Details

See the arimapred function.

Value

A vector of time series of predictions, if the number of consecutive values predicted of each time series in TimeSeries is the same, otherwise a list of time series of predictions.

If se.fit is TRUE, a vector of lists, each one with the components pred, the predictions, and se, the estimated standard errors. Both components are time series. See the predict.Arima function in the stats package and the function arimapred.

Author(s)

Rebecca Pontes Salles

References

See the arimapred function. the literature/web site here ~

See Also

arimapred ~

Examples

```
data(SantaFe.A,SantaFe.A.cont)
marimapred(SantaFe.A,SantaFe.A.cont)
```

Description

The mas() function returns a simple moving average smoother of the provided time series. mas.rev() reverses the transformation(smoothing) process.

Usage

mas(x, order, ...)

mas.rev(xm, xi, order, addinit = TRUE)

Arguments

х	A numeric vector or univariate time series.
order	Order of moving average smoother. If NULL, it is automatically selected by fittestMAS.
	Additional arguments passed to fittestMAS.
xm	A numeric vector or univariate time series that has been moving average smoothed. Possibly returned by mas().
xi	Initial order-1 values/observations used for reverse smoothing. First order-1 known non-transformed values used to recursively obtain the original series. By default, mas() returns xi as an attribute.
addinit	If TRUE, xi is included in the return.

Details

The moving average smoother transformation is given by

 $(1/k) * (x[t] + x[t+1] + \dots + x[t+k-1])$

where k=order, t assume values in the range 1: (n-k+1), and n=length(x). See also the ma of the forecast package.

Value

Numerical time series of length length(x)-order+1 containing the simple moving average smoothed values.

Author(s)

Rebecca Pontes Salles

mas

mas

References

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

Other transformation methods: Diff(), LogT(), WaveletT(), emd(), mlm_io(), outliers_bp(),
pct(), train_test_subset()

Examples

```
data(CATS)
m <- mas(CATS[,1],order=5)
#automatically select order of moving average
m <- mas(CATS[,1],order=NULL,h=20)
x <- mas.rev(m, attributes(m)$xi, attributes(m)$order)
all(round(x,4)==round(CATS[,1],4))</pre>
```

MAXError

Maximal error of prediction

Description

The function calculates the maximal error between actual and predicted values.

Usage

```
MAXError(actual, prediction)
```

Arguments

actual	A vector or univariate time series containing actual values for a time series that are to be compared against its respective predictions.
prediction	A vector or univariate time series containing time series predictions that are to be compared against the values in actual.

Value

A numeric value of the maximal error of prediction.

Author(s)

Rebecca Pontes Salles

minmax

See Also

sMAPE, MAPE

Examples

```
data(SantaFe.A,SantaFe.A.cont)
pred <- marimapred(SantaFe.A,n.ahead=100)
MAXError(SantaFe.A.cont[,1], pred)</pre>
```

minmax

Minmax Data Normalization

Description

The minmax() function normalizes data of the provided time series to bring values into the range [0,1]. minmax.rev() reverses the normalization.

Usage

minmax(data, max = NULL, min = NULL, byRow = FALSE)

```
minmax.rev(data, max, min)
```

Arguments

data	A numeric vector, a univariate time series containing the values to be normal- ized, or a matrix with sliding windows as returned by sw.
max	Integer indicating the maximal value in data, or a vector with the maximal values of each row (sliding window) in data. If NULL it is automatically computed.
min	Integer indicating the minimum value in data, or a vector with the minimum values of each row (sliding window) in data. If NULL it is automatically computed.
byRow	If TRUE, the normalization is performed by rows (sliding windows). Default set to FALSE.

Details

Ranging is done by using:

$$X' = \frac{(x - x_{min})}{(x_{max} - x_{min})}$$

Value

•

data normalized between 0 and 1. If byRow is TRUE, the function returns data normalized by rows (sliding windows). max and min are returned as attributes.

Author(s)

Rebecca Pontes Salles

References

R.J. Hyndman and G. Athanasopoulos, 2013, Forecasting: principles and practice. OTexts.

E. Ogasawara, L. C. Martinez, D. De Oliveira, G. Zimbrao, G. L. Pappa, and M. Mattoso, 2010, Adaptive Normalization: A novel data normalization approach for non-stationary time series, Proceedings of the International Joint Conference on Neural Networks.

See Also

Other normalization methods: an()

Examples

```
data(CATS)
d <- minmax(CATS[,1])
x <- minmax.rev(d, max = attributes(d)$max, min = attributes(d)$min)
all(round(x,4)==round(CATS[,1],4))
d <- minmax(sw(CATS[,1],5), byRow = TRUE)
x <- minmax.rev(d, max = attributes(d)$max, min = attributes(d)$min)
all(round(x,4)==round(sw(CATS[,1],5),4))
```

```
modeling
```

Time series modeling and prediction

Description

Constructor for the modeling class representing a time series modeling and prediction method based on a particular model. The modeling class has two specialized subclasses linear and MLM reagarding linear models and machine learning based models, respectively.

Usage

```
modeling(
  train_func,
  train_par = NULL,
  pred_func = NULL,
  pred_par = NULL,
  ...,
  subclass = NULL
)
MLM(
```

modeling

```
train_func,
  train_par = NULL,
 pred_func = NULL,
 pred_par = NULL,
  sw = NULL,
 proc = NULL,
  ...,
  subclass = NULL
)
linear(
  train_func,
  train_par = NULL,
 pred_func = NULL,
 pred_par = NULL,
  . . . ,
  subclass = NULL
)
```

Arguments

train_func	A function for training a particular model.
train_par	List of named parameters required by train_func.
pred_func	A function for prediction based on the model trained by train_func.
pred_par	List of named parameters required by pred_func.
	Other parameters to be encapsulated in the class object.
subclass	Name of new specialized subclass object created in case it is provided.
SW	A SW object regarding sliding windows processing. Optional.
proc	A list of processing objects regarding any pre(post)processing needed during training or prediction. Optional.

Value

An object of class modeling.

Author(s)

Rebecca Pontes Salles

See Also

Other constructors: ARIMA(), LT(), MSE_eval(), evaluating(), processing(), tspred()

```
forecast_mean <- function(...){
    do.call(forecast::forecast,c(list(...)))$mean
}</pre>
```

MSE

MSE error of prediction

Description

The function calculates the MSE error between actual and predicted values.

Usage

MSE(actual, prediction)

Arguments

actual	A vector or univariate time series containing actual values for a time series that are to be compared against its respective predictions.
prediction	A vector or univariate time series containing time series predictions that are to be compared against the values in actual.

Value

A numeric value of the MSE error of prediction.

Author(s)

Rebecca Pontes Salles

References

Z. Chen and Y. Yang, 2004, Assessing forecast accuracy measures, Preprint Series, n. 2004-2010, p. 2004-10.

See Also

NMSE, MAPE, sMAPE, MAXError

Ξ

MSE_eval

Examples

```
data(SantaFe.A,SantaFe.A.cont)
pred <- marimapred(SantaFe.A,n.ahead=100)
MSE(SantaFe.A.cont[,1], pred)</pre>
```

MSE_eval

Prediction/modeling quality metrics

Description

Constructors for the evaluating class representing a time series prediction or modeling fitness quality evaluation based on particular metrics.

Usage

MSE_eval()
MMSE_eval(eval_par = list(train.actual = NULL))
RMSE_eval()
MAPE_eval()
sMAPE_eval()
MAXError_eval()
AIC_eval()
BIC_eval()
LogLik_eval()

Arguments

eval_par List of named parameters required by NMSE such as train.actual.

Value

An object of class evaluating.

Error metrics

MSE_eval: Mean Squared Error. NMSE_eval: Normalised Mean Squared Error. RMSE_eval: Root Mean Squared Error. MAPE_eval: Mean Absolute Percentage Error. sMAPE_eval: Symmetric Mean Absolute Percentage Error. MAXError_eval: Maximal Error.

Fitness criteria

AIC_eval: Akaike's Information Criterion.BIC_eval: Schwarz's Bayesian Information Criterion.AICc_eval: Second-order Akaike's Information Criterion.LogLik_eval: Log-Likelihood.

Author(s)

Rebecca Pontes Salles

See Also

Other constructors: ARIMA(), LT(), evaluating(), modeling(), processing(), tspred()

NMSE	
------	--

NMSE error of prediction

Description

The function calculates the NMSE error between actual and predicted values.

Usage

```
NMSE(actual, prediction, train.actual)
```

Arguments

actual	A vector or univariate time series containing actual values for a time series that are to be compared against its respective predictions.
prediction	A vector or univariate time series containing time series predictions that are to be compared against the values in actual.
train.actual	A vector or univariate time series that was used to train the model that produced the predictions in prediction.

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NN3.A

Value

A numeric value of the NMSE error of prediction.

Author(s)

Rebecca Pontes Salles

References

Z. Chen and Y. Yang, 2004, Assessing forecast accuracy measures, Preprint Series, n. 2004-2010, p. 2004-10.

See Also

MSE, MAPE, sMAPE, MAXError

Examples

data(SantaFe.A,SantaFe.A.cont)
pred <- marimapred(SantaFe.A,n.ahead=100)
NMSE(SantaFe.A.cont[,1], pred, SantaFe.A[,1])</pre>

NN3.A

Dataset A of the NN3 Competition

Description

The NN3 Competition dataset composed of monthly time series drawn from homogeneous population of real empirical business time series.

Usage

NN3.A

Format

A data frame with 126 observations on the following 111 variables.

NN3.001 a numeric vector containing the 51 observations of a univariate time series.

NN3.002 a numeric vector containing the 51 observations of a univariate time series.

NN3.003 a numeric vector containing the 51 observations of a univariate time series.

NN3.004 a numeric vector containing the 51 observations of a univariate time series.

NN3.005 a numeric vector containing the 51 observations of a univariate time series.

NN3.006 a numeric vector containing the 51 observations of a univariate time series.

NN3.007 a numeric vector containing the 51 observations of a univariate time series.

NN3.008 a numeric vector containing the 51 observations of a univariate time series. NN3.009 a numeric vector containing the 51 observations of a univariate time series. NN3.010 a numeric vector containing the 51 observations of a univariate time series. **NN3.011** a numeric vector containing the 51 observations of a univariate time series. **NN3.012** a numeric vector containing the 51 observations of a univariate time series. **NN3.013** a numeric vector containing the 51 observations of a univariate time series. **NN3.014** a numeric vector containing the 51 observations of a univariate time series. NN3.015 a numeric vector containing the 51 observations of a univariate time series. **NN3.016** a numeric vector containing the 51 observations of a univariate time series. NN3.017 a numeric vector containing the 51 observations of a univariate time series. NN3.018 a numeric vector containing the 51 observations of a univariate time series. NN3.019 a numeric vector containing the 51 observations of a univariate time series. NN3.020 a numeric vector containing the 51 observations of a univariate time series. **NN3.021** a numeric vector containing the 51 observations of a univariate time series. **NN3.022** a numeric vector containing the 50 observations of a univariate time series. **NN3.023** a numeric vector containing the 51 observations of a univariate time series. NN3.024 a numeric vector containing the 51 observations of a univariate time series. NN3.025 a numeric vector containing the 51 observations of a univariate time series. NN3.026 a numeric vector containing the 51 observations of a univariate time series. NN3.027 a numeric vector containing the 51 observations of a univariate time series. NN3.028 a numeric vector containing the 51 observations of a univariate time series. NN3.029 a numeric vector containing the 51 observations of a univariate time series. NN3.030 a numeric vector containing the 51 observations of a univariate time series. **NN3.031** a numeric vector containing the 51 observations of a univariate time series. **NN3.032** a numeric vector containing the 51 observations of a univariate time series. **NN3.033** a numeric vector containing the 51 observations of a univariate time series. **NN3.034** a numeric vector containing the 51 observations of a univariate time series. NN3.035 a numeric vector containing the 51 observations of a univariate time series. NN3.036 a numeric vector containing the 51 observations of a univariate time series. NN3.037 a numeric vector containing the 51 observations of a univariate time series. NN3.038 a numeric vector containing the 51 observations of a univariate time series. NN3.039 a numeric vector containing the 51 observations of a univariate time series. NN3.040 a numeric vector containing the 51 observations of a univariate time series. NN3.041 a numeric vector containing the 51 observations of a univariate time series. NN3.042 a numeric vector containing the 51 observations of a univariate time series. **NN3.043** a numeric vector containing the 51 observations of a univariate time series. NN3.044 a numeric vector containing the 51 observations of a univariate time series.

NN3.045 a numeric vector containing the 51 observations of a univariate time series. NN3.046 a numeric vector containing the 51 observations of a univariate time series. **NN3.047** a numeric vector containing the 51 observations of a univariate time series. **NN3.048** a numeric vector containing the 51 observations of a univariate time series. **NN3.049** a numeric vector containing the 51 observations of a univariate time series. **NN3.050** a numeric vector containing the 51 observations of a univariate time series. **NN3.051** a numeric vector containing the 123 observations of a univariate time series. NN3.052 a numeric vector containing the 126 observations of a univariate time series. **NN3.053** a numeric vector containing the 126 observations of a univariate time series. NN3.054 a numeric vector containing the 126 observations of a univariate time series. NN3.055 a numeric vector containing the 126 observations of a univariate time series. NN3.056 a numeric vector containing the 126 observations of a univariate time series. NN3.057 a numeric vector containing the 123 observations of a univariate time series. **NN3.058** a numeric vector containing the 122 observations of a univariate time series. **NN3.059** a numeric vector containing the 116 observations of a univariate time series. **NN3.060** a numeric vector containing the 126 observations of a univariate time series. NN3.061 a numeric vector containing the 126 observations of a univariate time series. NN3.062 a numeric vector containing the 122 observations of a univariate time series. NN3.063 a numeric vector containing the 126 observations of a univariate time series. NN3.064 a numeric vector containing the 116 observations of a univariate time series. NN3.065 a numeric vector containing the 126 observations of a univariate time series. NN3.066 a numeric vector containing the 126 observations of a univariate time series. NN3.067 a numeric vector containing the 126 observations of a univariate time series. **NN3.068** a numeric vector containing the 121 observations of a univariate time series. **NN3.069** a numeric vector containing the 121 observations of a univariate time series. **NN3.070** a numeric vector containing the 121 observations of a univariate time series. **NN3.071** a numeric vector containing the 126 observations of a univariate time series. NN3.072 a numeric vector containing the 126 observations of a univariate time series. NN3.073 a numeric vector containing the 126 observations of a univariate time series. NN3.074 a numeric vector containing the 126 observations of a univariate time series. NN3.075 a numeric vector containing the 126 observations of a univariate time series. NN3.076 a numeric vector containing the 126 observations of a univariate time series. NN3.077 a numeric vector containing the 126 observations of a univariate time series. NN3.078 a numeric vector containing the 126 observations of a univariate time series. NN3.079 a numeric vector containing the 126 observations of a univariate time series. **NN3.080** a numeric vector containing the 126 observations of a univariate time series. NN3.081 a numeric vector containing the 126 observations of a univariate time series.

NN3.082 a numeric vector containing the 116 observations of a univariate time series. NN3.083 a numeric vector containing the 126 observations of a univariate time series. NN3.084 a numeric vector containing the 122 observations of a univariate time series. NN3.085 a numeric vector containing the 126 observations of a univariate time series. NN3.086 a numeric vector containing the 126 observations of a univariate time series. NN3.087 a numeric vector containing the 121 observations of a univariate time series. NN3.088 a numeric vector containing the 78 observations of a univariate time series. NN3.089 a numeric vector containing the 126 observations of a univariate time series. NN3.090 a numeric vector containing the 126 observations of a univariate time series. NN3.091 a numeric vector containing the 116 observations of a univariate time series. NN3.092 a numeric vector containing the 115 observations of a univariate time series. NN3.093 a numeric vector containing the 126 observations of a univariate time series. NN3.094 a numeric vector containing the 116 observations of a univariate time series. **NN3.095** a numeric vector containing the 126 observations of a univariate time series. NN3.096 a numeric vector containing the 126 observations of a univariate time series. NN3.097 a numeric vector containing the 126 observations of a univariate time series. **NN3.098** a numeric vector containing the 126 observations of a univariate time series. NN3.099 a numeric vector containing the 115 observations of a univariate time series. NN3.100 a numeric vector containing the 116 observations of a univariate time series. NN3_101 a numeric vector containing the 126 observations of a univariate time series. NN3_102 a numeric vector containing the 126 observations of a univariate time series. NN3_103 a numeric vector containing the 126 observations of a univariate time series. NN3_104 a numeric vector containing the 115 observations of a univariate time series. NN3_105 a numeric vector containing the 126 observations of a univariate time series. NN3_106 a numeric vector containing the 126 observations of a univariate time series. NN3_107 a numeric vector containing the 126 observations of a univariate time series. NN3_108 a numeric vector containing the 115 observations of a univariate time series. NN3_109 a numeric vector containing the 123 observations of a univariate time series. NN3_110 a numeric vector containing the 126 observations of a univariate time series. NN3_111 a numeric vector containing the 126 observations of a univariate time series.

Details

The NN3 Competition's Dataset A contains 111 different monthly time series. Each of this time series possess from 50 to 126 observations. Each competitor in NN3 was asked to predict the next 18 corresponding observations of each times series (NN3.A.cont). The performance evaluation done by NN3 Competition was based on the mean SMAPE error of prediction found by the competitors across all time series.

NN3.A.cont

Source

NN3 2007, The NN3 Competition: Forecasting competition for artificial neural networks and computational intelligence. URL: http://www.neural-forecasting-competition.com/NN3/index.htm.

References

S.F. Crone, M. Hibon, and K. Nikolopoulos, 2011, Advances in forecasting with neural networks? Empirical evidence from the NN3 competition on time series prediction, International Journal of Forecasting, v. 27, n. 3 (Jul.), p. 635-660.

See Also

NN3.A.cont ~

Examples

```
data(NN3.A)
str(NN3.A)
plot(ts(NN3.A["NN3_111"]))
```

NN3.A.cont

Continuation dataset of the Dataset A of the NN3 Competition

Description

A dataset of univariate time series providing 18 points beyond the end of the time series in NN3.A.

Usage

NN3.A.cont

Format

A data frame with 18 observations on the following 111 variables.

NN3.001 a numeric vector containing further observations of NN3.001 in NN3.A.

NN3.002 a numeric vector containing further observations of NN3.002 in NN3.A.

NN3.003 a numeric vector containing further observations of NN3.003 in NN3.A.

NN3.004 a numeric vector containing further observations of NN3.004 in NN3.A.

NN3.005 a numeric vector containing further observations of NN3.005 in NN3.A.

NN3.006 a numeric vector containing further observations of NN3.006 in NN3.A.

NN3.007 a numeric vector containing further observations of NN3.007 in NN3.A.

NN3.008 a numeric vector containing further observations of NN3.008 in NN3.A.

NN3.009 a numeric vector containing further observations of NN3.009 in NN3.A. NN3.010 a numeric vector containing further observations of NN3.010 in NN3.A. NN3.011 a numeric vector containing further observations of NN3.011 in NN3.A. **NN3.012** a numeric vector containing further observations of NN3.012 in NN3.A. **NN3.013** a numeric vector containing further observations of NN3.013 in NN3.A. **NN3.014** a numeric vector containing further observations of NN3.014 in NN3.A. **NN3.015** a numeric vector containing further observations of NN3.015 in NN3.A. **NN3.016** a numeric vector containing further observations of NN3.016 in NN3.A. **NN3.017** a numeric vector containing further observations of NN3.017 in NN3.A. NN3.018 a numeric vector containing further observations of NN3.018 in NN3.A. NN3.019 a numeric vector containing further observations of NN3.019 in NN3.A. NN3.020 a numeric vector containing further observations of NN3.020 in NN3.A. NN3.021 a numeric vector containing further observations of NN3.021 in NN3.A. **NN3.022** a numeric vector containing further observations of NN3.022 in NN3.A. **NN3.023** a numeric vector containing further observations of NN3.023 in NN3.A. **NN3.024** a numeric vector containing further observations of NN3.024 in NN3.A. NN3.025 a numeric vector containing further observations of NN3.025 in NN3.A. **NN3.026** a numeric vector containing further observations of NN3.026 in NN3.A. NN3.027 a numeric vector containing further observations of NN3.027 in NN3.A. NN3.028 a numeric vector containing further observations of NN3.028 in NN3.A. NN3.029 a numeric vector containing further observations of NN3.029 in NN3.A. NN3.030 a numeric vector containing further observations of NN3.030 in NN3.A. NN3.031 a numeric vector containing further observations of NN3.031 in NN3.A. **NN3.032** a numeric vector containing further observations of NN3.032 in NN3.A. **NN3.033** a numeric vector containing further observations of NN3.033 in NN3.A. **NN3.034** a numeric vector containing further observations of NN3.034 in NN3.A. **NN3.035** a numeric vector containing further observations of NN3.035 in NN3.A. NN3.036 a numeric vector containing further observations of NN3.036 in NN3.A. NN3.037 a numeric vector containing further observations of NN3.037 in NN3.A. NN3.038 a numeric vector containing further observations of NN3.038 in NN3.A. NN3.039 a numeric vector containing further observations of NN3.039 in NN3.A. NN3.040 a numeric vector containing further observations of NN3.040 in NN3.A. NN3.041 a numeric vector containing further observations of NN3.041 in NN3.A. NN3.042 a numeric vector containing further observations of NN3.042 in NN3.A. NN3.043 a numeric vector containing further observations of NN3.043 in NN3.A. **NN3.044** a numeric vector containing further observations of NN3.044 in NN3.A. NN3.045 a numeric vector containing further observations of NN3.045 in NN3.A.

NN3.046 a numeric vector containing further observations of NN3.046 in NN3.A. NN3.047 a numeric vector containing further observations of NN3.047 in NN3.A. NN3.048 a numeric vector containing further observations of NN3.048 in NN3.A. **NN3.049** a numeric vector containing further observations of NN3.049 in NN3.A. **NN3.050** a numeric vector containing further observations of NN3.050 in NN3.A. **NN3.051** a numeric vector containing further observations of NN3.051 in NN3.A. **NN3.052** a numeric vector containing further observations of NN3.052 in NN3.A. **NN3.053** a numeric vector containing further observations of NN3.053 in NN3.A. **NN3.054** a numeric vector containing further observations of NN3.054 in NN3.A. NN3.055 a numeric vector containing further observations of NN3.055 in NN3.A. NN3.056 a numeric vector containing further observations of NN3.056 in NN3.A. NN3.057 a numeric vector containing further observations of NN3.057 in NN3.A. NN3.058 a numeric vector containing further observations of NN3.058 in NN3.A. **NN3.059** a numeric vector containing further observations of NN3.059 in NN3.A. **NN3.060** a numeric vector containing further observations of NN3.060 in NN3.A. **NN3.061** a numeric vector containing further observations of NN3.061 in NN3.A. NN3.062 a numeric vector containing further observations of NN3.062 in NN3.A. NN3.063 a numeric vector containing further observations of NN3.063 in NN3.A. NN3.064 a numeric vector containing further observations of NN3.064 in NN3.A. NN3.065 a numeric vector containing further observations of NN3.065 in NN3.A. NN3.066 a numeric vector containing further observations of NN3.066 in NN3.A. NN3.067 a numeric vector containing further observations of NN3.067 in NN3.A. NN3.068 a numeric vector containing further observations of NN3.068 in NN3.A. **NN3.069** a numeric vector containing further observations of NN3.069 in NN3.A. **NN3.070** a numeric vector containing further observations of NN3.070 in NN3.A. **NN3.071** a numeric vector containing further observations of NN3.071 in NN3.A. **NN3.072** a numeric vector containing further observations of NN3.072 in NN3.A. NN3.073 a numeric vector containing further observations of NN3.073 in NN3.A. NN3.074 a numeric vector containing further observations of NN3.074 in NN3.A. NN3.075 a numeric vector containing further observations of NN3.075 in NN3.A. NN3.076 a numeric vector containing further observations of NN3.076 in NN3.A. NN3.077 a numeric vector containing further observations of NN3.077 in NN3.A. NN3.078 a numeric vector containing further observations of NN3.078 in NN3.A. NN3.079 a numeric vector containing further observations of NN3.079 in NN3.A. NN3.080 a numeric vector containing further observations of NN3.080 in NN3.A. NN3.081 a numeric vector containing further observations of NN3.081 in NN3.A. NN3.082 a numeric vector containing further observations of NN3.082 in NN3.A.

NN3.083 a numeric vector containing further observations of NN3.083 in NN3.A. NN3.084 a numeric vector containing further observations of NN3.084 in NN3.A. **NN3.085** a numeric vector containing further observations of NN3.085 in NN3.A. **NN3.086** a numeric vector containing further observations of NN3.086 in NN3.A. **NN3.087** a numeric vector containing further observations of NN3.087 in NN3.A. **NN3.088** a numeric vector containing further observations of NN3.088 in NN3.A. **NN3.089** a numeric vector containing further observations of NN3.089 in NN3.A. **NN3.090** a numeric vector containing further observations of NN3.090 in NN3.A. **NN3.091** a numeric vector containing further observations of NN3.091 in NN3.A. NN3.092 a numeric vector containing further observations of NN3.092 in NN3.A. NN3.093 a numeric vector containing further observations of NN3.093 in NN3.A. NN3.094 a numeric vector containing further observations of NN3.094 in NN3.A. NN3.095 a numeric vector containing further observations of NN3.095 in NN3.A. NN3.096 a numeric vector containing further observations of NN3.096 in NN3.A. **NN3.097** a numeric vector containing further observations of NN3.097 in NN3.A. NN3.098 a numeric vector containing further observations of NN3.098 in NN3.A. NN3.099 a numeric vector containing further observations of NN3.099 in NN3.A. NN3.100 a numeric vector containing further observations of NN3.100 in NN3.A. NN3_101 a numeric vector containing further observations of NN3_101 in NN3.A. NN3_102 a numeric vector containing further observations of NN3_102 in NN3.A. NN3_103 a numeric vector containing further observations of NN3_103 in NN3.A. NN3_104 a numeric vector containing further observations of NN3_104 in NN3.A. NN3_105 a numeric vector containing further observations of NN3_105 in NN3.A. **NN3_106** a numeric vector containing further observations of NN3_106 in NN3.A. NN3_107 a numeric vector containing further observations of NN3_107 in NN3.A. **NN3** 108 a numeric vector containing further observations of NN3_108 in NN3.A. **NN3_109** a numeric vector containing further observations of NN3_109 in NN3.A. **NN3_110** a numeric vector containing further observations of NN3_110 in NN3.A. **NN3** 111 a numeric vector containing further observations of NN3_111 in NN3.A.

Details

Contains the 18 observations which were to be predicted of each time series in Dataset A (NN3.A) as demanded by the NN3 Competition.

Source

NN3 2007, The NN3 Competition: Forecasting competition for artificial neural networks and computational intelligence. URL: http://www.neural-forecasting-competition.com/NN3/ index.htm.

NN5.A

References

S.F. Crone, M. Hibon, and K. Nikolopoulos, 2011, Advances in forecasting with neural networks? Empirical evidence from the NN3 competition on time series prediction, International Journal of Forecasting, v. 27, n. 3 (Jul.), p. 635-660.

See Also

NN3.A~

Examples

```
data(NN3.A.cont)
str(NN3.A.cont)
plot(ts(NN3.A.cont["NN3_111"]))
```

NN5.A

Dataset A of the NN5 Competition

Description

The NN5 Competition dataset composed of daily time series originated from the observation of daily withdrawals at 111 randomly selected different cash machines at different locations within England.

Usage

NN5.A

Format

A data frame with 735 observations on the following 111 variables.

NN5.001 a numeric vector containing observations of a univariate time series.
NN5.002 a numeric vector containing observations of a univariate time series.
NN5.003 a numeric vector containing observations of a univariate time series.
NN5.004 a numeric vector containing observations of a univariate time series.
NN5.005 a numeric vector containing observations of a univariate time series.
NN5.006 a numeric vector containing observations of a univariate time series.
NN5.007 a numeric vector containing observations of a univariate time series.
NN5.008 a numeric vector containing observations of a univariate time series.
NN5.009 a numeric vector containing observations of a univariate time series.
NN5.010 a numeric vector containing observations of a univariate time series.
NN5.011 a numeric vector containing observations of a univariate time series.

NN5.012 a numeric vector containing observations of a univariate time series. NN5.013 a numeric vector containing observations of a univariate time series. NN5.014 a numeric vector containing observations of a univariate time series. NN5.015 a numeric vector containing observations of a univariate time series. NN5.016 a numeric vector containing observations of a univariate time series. **NN5.017** a numeric vector containing observations of a univariate time series. **NN5.018** a numeric vector containing observations of a univariate time series. NN5.019 a numeric vector containing observations of a univariate time series. NN5.020 a numeric vector containing observations of a univariate time series. NN5.021 a numeric vector containing observations of a univariate time series. NN5.022 a numeric vector containing observations of a univariate time series. NN5.023 a numeric vector containing observations of a univariate time series. NN5.024 a numeric vector containing observations of a univariate time series. NN5.025 a numeric vector containing observations of a univariate time series. NN5.026 a numeric vector containing observations of a univariate time series. NN5.027 a numeric vector containing observations of a univariate time series. NN5.028 a numeric vector containing observations of a univariate time series. NN5.029 a numeric vector containing observations of a univariate time series. NN5.030 a numeric vector containing observations of a univariate time series. NN5.031 a numeric vector containing observations of a univariate time series. NN5.032 a numeric vector containing observations of a univariate time series. NN5.033 a numeric vector containing observations of a univariate time series. NN5.034 a numeric vector containing observations of a univariate time series. NN5.035 a numeric vector containing observations of a univariate time series. NN5.036 a numeric vector containing observations of a univariate time series. NN5.037 a numeric vector containing observations of a univariate time series. NN5.038 a numeric vector containing observations of a univariate time series. NN5.039 a numeric vector containing observations of a univariate time series. NN5.040 a numeric vector containing observations of a univariate time series. NN5.041 a numeric vector containing observations of a univariate time series. NN5.042 a numeric vector containing observations of a univariate time series. NN5.043 a numeric vector containing observations of a univariate time series. NN5.044 a numeric vector containing observations of a univariate time series. NN5.045 a numeric vector containing observations of a univariate time series. NN5.046 a numeric vector containing observations of a univariate time series. NN5.047 a numeric vector containing observations of a univariate time series. NN5.048 a numeric vector containing observations of a univariate time series.

NN5.049 a numeric vector containing observations of a univariate time series. NN5.050 a numeric vector containing observations of a univariate time series. NN5.051 a numeric vector containing observations of a univariate time series. NN5.052 a numeric vector containing observations of a univariate time series. NN5.053 a numeric vector containing observations of a univariate time series. **NN5.054** a numeric vector containing observations of a univariate time series. **NN5.055** a numeric vector containing observations of a univariate time series. NN5.056 a numeric vector containing observations of a univariate time series. NN5.057 a numeric vector containing observations of a univariate time series. NN5.058 a numeric vector containing observations of a univariate time series. NN5.059 a numeric vector containing observations of a univariate time series. NN5.060 a numeric vector containing observations of a univariate time series. NN5.061 a numeric vector containing observations of a univariate time series. NN5.062 a numeric vector containing observations of a univariate time series. NN5.063 a numeric vector containing observations of a univariate time series. NN5.064 a numeric vector containing observations of a univariate time series. NN5.065 a numeric vector containing observations of a univariate time series. NN5.066 a numeric vector containing observations of a univariate time series. NN5.067 a numeric vector containing observations of a univariate time series. NN5.068 a numeric vector containing observations of a univariate time series. NN5.069 a numeric vector containing observations of a univariate time series. NN5.070 a numeric vector containing observations of a univariate time series. NN5.071 a numeric vector containing observations of a univariate time series. NN5.072 a numeric vector containing observations of a univariate time series. NN5.073 a numeric vector containing observations of a univariate time series. NN5.074 a numeric vector containing observations of a univariate time series. NN5.075 a numeric vector containing observations of a univariate time series. NN5.076 a numeric vector containing observations of a univariate time series. NN5.077 a numeric vector containing observations of a univariate time series. NN5.078 a numeric vector containing observations of a univariate time series. NN5.079 a numeric vector containing observations of a univariate time series. NN5.080 a numeric vector containing observations of a univariate time series. NN5.081 a numeric vector containing observations of a univariate time series. NN5.082 a numeric vector containing observations of a univariate time series. NN5.083 a numeric vector containing observations of a univariate time series. NN5.084 a numeric vector containing observations of a univariate time series. NN5.085 a numeric vector containing observations of a univariate time series.

NN5.086 a numeric vector containing observations of a univariate time series. NN5.087 a numeric vector containing observations of a univariate time series. NN5.088 a numeric vector containing observations of a univariate time series. NN5.089 a numeric vector containing observations of a univariate time series. **NN5.090** a numeric vector containing observations of a univariate time series. **NN5.091** a numeric vector containing observations of a univariate time series. NN5.092 a numeric vector containing observations of a univariate time series. NN5.093 a numeric vector containing observations of a univariate time series. NN5.094 a numeric vector containing observations of a univariate time series. NN5.095 a numeric vector containing observations of a univariate time series. NN5.096 a numeric vector containing observations of a univariate time series. NN5.097 a numeric vector containing observations of a univariate time series. NN5.098 a numeric vector containing observations of a univariate time series. NN5.099 a numeric vector containing observations of a univariate time series. NN5.100 a numeric vector containing observations of a univariate time series. NN5.101 a numeric vector containing observations of a univariate time series. NN5.102 a numeric vector containing observations of a univariate time series. NN5.103 a numeric vector containing observations of a univariate time series. NN5.104 a numeric vector containing observations of a univariate time series. NN5.105 a numeric vector containing observations of a univariate time series. NN5.106 a numeric vector containing observations of a univariate time series. NN5.107 a numeric vector containing observations of a univariate time series. NN5.108 a numeric vector containing observations of a univariate time series. **NN5.109** a numeric vector containing observations of a univariate time series. NN5.110 a numeric vector containing observations of a univariate time series. NN5.111 a numeric vector containing observations of a univariate time series.

Details

The NN5 Competition's Dataset A contains 111 different daily time series. Each of these time series possesses 735 observations, and may present missing data. The time series also show different patterns of single or multiple overlying seasonal properties. Each competitor in NN5 was asked to predict the next 56 corresponding observations of each times series (NN5.A.cont). The performance evaluation done by NN5 Competition was based on the mean SMAPE error of prediction found by the competitors across all time series.

Source

NN5 2008, The NN5 Competition: Forecasting competition for artificial neural networks and computational intelligence. URL: http://www.neural-forecasting-competition.com/NN5/index.htm.

NN5.A.cont

References

S.F. Crone, 2008, Results of the NN5 time series forecasting competition. Hong Kong, Presentation at the IEEE world congress on computational intelligence. WCCI'2008.

See Also

NN5.A.cont ~

Examples

```
data(NN5.A)
str(NN5.A)
plot(ts(NN5.A["NN5.111"]))
```

NN5.A.cont

Continuation dataset of the Dataset A of the NN5 Competition

Description

A dataset of univariate time series providing 56 points beyond the end of the time series in NN5.A.

Usage

NN5.A.cont

Format

A data frame with 56 observations on the following 111 variables.

NN5.001 a numeric vector containing further observations of NN5.001 in NN5.A.
NN5.002 a numeric vector containing further observations of NN5.002 in NN5.A.
NN5.003 a numeric vector containing further observations of NN5.003 in NN5.A.
NN5.004 a numeric vector containing further observations of NN5.004 in NN5.A.
NN5.005 a numeric vector containing further observations of NN5.005 in NN5.A.
NN5.006 a numeric vector containing further observations of NN5.006 in NN5.A.
NN5.007 a numeric vector containing further observations of NN5.007 in NN5.A.
NN5.008 a numeric vector containing further observations of NN5.008 in NN5.A.
NN5.009 a numeric vector containing further observations of NN5.009 in NN5.A.
NN5.010 a numeric vector containing further observations of NN5.010 in NN5.A.
NN5.011 a numeric vector containing further observations of NN5.011 in NN5.A.
NN5.012 a numeric vector containing further observations of NN5.012 in NN5.A.
NN5.013 a numeric vector containing further observations of NN5.013 in NN5.A.
NN5.014 a numeric vector containing further observations of NN5.014 in NN5.A.

NN5.015 a numeric vector containing further observations of NN5.015 in NN5.A. NN5.016 a numeric vector containing further observations of NN5.016 in NN5.A. NN5.017 a numeric vector containing further observations of NN5.017 in NN5.A. **NN5.018** a numeric vector containing further observations of NN5.018 in NN5.A. **NN5.019** a numeric vector containing further observations of NN5.019 in NN5.A. **NN5.020** a numeric vector containing further observations of NN5.020 in NN5.A. **NN5.021** a numeric vector containing further observations of NN5.021 in NN5.A. **NN5.022** a numeric vector containing further observations of NN5.022 in NN5.A. **NN5.023** a numeric vector containing further observations of NN5.023 in NN5.A. NN5.024 a numeric vector containing further observations of NN5.024 in NN5.A. NN5.025 a numeric vector containing further observations of NN5.025 in NN5.A. NN5.026 a numeric vector containing further observations of NN5.026 in NN5.A. NN5.027 a numeric vector containing further observations of NN5.027 in NN5.A. **NN5.028** a numeric vector containing further observations of NN5.028 in NN5.A. **NN5.029** a numeric vector containing further observations of NN5.029 in NN5.A. **NN5.030** a numeric vector containing further observations of NN5.030 in NN5.A. NN5.031 a numeric vector containing further observations of NN5.031 in NN5.A. NN5.032 a numeric vector containing further observations of NN5.032 in NN5.A. NN5.033 a numeric vector containing further observations of NN5.033 in NN5.A. NN5.034 a numeric vector containing further observations of NN5.034 in NN5.A. NN5.035 a numeric vector containing further observations of NN5.035 in NN5.A. NN5.036 a numeric vector containing further observations of NN5.036 in NN5.A. NN5.037 a numeric vector containing further observations of NN5.037 in NN5.A. **NN5.038** a numeric vector containing further observations of NN5.038 in NN5.A. **NN5.039** a numeric vector containing further observations of NN5.039 in NN5.A. **NN5.040** a numeric vector containing further observations of NN5.040 in NN5.A. **NN5.041** a numeric vector containing further observations of NN5.041 in NN5.A. NN5.042 a numeric vector containing further observations of NN5.042 in NN5.A. NN5.043 a numeric vector containing further observations of NN5.043 in NN5.A. NN5.044 a numeric vector containing further observations of NN5.044 in NN5.A. NN5.045 a numeric vector containing further observations of NN5.045 in NN5.A. NN5.046 a numeric vector containing further observations of NN5.046 in NN5.A. NN5.047 a numeric vector containing further observations of NN5.047 in NN5.A. NN5.048 a numeric vector containing further observations of NN5.048 in NN5.A. NN5.049 a numeric vector containing further observations of NN5.049 in NN5.A. **NN5.050** a numeric vector containing further observations of NN5.050 in NN5.A. NN5.051 a numeric vector containing further observations of NN5.051 in NN5.A.

NN5.052 a numeric vector containing further observations of NN5.052 in NN5.A. NN5.053 a numeric vector containing further observations of NN5.053 in NN5.A. NN5.054 a numeric vector containing further observations of NN5.054 in NN5.A. **NN5.055** a numeric vector containing further observations of NN5.055 in NN5.A. **NN5.056** a numeric vector containing further observations of NN5.056 in NN5.A. **NN5.057** a numeric vector containing further observations of NN5.057 in NN5.A. **NN5.058** a numeric vector containing further observations of NN5.058 in NN5.A. **NN5.059** a numeric vector containing further observations of NN5.059 in NN5.A. **NN5.060** a numeric vector containing further observations of NN5.060 in NN5.A. NN5.061 a numeric vector containing further observations of NN5.061 in NN5.A. NN5.062 a numeric vector containing further observations of NN5.062 in NN5.A. NN5.063 a numeric vector containing further observations of NN5.063 in NN5.A. NN5.064 a numeric vector containing further observations of NN5.064 in NN5.A. **NN5.065** a numeric vector containing further observations of NN5.065 in NN5.A. **NN5.066** a numeric vector containing further observations of NN5.066 in NN5.A. **NN5.067** a numeric vector containing further observations of NN5.067 in NN5.A. NN5.068 a numeric vector containing further observations of NN5.068 in NN5.A. NN5.069 a numeric vector containing further observations of NN5.069 in NN5.A. NN5.070 a numeric vector containing further observations of NN5.070 in NN5.A. NN5.071 a numeric vector containing further observations of NN5.071 in NN5.A. NN5.072 a numeric vector containing further observations of NN5.072 in NN5.A. NN5.073 a numeric vector containing further observations of NN5.073 in NN5.A. NN5.074 a numeric vector containing further observations of NN5.074 in NN5.A. **NN5.075** a numeric vector containing further observations of NN5.075 in NN5.A. **NN5.076** a numeric vector containing further observations of NN5.076 in NN5.A. NN5.077 a numeric vector containing further observations of NN5.077 in NN5.A. NN5.078 a numeric vector containing further observations of NN5.078 in NN5.A. NN5.079 a numeric vector containing further observations of NN5.079 in NN5.A. NN5.080 a numeric vector containing further observations of NN5.080 in NN5.A. NN5.081 a numeric vector containing further observations of NN5.081 in NN5.A. NN5.082 a numeric vector containing further observations of NN5.082 in NN5.A. NN5.083 a numeric vector containing further observations of NN5.083 in NN5.A. NN5.084 a numeric vector containing further observations of NN5.084 in NN5.A. NN5.085 a numeric vector containing further observations of NN5.085 in NN5.A. NN5.086 a numeric vector containing further observations of NN5.086 in NN5.A. NN5.087 a numeric vector containing further observations of NN5.087 in NN5.A. NN5.088 a numeric vector containing further observations of NN5.088 in NN5.A.

NN5.089 a numeric vector containing further observations of NN5.089 in NN5.A. NN5.090 a numeric vector containing further observations of NN5.090 in NN5.A. NN5.091 a numeric vector containing further observations of NN5.091 in NN5.A. NN5.092 a numeric vector containing further observations of NN5.092 in NN5.A. **NN5.093** a numeric vector containing further observations of NN5.093 in NN5.A. NN5.094 a numeric vector containing further observations of NN5.094 in NN5.A. NN5.095 a numeric vector containing further observations of NN5.095 in NN5.A. NN5.096 a numeric vector containing further observations of NN5.096 in NN5.A. NN5.097 a numeric vector containing further observations of NN5.097 in NN5.A. **NN5.098** a numeric vector containing further observations of NN5.098 in NN5.A. **NN5.099** a numeric vector containing further observations of NN5.099 in NN5.A. NN5.100 a numeric vector containing further observations of NN5.100 in NN5.A. **NN5.101** a numeric vector containing further observations of NN5.101 in NN5.A. NN5.102 a numeric vector containing further observations of NN5.102 in NN5.A. NN5.103 a numeric vector containing further observations of NN5.103 in NN5.A. NN5.104 a numeric vector containing further observations of NN5.104 in NN5.A. NN5.105 a numeric vector containing further observations of NN5.105 in NN5.A. NN5.106 a numeric vector containing further observations of NN5.106 in NN5.A. NN5.107 a numeric vector containing further observations of NN5.107 in NN5.A. NN5.108 a numeric vector containing further observations of NN5.108 in NN5.A. NN5.109 a numeric vector containing further observations of NN5.109 in NN5.A. NN5.110 a numeric vector containing further observations of NN5.110 in NN5.A. NN5.111 a numeric vector containing further observations of NN5.111 in NN5.A.

Details

Contains the 56 observations which were to be predicted of each time series in Dataset A (NN5.A) as demanded by the NN5 Competition.

Source

NN5 2008, The NN5 Competition: Forecasting competition for artificial neural networks and computational intelligence. URL: http://www.neural-forecasting-competition.com/NN5/index.htm.

References

S.F. Crone, 2008, Results of the NN5 time series forecasting competition. Hong Kong, Presentation at the IEEE world congress on computational intelligence. WCCI'2008.

See Also

NN5.A~

outliers_bp

Examples

```
data(NN5.A.cont)
str(NN5.A.cont)
plot(ts(NN5.A.cont["NN5.111"]))
```

outliers_bp

Outlier removal from sliding windows of data

Description

Function to perform outlier removal from sliding windows of data. The outliers_bp() function removes windows with extreme values using a method based on Box plots for detecting outliers.

Usage

outliers_bp(data, alpha = 1.5)

Arguments

data	A numeric matrix with sliding windows of time series data as returned by sw.
alpha	The multiplier for the interquartile range used as base for outlier removal. The default is set to 1.5 . The value 3.0 is also commonly used to remove only the extreme outliers.

Details

The method applied prune any value smaller than the first quartile minus 1.5 times the interquartile range, and also any value larger than the third quartile plus 1.5 times the interquartile range, that is, all the values that are not in the range [Q1-1.5xIQR, Q3+1.5xIQR] are considered outliers and are consequently removed.

Value

Same as data with outliers removed.

Author(s)

Rebecca Pontes Salles

References

E. Ogasawara, L. C. Martinez, D. De Oliveira, G. Zimbrao, G. L. Pappa, and M. Mattoso, 2010, Adaptive Normalization: A novel data normalization approach for non-stationary time series, Proceedings of the International Joint Conference on Neural Networks.

See Also

Other transformation methods: Diff(), LogT(), WaveletT(), emd(), mas(), mlm_io(), pct(), train_test_subset()

Examples

```
data(CATS)
swin <- sw(CATS[,1],5)
d <- outliers_bp(swin)</pre>
```

pct

Percentage Change Transformation

Description

The pct() function returns a transformation of the provided time series using a Percentage Change transformation. pct.rev() reverses the transformation.

Usage

pct(x)

pct.rev(p, xi, addinit = TRUE)

Arguments

x	A numeric vector or univariate time series of class ts.
р	A numeric vector or univariate time series of percentage changes. Possibly returned by $pct()$.
xi	Initial value/observation of x (x[1]). First known non-transformed value used to recursively obtain the original series.
addinit	If TRUE, xi is included in the return.

Details

The Percentage Change transformation is given approximately by

$$log(x[2:n]/x[1:(n-1)]) = log(x[2:n]) - log(x[1:(n-1)])$$

where n=length(x).

Value

A vector of length length(x)-1 containing the transformed values.

plotarimapred

Author(s)

Rebecca Pontes Salles

References

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

See Also

Other transformation methods: Diff(), LogT(), WaveletT(), emd(), mas(), mlm_io(), outliers_bp(), train_test_subset()

Examples

```
data(NN5.A)
ts <- na.omit(NN5.A[,10])
length(ts)
p <- pct(ts)
length(p)
p_rev <- pct.rev(p, attributes(p)$xi)</pre>
```

all(round(p_rev,4)==round(ts,4))

plotarimapred

Plot ARIMA predictions against actual values

Description

The function plots ARIMA predictions against its actual values with prediction intervals.

Usage

```
plotarimapred(
  ts.cont,
  fit.arima,
  xlim,
  range.percent = 0.2,
  xreg = NULL,
  ylab = NULL,
  xlab = NULL,
  main = NULL
)
```

Arguments

ts.cont	A vector or univariate time series containing actual values for a time series that are to be plotted against its respective predictions. The number of consecutive values to be predicted is assumed to be equal to the number of rows in ts.cont. If xreg is used, the number of values to be predicted is set to the number of rows of xreg. ~~Describe ts.cont here~~
fit.arima	A fitted ARIMA model for the time series that is to be predicted. An object of class "Arima", "ar" or "fracdiff". See the object argument of the forecast.Arima function in the forecast package.
xlim	Numeric vector containing the initial and final limits of the x-axis to be plotted, respectively.
range.percent	A percentage which defines how much the range of the graphic's y-axis will be increased from the minimum limits imposed by data.
xreg	A vector, matrix, data frame or times series with new values of external re- gressors to be used for prediction (for class Arima objects only). See the xreg argument of the forecast.Arima function in the forecast package.
ylab	A title for the graphic's y-axis. Ignored if NULL. ~~Describe ylab here~~
xlab	A title for the graphic's x-axis. Ignored if NULL. ~~Describe xlab here~~
main	An overall title for the graphic. Ignored if NULL. ~~Describe main here~~

Details

The model in fit.arima is used for prediction by the forecast.Arima function in the forecast package. The resulting forecast object is then used for plotting the predictions and their intervals by the plot.forecast function also in the forecast package. For more details, see the forecast.Arima and the plot.forecast functions in the forecast package.

Value

None.

Author(s)

Rebecca Pontes Salles

References

See the forecast.Arima and the plot.forecast functions in the forecast package. references to the literature/web site here ~

See Also

forecast.Arima, plot.forecast, arimapred ~

postprocess.tspred

Examples

```
data(SantaFe.A,SantaFe.A.cont)
fit <- forecast::auto.arima(SantaFe.A)
ts.cont <- ts(SantaFe.A.cont,start=1001)
plotarimapred(ts.cont, fit, xlim=c(1001,1100))</pre>
```

postprocess.tspred Postprocess method for tspred objects

Description

Performs postprocessing of the predicted time series data contained in a tspred class object reversing a particular set of transformation methods. Each transformation method is defined by a processing object in the list contained in the tspred class object.

Usage

```
## S3 method for class 'tspred'
postprocess(obj, ...)
```

Arguments

obj	An object of class tspred defining a particular time series prediction process.
	Other parameters passed to the method postprocess of the processing objects from obj.

Details

The function postprocess.tspred recursively calls the method postprocess on each processing object contained in obj in the inverse order as done by preprocess.tspred. The postprocessed predictions resulting from each of these calls is used as input to the next call. Finally, the produced postprocessed time series predictions are introduced in the structure of the tspred class object in obj.

The same transformation method parameters used/computed during preprocessing, duly saved in the structure of the tspred class object in obj, are used for reversing the transformations during postprocessing.

Value

An object of class tspred with updated structure containing postprocessed time series predictions.

Author(s)

Rebecca Pontes Salles

See Also

[tspred()] for defining a particular time series prediction process, and [LT()] for defining a time series transformation method.

```
Other preprocess: preprocess.tspred(), subset()
```

Examples

data(CATS)

```
#Obtaining objects of the processing class
proc1 <- subsetting(test_len=20)</pre>
proc2 <- BoxCoxT(lambda=NULL)</pre>
proc3 <- WT(level=1, filter="bl14")</pre>
#Obtaining objects of the modeling class
modl1 <- ARIMA()</pre>
#Obtaining objects of the evaluating class
eval1 <- MSE_eval()</pre>
#Defining a time series prediction process
tspred_1 <- tspred(subsetting=proc1,</pre>
                     processing=list(BCT=proc2,
                                      WT=proc3),
                     modeling=modl1,
                     evaluating=list(MSE=eval1)
)
summary(tspred_1)
tspred_1 <- subset(tspred_1, data=CATS[3])</pre>
tspred_1 <- preprocess(tspred_1,prep_test=FALSE)</pre>
tspred_1 <- train(tspred_1)</pre>
tspred_1 <- predict(tspred_1, onestep=TRUE)</pre>
tspred_1 <- postprocess(tspred_1)</pre>
```

predict

Predict method for modeling objects

Description

Obtains time series predictions based on a trained model and a particular prediction function defined in a modeling object.

predict

Usage

```
## S3 method for class 'MLM'
predict(object, mdl, data, n.ahead, ..., onestep = TRUE)
## S3 method for class 'linear'
predict(object, mdl, data, n.ahead, ..., onestep = TRUE)
```

Arguments

object	An object of class modeling defining a particular model.
mdl	A time series model object used for prediction.
data	A list of time series data input for prediction.
n.ahead	Integer defining the number of observations to be predicted.
	Other parameters passed to pred_func of object.
onestep	Should the function produce one-step ahead predictions? If FALSE, a multi-step ahead prediction approach is adopted.
	For predict.MLM, sw of object may be used to transform the time series input in data into sliding windows used during prediction. Also, proc of object may be used to preprocess/postprocess the input during prediction.

Value

A list containing object and the produced predictions.

Author(s)

Rebecca Pontes Salles

See Also

Other predict: predict.tspred()

Examples

data(CATS,CATS.cont)

```
a <- ARIMA()
model <- train(a,list(CATS[,1]))$results[[1]]$res
pred_data <- predict(a,model,data=NULL,n.ahead=20,onestep=FALSE)</pre>
```

```
n <- NNET(size=5, sw=SW(window_len = 5+1), proc=list(MM=MinMax()))
model <- train(n,list(CATS[,1]))$results[[1]]$res
pred_data <- predict(n,model,data=list(CATS.cont[,1]),n.ahead=20)</pre>
```

predict.tspred

Description

Obtains predictions for the time series data contained in a tspred class object based on a particular trained model and a prediction method. The model training and prediction method is defined by a modeling object contained in the tspred class object.

Usage

```
## S3 method for class 'tspred'
predict(object, onestep = obj$one_step, ...)
```

Arguments

object	An object of class tspred defining a particular time series prediction process.
onestep	Should the function produce one-step ahead predictions? If FALSE, a multi-step ahead prediction approach is adopted.
	Other parameters passed to the method predict of the modeling object from object.

Details

The function predict.tspred calls the method predict on the modeling objects for each trained model and time series contained in object. Finally, the produced time series predictions are introduced in the structure of the tspred class object in object.

Value

An object of class tspred with updated structure containing the produced time series predictions.

Author(s)

Rebecca Pontes Salles

See Also

[tspred()] for defining a particular time series prediction process, and [ARIMA()] for defining a time series modeling and prediction method.

Other predict: predict()

preprocess

Examples

data(CATS)

```
#Obtaining objects of the processing class
proc1 <- subsetting(test_len=20)</pre>
proc2 <- BoxCoxT(lambda=NULL)</pre>
proc3 <- WT(level=1, filter="bl14")</pre>
#Obtaining objects of the modeling class
modl1 <- ARIMA()
#Obtaining objects of the evaluating class
eval1 <- MSE_eval()</pre>
#Defining a time series prediction process
tspred_1 <- tspred(subsetting=proc1,</pre>
                    processing=list(BCT=proc2,
                                      WT=proc3),
                    modeling=modl1,
                     evaluating=list(MSE=eval1)
)
summary(tspred_1)
tspred_1 <- subset(tspred_1, data=CATS[3])</pre>
tspred_1 <- preprocess(tspred_1,prep_test=FALSE)</pre>
tspred_1 <- train(tspred_1)</pre>
tspred_1 <- predict(tspred_1, onestep=TRUE)</pre>
```

preprocess

Preprocessing/Postprocessing time series data

Description

preprocess and postprocess are generic functions for preprocessing and postprocessing time series data, respectively, based on a particular transformation method defined in a processing object. Generally, postprocessing reverses the transformation performed during preprocessing.

Usage

```
preprocess(obj, ...)
## S3 method for class 'processing'
preprocess(obj, data, ..., map = TRUE)
postprocess(obj, ...)
## S3 method for class 'processing'
postprocess(obj, data, ..., map = TRUE)
```

Arguments

obj	An object of class processing defining a particular transformation method.
	Other parameters passed to prep_func/postp_func of obj.
data	A list of time series to be transformed.
map	Should the transformation be performed in each individual time series? If FALSE the function processes the provided set of time series as a whole.

Value

A list containing obj and the transformed time series.

Author(s)

Rebecca Pontes Salles

Examples

```
data(NN5.A)
t <- LT(base = exp(1))
prep_ts <- preprocess(t,list(NN5.A[,10]))$results[[1]]$res
postp_ts <- postprocess(t,list(prep_ts))$results[[1]]$res</pre>
```

preprocess.tspred Preprocess method for tspred objects

Description

Performs preprocessing of the time series data contained in a tspred class object based on a particular set of transformation methods. Each transformation method is defined by a processing object in the list contained in the tspred class object.

Usage

S3 method for class 'tspred'
preprocess(obj, prep_test = FALSE, ...)

Arguments

obj	An object of class tspred defining a particular time series prediction process.
prep_test	Should the testing set of data be preprocessed as well?
	Other parameters passed to the method preprocess of the processing objects from obj.

preprocess.tspred

Details

The function preprocess.tspred recursively calls the method preprocess on each processing object contained in obj. The preprocessed time series resulting from each of these calls is used as input to the next call. Thus, the order of the list of processing objects in obj becomes important. Finally, the produced preprocessed time series data are introduced in the structure of the tspred class object in obj.

If any transformation method parameters are computed during preprocessing, they are duly updated in the structure of the tspred class object in obj. This is important not only for provenance and reprodutibility of the prediction process, but it is also crucial for the postprocessing step, since the same parameters must be used for reversing any transformations. Furthermore, if prep_test is TRUE, testing sets are preprocessed with the same parameters saved from preprocessing the training set.

Value

An object of class tspred with updated structure containing preprocessed time series data.

Author(s)

Rebecca Pontes Salles

See Also

[tspred()] for defining a particular time series prediction process, and [LT()] for defining a time series transformation method.

Other preprocess: postprocess.tspred(), subset()

```
data(CATS)
```

```
#Obtaining objects of the processing class
proc1 <- subsetting(test_len=20)</pre>
proc2 <- BoxCoxT(lambda=NULL)</pre>
proc3 <- WT(level=1, filter="bl14")</pre>
#Obtaining objects of the modeling class
modl1 <- ARIMA()
#Obtaining objects of the evaluating class
eval1 <- MSE_eval()</pre>
#Defining a time series prediction process
tspred_1 <- tspred(subsetting=proc1,</pre>
                    processing=list(BCT=proc2,
                                      WT=proc3),
                    modeling=modl1,
                    evaluating=list(MSE=eval1)
)
summary(tspred_1)
```

```
tspred_1 <- subset(tspred_1, data=CATS[3])
tspred_1 <- preprocess(tspred_1,prep_test=FALSE)</pre>
```

processing

Time series data processing

Description

Constructor for the processing class representing a time series processing method based on a particular time series transformation.

Usage

```
processing(
    prep_func,
    prep_par = NULL,
    postp_func = NULL,
    postp_par = NULL,
    ...,
    subclass = NULL
)
```

Arguments

prep_func	A function for preprocessing the time series data.
prep_par	List of named parameters required by prep_func.
postp_func	A function for postprocessing the time series data. Generally reverses the trans- formation performed by prep_func.
postp_par	List of named parameters required by postp_func.
	Other parameters to be encapsulated in the class object.
subclass	Name of new specialized subclass object created in case it is provided.

Value

An object of class processing.

Author(s)

Rebecca Pontes Salles

See Also

Other constructors: ARIMA(), LT(), MSE_eval(), evaluating(), modeling(), tspred()

SantaFe.A

Examples

SantaFe.A

Time series A of the Santa Fe Time Series Competition

Description

A univariate time series derived from laser-generated data recorded from a Far-Infrared-Laser in a chaotic state.

Usage

SantaFe.A

Format

A data frame with 1000 observations on the following variable.

V1 a numeric vector containing the observations of the univariate time series A of the Santa Fe Time Series Competition.

Details

The main benchmark of the Santa Fe Time Series Competition, time series A, is composed of a clean low-dimensional nonlinear and stationary time series with 1,000 observations. Competitors were asked to correctly predict the next 100 observations (SantaFe.A.cont). The performance evaluation done by the Santa Fe Competition was based on the NMSE errors of prediction found by the competitors.

References

A.S. Weigend, 1993, Time Series Prediction: Forecasting The Future And Understanding The Past. Reading, MA, Westview Press.

See Also

SantaFe.A.cont, SantaFe.D, SantaFe.D.cont ~

```
data(SantaFe.A)
str(SantaFe.A)
plot(ts(SantaFe.A))
```

SantaFe.A.cont

Description

A univariate time series providing 100 points beyond the end of the time series A in SantaFe.A.

Usage

SantaFe.A.cont

Format

A data frame with 100 observations on the following variable.

V1 a numeric vector containing further observations of the univariate time series A of the Santa Fe Time Series Competition in SantaFe.A.

Details

Contains the 100 observations which were to be predicted of the time series A (SantaFe.A) as demanded by the Santa Fe Time Series Competition.

References

A.S. Weigend, 1993, Time Series Prediction: Forecasting The Future And Understanding The Past. Reading, MA, Westview Press.

See Also

SantaFe.A, SantaFe.D, SantaFe.D.cont ~

```
data(SantaFe.A.cont)
str(SantaFe.A.cont)
plot(ts(SantaFe.A.cont))
```

SantaFe.D

Description

A univariate computer-generated time series.

Usage

SantaFe.D

Format

A data frame with 100000 observations on the following variable.

V1 a numeric vector containing the observations of the univariate time series D of the Santa Fe Time Series Competition.

Details

One of the benchmarks of the Santa Fe Time Series Competition, time series D, is composed of a four-dimensional nonlinear time series with non-stationary properties and 100,000 observations. Competitors were asked to correctly predict the next 500 observations of this time series (SantaFe.D.cont). The performance evaluation done by the Santa Fe Competition was based on the NMSE errors of prediction found by the competitors.

References

A.S. Weigend, 1993, Time Series Prediction: Forecasting The Future And Understanding The Past. Reading, MA, Westview Press.

See Also

SantaFe.D.cont, SantaFe.A, SantaFe.A.cont ~

```
data(SantaFe.D)
str(SantaFe.D)
plot(ts(SantaFe.D),xlim=c(1,2000))
```

SantaFe.D.cont

Description

A univariate time series providing 500 points beyond the end of the time series D in SantaFe.D.

Usage

SantaFe.D.cont

Format

A data frame with 500 observations on the following variable.

V1 a numeric vector containing further observations of the univariate time series D of the Santa Fe Time Series Competition in SantaFe.D.

Details

Contains the 500 observations which were to be predicted of the time series D (SantaFe.D) as demanded by the Santa Fe Time Series Competition.

References

A.S. Weigend, 1993, Time Series Prediction: Forecasting The Future And Understanding The Past. Reading, MA, Westview Press.

See Also

SantaFe.D, SantaFe.A, SantaFe.A.cont ~

```
data(SantaFe.D.cont)
str(SantaFe.D.cont)
plot(ts(SantaFe.D.cont))
```

sMAPE

Description

The function calculates the sMAPE error between actual and predicted values.

Usage

sMAPE(actual, prediction)

Arguments

actual	A vector or univariate time series containing actual values for a time series that are to be compared against its respective predictions.
prediction	A vector or univariate time series containing time series predictions that are to be compared against the values in actual. ~~Describe forecast here~~

Value

A numeric value of the sMAPE error of prediction.

Author(s)

Rebecca Pontes Salles

References

Z. Chen and Y. Yang, 2004, Assessing forecast accuracy measures, Preprint Series, n. 2004-2010, p. 2004-10. literature/web site here ~

See Also

MAPE, MSE, NMSE, MAXError ~

Examples

```
data(SantaFe.A,SantaFe.A.cont)
pred <- marimapred(SantaFe.A,n.ahead=100)
sMAPE(SantaFe.A.cont[,1], pred)</pre>
```

subset

Description

subset is a generic function for subsetting time series data into training and testing sets. The function invokes particular *methods* which depend on the class of the first argument.

Usage

```
subset(obj, ...)
```

```
## S3 method for class 'tspred'
subset(obj, data = NULL, ...)
```

Arguments

obj	An object of class tspred defining a particular time series prediction process.
	Other parameters passed to the method preprocess of object subsetting from obj.
data	A list of time series to be transformed.

Details

The function subset.tspred calls the method preprocess on the subsetting object from obj. The produced training and testing sets of time series data are introduced in the structure of the tspred class object in obj.

Value

An object of class tspred with updated structure containing the produced training and testing sets of time series data.

Author(s)

Rebecca Pontes Salles

See Also

[tspred()] for defining a particular time series prediction process, and [subsetting()] for defining a time series subsetting transformation.

Other preprocess: postprocess.tspred(), preprocess.tspred()

SW

Examples

data(CATS)

SW

Generating sliding windows of data

Description

The function extracts all possible subsequences (of the same length) of a time series (or numeric vector), generating a set of sliding windows of data, often used to train machine learning methods.

Usage

sw(x, k)

Arguments

X	A vector or univariate time series from which the sliding windows are to be extracted.
k	Numeric value corresponding to the required size (length) of each sliding window.

Details

The function returns all (overlapping) subsequences of size swSize of timeseries.

Value

A numeric matrix of size (length(x)-k+1) by k, where each line is a sliding window.

Author(s)

Rebecca Pontes Salles

References

Lampert, C. H., Blaschko, M. B., and Hofmann, T. (2008). Beyond sliding windows: Object localization by efficient subwindow search. In Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on, pages 1-8. IEEE.

Keogh, E. and Lin, J. (2005). Clustering of time series subsequences is meaningless: Implications for previous and future research. Knowledge and Information Systems, 8(2):154-177.

Examples

data("CATS")
s <- sw(CATS[,1],4)</pre>

train

Training a time series model

Description

train is a generic function for training a time series model based on a particular training function defined in a modeling object. The function invokes particular *methods* which depend on the class of the first argument.

Usage

```
train(obj, ...)
## S3 method for class 'MLM'
train(obj, data, ...)
## S3 method for class 'linear'
train(obj, data, ...)
```

Arguments

obj	An object of class modeling defining a particular model.
	Other parameters passed to train_func of obj.
	For train.MLM, sw of obj may be used to transform the time series in data
	into sliding windows used during training. Also, proc of obj may be used to
	preprocess the time series before training.
data	A list of time series to be modelled.

train.tspred

Value

A list containing obj and the trained models.

Author(s)

Rebecca Pontes Salles

See Also

Other train: train.tspred()

Examples

data(CATS,CATS.cont)

```
a <- ARIMA()
model <- train(a,list(CATS[,1]))</pre>
```

```
n <- NNET(size=5, sw=SW(window_len = 5+1), proc=list(MM=MinMax()))
model <- train(n,list(CATS[,1]))</pre>
```

train.tspred Train method for tspred objects

Description

Fits a model to the time series data contained in a tspred class object based on a particular model training method. The model training method is defined by a modeling object contained in the tspred class object.

Usage

```
## S3 method for class 'tspred'
train(obj, ...)
```

Arguments

obj	An object of class tspred defining a particular time series prediction process.
•••	Ignored

Details

The function train.tspred calls the method train on the modeling object for each time series contained in obj. Finally, the produced time series model is introduced in the structure of the tspred class object in obj.

If any modeling parameters are computed during training, they are duly updated in the structure of the tspred class object in obj. This is important for provenance and reprodutibility of the training process.

Value

An object of class tspred with updated structure containing the produced trained time series models.

Author(s)

Rebecca Pontes Salles

See Also

[tspred()] for defining a particular time series prediction process, and [ARIMA()] for defining a time series modeling and prediction method.

Other train: train()

Examples

```
data(CATS)
#Obtaining objects of the processing class
proc1 <- subsetting(test_len=20)</pre>
proc2 <- BoxCoxT(lambda=NULL)</pre>
proc3 <- WT(level=1, filter="bl14")</pre>
#Obtaining objects of the modeling class
modl1 <- ARIMA()</pre>
#Obtaining objects of the evaluating class
eval1 <- MSE_eval()</pre>
#Defining a time series prediction process
tspred_1 <- tspred(subsetting=proc1,</pre>
                     processing=list(BCT=proc2,
                                      WT=proc3),
                     modeling=modl1,
                     evaluating=list(MSE=eval1)
)
summary(tspred_1)
tspred_1 <- subset(tspred_1, data=CATS[3])</pre>
tspred_1 <- preprocess(tspred_1,prep_test=FALSE)</pre>
tspred_1 <- train(tspred_1)</pre>
```

train_test_subset Get training and testing subsets of data

Description

Function subsets data into training and testing datasets.

tspred

Usage

train_test_subset(data, train_perc = 0.8, test_len = NULL)

Arguments

data	A numeric vector, time series, data.frame or matrix containg data to be subset- ted.
train_perc	Percentage of data observations to compose the training dataset. Ignored if test_len is given.
test_len	Required length of testing dataset. If NULL, 1-train_perc is used for computing the number of data observations in the testing dataset.

Value

A list with train and test subsets of data.

Author(s)

Rebecca Pontes Salles

See Also

Other transformation methods: Diff(), LogT(), WaveletT(), emd(), mas(), mlm_io(), outliers_bp(),
pct()

Examples

```
data(CATS)
d <- train_test_subset(CATS[,1])
swin <- sw(CATS[,1],5)
d_sw <- train_test_subset(swin)</pre>
```

tspred

Time series prediction process

Description

Constructor for the tspred class representing a time series prediction process. This process may involve subsetting the time series data into training and testing sets, preprocessing/postprocessing the data, modeling, prediction and finally an evaluation of modeling fitness and prediction quality. All these process steps should be based on particular time series transformation methods, a modeling and prediction method, and quality metrics which are defined in a tspred class object.

tspred

Usage

```
tspred(
  subsetting = NULL,
  processing = NULL,
  modeling = NULL,
  evaluating = NULL,
  data = NULL,
  n.ahead = NULL,
  one_step = FALSE,
  ...,
  subclass = NULL
)
```

Arguments

subsetting	A subsetting object regarding subsetting processing.
processing	List of named processing objects used for pre(post)processing the data.
modeling	A modeling object used for time series modeling and prediction.
evaluating	List of named evaluating objects used for prediction/modeling quality evalua- tion.
data	A list of time series to be pre(post)processed, modelled and/or predicted.
n.ahead	Integer defining the number of observations to be predicted.
one_step	Should the function produce one-step ahead predictions? If FALSE, a multi-step ahead prediction approach is adopted.
	Other parameters to be encapsulated in the class object.
subclass	Name of new specialized subclass object created in case it is provided.

Value

An object of class tspred.

Author(s)

Rebecca Pontes Salles

See Also

Other constructors: ARIMA(), LT(), MSE_eval(), evaluating(), modeling(), processing()

Examples

```
#Obtaining objects of the processing class
proc1 <- subsetting(test_len=20)
proc2 <- BoxCoxT(lambda=NULL)
proc3 <- WT(level=1, filter="bl14")</pre>
```

#Obtaining objects of the modeling class

WaveletT

```
modl1 <- ARIMA()</pre>
#Obtaining objects of the evaluating class
eval1 <- MSE_eval()</pre>
eval2 <- MAPE_eval()</pre>
#Defining a time series prediction process
tspred_1 <- tspred(subsetting=proc1,</pre>
                     processing=list(BCT=proc2,
                                       WT=proc3),
                     modeling=modl1,
                     evaluating=list(MSE=eval1,
                                       MAPE=eval2)
                    )
summary(tspred_1)
#Obtaining objects of the processing class
proc4 <- SW(window_len = 6)</pre>
proc5 <- MinMax()</pre>
#Obtaining objects of the modeling class
modl2 <- NNET(size=5,sw=proc4,proc=list(MM=proc5))</pre>
#Defining a time series prediction process
tspred_2 <- tspred(subsetting=proc1,</pre>
                     processing=list(BCT=proc2,
                                       WT=proc3),
                     modeling=modl2,
                     evaluating=list(MSE=eval1,
                                       MAPE=eval2)
                    )
summary(tspred_2)
```

WaveletT

Automatic wavelet transform

Description

The function automatically applies a maximal overlap discrete wavelet transform to a provided univariate time series. Wrapper function for modwt of the wavelets package. It also allows the automatic selection of the level and filter of the transform using fittestWavelet. WaveletT.rev() reverses the transformation based on the imodwt function.

Usage

```
WaveletT(
    x,
    level = NULL,
    filter = c("haar", "d4", "la8", "bl14", "c6"),
```

```
boundary = "periodic",
...
```

WaveletT.rev(pred = NULL, wt_obj)

Arguments

x	A numeric vector or univariate time series to be decomposed.
level	An integer specifying the level of the decomposition. If NULL, it is automatically selected using fittestWavelet.
filter	A character string indicating which wavelet filter to use in the decomposition. If NULL, or a vector and length(filters)>1, the wavelet transform filter is automatically selected using fittestWavelet.
boundary	See modwt.
	Additional arguments passed to fittestWavelet.
pred	A list containing component series (such as) resulting from wavelet transform (WaveletT()).
wt_obj	Object of class modwt containing the wavelet transformed series.

Value

A list containing each component series resulting from the decomposition of x (level wavelet coefficients series and level scaling coefficients series). An object of class modwt containing the wavelet transformed/decomposed time series is passed as an attribute named "wt_obj". This attribute is passed to wt_obj in WaveletT.rev().

Author(s)

Rebecca Pontes Salles

References

A. J. Conejo, M. A. Plazas, R. Espinola, A. B. Molina, Day-ahead electricity price forecasting using the wavelet transform and ARIMA models, IEEE Transactions on Power Systems 20 (2005) 1035-1042.

T. Joo, S. Kim, Time series forecasting based on wavelet filtering, Expert Systems with Applications 42 (2015) 3868-3874.

C. Stolojescu, I. Railean, S. M. P. Lenca, A. Isar, A wavelet based prediction method for time series. In Proceedings of the 2010 International Conference Stochastic Modeling Techniques and Data Analysis, Chania, Greece (pp. 8-11) (2010).

See Also

fittestWavelet, fittestEMD

Other transformation methods: Diff(), LogT(), emd(), mas(), mlm_io(), outliers_bp(), pct(), train_test_subset()

workflow

Examples

```
data(CATS)
w <- WaveletT(CATS[,1])
#plot wavelet transform/decomposition
plot(attr(w,"wt_obj"))
x <- WaveletT.rev(pred=NULL, attr(w,"wt_obj"))
all(round(x,4)==round(CATS[,1],4))</pre>
```

workflow

Executing a time series prediction process

Description

workflow is a generic function for executing the steps of a particular data workflow. The function invokes particular *methods* which depend on the class of the first argument.

Usage

```
workflow(obj, ...)
## S3 method for class 'tspred'
workflow(
   obj,
   data = NULL,
   prep_test = FALSE,
   onestep = obj$one_step,
   eval_fitness = TRUE,
   seed = 1234,
   ...
)
```

Arguments

obj	An object of class tspred defining a particular time series prediction process.
	Ignored
data	See subset.tspred
prep_test	See preprocess.tspred
onestep	See predict.tspred
eval_fitness	See evaluate.tspred
seed	See set.seed

Details

The function workflow.tspred executes a time series prediction process defined by a tspred object. It is a wrapper for the methods subset preprocess, train, predict, postprocess, and evaluate, which are called in this order. The artifacts generated by the execution of the time series prediction process are introduced in the structure of the tspred class object in obj.

Value

An object of class tspred with updated structure containing all artifacts generated by the execution of the time series prediction process.

Author(s)

Rebecca Pontes Salles

See Also

[tspred()] for defining a particular time series prediction process.

Examples

data(CATS)

```
#Obtaining objects of the processing class
proc1 <- subsetting(test_len=20)</pre>
proc2 <- BoxCoxT(lambda=NULL)</pre>
proc3 <- WT(level=1, filter="bl14")</pre>
#Obtaining objects of the modeling class
modl1 <- ARIMA()</pre>
#Obtaining objects of the evaluating class
eval1 <- MSE_eval()</pre>
#Defining a time series prediction process
tspred_1 <- tspred(subsetting=proc1,</pre>
                    processing=list(BCT=proc2,
                                      WT=proc3),
                    modeling=modl1,
                    evaluating=list(MSE=eval1)
)
summary(tspred_1)
```

tspred_1 <- workflow(tspred_1,data=CATS[3],onestep=TRUE)</pre>

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