

Package ‘smimodel’

May 9, 2026

Title Sparse Multiple Index Models for Nonparametric Forecasting

Version 0.1.3

Description Implements a general algorithm for estimating Sparse Multiple Index (SMI) models for nonparametric forecasting and prediction. Estimation of SMI models requires the Gurobi mixed integer programming (MIP) solver via the gurobi R package. To use this functionality, the Gurobi Optimizer must be installed, and a valid license obtained and activated from <https://www.gurobi.com>. The gurobi R package must then be installed and configured following the instructions at

<https://support.gurobi.com/hc/en-us/articles/14462206790033-How-do-I-install-Gurobi-for-R>.

The package also includes functions for fitting nonparametric additive models with backward elimination, group-wise additive index models, and projection pursuit regression models as benchmark comparison methods. In addition, it provides tools for generating prediction intervals to quantify uncertainty in point forecasts produced by the SMI model and benchmark models, using the classical block bootstrap and a new method called conformal bootstrap, which integrates block bootstrap with split conformal prediction.

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<https://nuwani-palihawadana.github.io/smimodel/>

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smimodel-package	<i>smimodel: Sparse Multiple Index Models for Nonparametric Forecasting</i>
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Description

Implements a general algorithm for estimating Sparse Multiple Index (SMI) models for nonparametric forecasting and prediction. Estimation of SMI models requires the Gurobi mixed integer programming (MIP) solver via the gurobi R package. To use this functionality, the Gurobi Optimizer must be installed, and a valid license obtained and activated from <https://www.gurobi.com>. The gurobi R package must then be installed and configured following the instructions at <https://support.gurobi.com/hc/en-us/articles/14462206790033-How-do-I-install-Gurobi-for-R>. The package also includes functions for fitting nonparametric additive models with backward elimination, group-wise additive index models, and projection pursuit regression models as benchmark comparison methods. In addition, it provides tools for generating prediction intervals to quantify

uncertainty in point forecasts produced by the SMI model and benchmark models, using the classical block bootstrap and a new method called conformal bootstrap, which integrates block bootstrap with split conformal prediction.

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See Also

Useful links:

- <https://github.com/nuwani-palihawadana/smimodel>
- <https://nuwani-palihawadana.github.io/smimodel/>
- Report bugs at <https://github.com/nuwani-palihawadana/smimodel/issues>

allpred_index	<i>Constructing index coefficient vectors with all predictors in each index</i>
---------------	---

Description

Constructs vectors of coefficients for each index including a coefficient for all the predictors that are entering indices. i.e. if a coefficient is not provided for a particular predictor in a particular index, the function will replace the missing coefficient with a zero.

Usage

```
allpred_index(num_pred, num_ind, ind_pos, alpha)
```

Arguments

num_pred	Number of predictors.
num_ind	Number of indices.
ind_pos	A list of length = num_ind that indicates which predictors belong to which index.
alpha	A vector of index coefficients.

Value

A list containing the following components:

alpha_init_new	A numeric vector of index coefficients.
index	An integer vector that assigns group indices for each predictor.
index_positions	A list of length = num_ind that indicates which predictors belong to which index.

augment.backward	<i>Augment function for class backward</i>
------------------	--

Description

Generates residuals and fitted values of a fitted backward object.

Usage

```
## S3 method for class 'backward'  
augment(x, ...)
```

Arguments

x	A backward object.
...	Other arguments not currently used.

Value

A tibble.

Examples

```
library(dplyr)  
library(tibble)  
library(tidyr)  
library(tsibble)  
  
# Simulate data  
n = 1205  
set.seed(123)  
sim_data <- tibble(x_lag_000 = runif(n)) |>  
  mutate(  
    # Add x_lags  
    x_lag = lag_matrix(x_lag_000, 5) |>  
    unpack(x_lag, names_sep = "_") |>  
    mutate(  
      # Response variable  
      y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),  
      # Add an index to the data set  
      inddd = seq(1, n)) |>  
    drop_na() |>  
    select(inddd, y, starts_with("x_lag")) |>  
    # Make the data set a `tsibble`  
    as_tsibble(index = inddd)  
  
# Training set  
sim_train <- sim_data[1:1000, ]  
# Validation set
```

```

sim_val <- sim_data[1001:1200, ]

# Predictors taken as non-linear variables
s.vars <- colnames(sim_data)[3:8]

# Model fitting
backwardModel <- model_backward(data = sim_train,
                                val.data = sim_val,
                                yvar = "y",
                                s.vars = s.vars)

# Obtain residuals and fitted values
augment(backwardModel)

```

```

augment.gaimFit      Augment function for class gaimFit

```

Description

Generates residuals and fitted values of a fitted `gaimFit` object.

Usage

```

## S3 method for class 'gaimFit'
augment(x, ...)

```

Arguments

```

x          A gaimFit object.
...       Other arguments not currently used.

```

Value

A tibble.

Examples

```

library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1005
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>

```

```

unpack(x_lag, names_sep = "_") |>
mutate(
  # Response variable
  y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
  # Add an index to the data set
  inddd = seq(1, n)) |>
drop_na() |>
select(inddd, y, starts_with("x_lag")) |>
# Make the data set a `tsibble`
as_tsibble(index = inddd)

# Predictors taken as index variables
index.vars <- colnames(sim_data)[3:7]

# Assign group indices for each predictor
index.ind = c(rep(1, 3), rep(2, 2))

# Predictors taken as non-linear variables not entering indices
s.vars = "x_lag_005"

# Model fitting
gaimModel <- model_gaim(data = sim_data,
  yvar = "y",
  index.vars = index.vars,
  index.ind = index.ind,
  s.vars = s.vars)

# Obtain residuals and fitted values
augment(gaimModel)

```

augment.gamFit

Augment function for class gamFit

Description

Generates residuals and fitted values of a fitted gamFit object.

Usage

```

## S3 method for class 'gamFit'
augment(x, ...)

```

Arguments

x	A gamFit object.
...	Other arguments not currently used.

Value

A tibble.

Examples

```

library(dplyr)
library(tibble)
library(tidy)
library(tsibble)

# Simulate data
n = 1005
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Predictors taken as non-linear variables
s.vars <- colnames(sim_data)[3:6]

# Predictors taken as linear variables
linear.vars <- colnames(sim_data)[7:8]

# Model fitting
gamModel <- model_gam(data = sim_data,
                      yvar = "y",
                      s.vars = s.vars,
                      linear.vars = linear.vars)

# Obtain residuals and fitted values
augment(gamModel)

```

augment.lmFit

Augment function for class lmFit

Description

Generates residuals and fitted values of a fitted `lmFit` object.

Usage

```

## S3 method for class 'lmFit'
augment(x, ...)

```

Arguments

x A lmFit object.
 ... Other arguments not currently used.

Value

A tibble.

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1005
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Predictor variables
linear.vars <- colnames(sim_data)[3:8]

# Model fitting
lmModel <- model_lm(data = sim_data,
                    yvar = "y",
                    linear.vars = linear.vars)

# Obtain residuals and fitted values
augment(lmModel)
```

augment.pprFit

Augment function for class pprFit

Description

Generates residuals and fitted values of a fitted pprFit object.

Usage

```
## S3 method for class 'pprFit'  
augment(x, ...)
```

Arguments

```
x          A pprFit object.  
...        Other arguments not currently used.
```

Value

A tibble.

Examples

```
library(dplyr)  
library(tibble)  
library(tidyr)  
library(tsibble)  
  
# Simulate data  
n = 1005  
set.seed(123)  
sim_data <- tibble(x_lag_000 = runif(n)) |>  
  mutate(  
    # Add x_lags  
    x_lag = lag_matrix(x_lag_000, 5) |>  
    unpack(x_lag, names_sep = "_") |>  
    mutate(  
      # Response variable  
      y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),  
      # Add an index to the data set  
      inddd = seq(1, n)) |>  
    drop_na() |>  
    select(inddd, y, starts_with("x_lag")) |>  
    # Make the data set a `tsibble`  
    as_tsibble(index = inddd)  
  
# Index variables  
index.vars <- colnames(sim_data)[3:8]  
  
# Model fitting  
pprModel <- model_ppr(data = sim_data,  
                      yvar = "y",  
                      index.vars = index.vars)  
  
# Obtain residuals and fitted values  
augment(pprModel)
```

augment.smimodel	<i>Augment function for class smimodel</i>
------------------	--

Description

Generates residuals and fitted values of a fitted smimodel object.

Usage

```
## S3 method for class 'smimodel'
augment(x, ...)
```

Arguments

x	A smimodel object.
...	Other arguments not currently used.

Value

A tibble.

Examples

```
if(requireNamespace("gurobi", quietly = TRUE)){
  library(dplyr)
  library(ROI)
  library(tibble)
  library(tidyr)
  library(tsibble)

  # Simulate data
  n = 1005
  set.seed(123)
  sim_data <- tibble(x_lag_000 = runif(n)) |>
    mutate(
      # Add x_lags
      x_lag = lag_matrix(x_lag_000, 5) |>
      unpack(x_lag, names_sep = "_") |>
      mutate(
        # Response variable
        y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
        # Add an index to the data set
        inddd = seq(1, n)) |>
      drop_na() |>
      select(inddd, y, starts_with("x_lag")) |>
      # Make the data set a `tsibble`
      as_tsibble(index = inddd)

  # Index variables
```

```

index.vars <- colnames(sim_data)[3:8]

# Model fitting
smimodel_ppr <- model_smimodel(data = sim_data,
                               yvar = "y",
                               index.vars = index.vars,
                               initialise = "ppr")

# Obtain residuals and fitted values
augment(smimodel_ppr)
}

```

augment.smimodelFit *Augment function for class smimodelFit*

Description

Generates residuals and fitted values of a fitted smimodelFit object.

Usage

```
## S3 method for class 'smimodelFit'
augment(x, ...)
```

Arguments

x A smimodelFit object.
... Other arguments not currently used.

Value

A tibble.

autoplot.smimodel *Plot estimated smooths from a fitted smimodel*

Description

Plots the graphs of fitted spline(s). If a set of multiple models are fitted, plots graphs of fitted spline(s) of a specified model (in argument model) out of the set of multiple models fitted.

Usage

```
## S3 method for class 'smimodel'
autoplot(object, model = 1, ...)
```

Arguments

object	A smimodel object.
model	An integer to indicate the smooths of which model (out of the set of multiple models fitted) to be plotted.
...	Other arguments not currently used.

Value

Plot(s) of fitted spline(s).

Examples

```

if(requireNamespace("gurobi", quietly = TRUE)){
  library(dplyr)
  library(ROI)
  library(tibble)
  library(tidyr)
  library(tsibble)

  # Simulate data
  n = 1005
  set.seed(123)
  sim_data <- tibble(x_lag_000 = runif(n)) |>
    mutate(
      # Add x_lags
      x_lag = lag_matrix(x_lag_000, 5)) |>
    unpack(x_lag, names_sep = "_") |>
    mutate(
      # Response variable
      y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
      # Add an index to the data set
      inddd = seq(1, n)) |>
    drop_na() |>
    select(inddd, y, starts_with("x_lag")) |>
    # Make the data set a `tsibble`
    as_tsibble(index = inddd)

  # Index variables
  index.vars <- colnames(sim_data)[3:8]

  # Model fitting
  smimodel_ppr <- model_smimodel(data = sim_data,
                                yvar = "y",
                                index.vars = index.vars,
                                initialise = "ppr")

  autoplot(smimodel_ppr)
}

```

avgCoverage	<i>Calculate interval forecast coverage</i>
-------------	---

Description

This is a wrapper for the function `conformalForecast::coverage`. Calculates the mean coverage and the `ifinn` matrix for prediction intervals on validation set. If `window` is not `NULL`, a matrix of the rolling means of interval forecast coverage is also returned.

Usage

```
avgCoverage(object, level = 95, window = NULL, na.rm = FALSE)
```

Arguments

<code>object</code>	An object of class <code>bb_cvforecast</code> or <code>cb_cvforecast</code> .
<code>level</code>	Target confidence level for prediction intervals.
<code>window</code>	If not <code>NULL</code> , the rolling mean matrix for coverage is also returned.
<code>na.rm</code>	A logical indicating whether NA values should be stripped before the rolling mean computation proceeds.

Value

A list of class `coverage` with the following components:

<code>mean</code>	Mean coverage across the validation set.
<code>ifinn</code>	A indicator matrix as a multivariate time series, where the h th column holds the coverage for forecast horizon h . The time index corresponds to the period for which the forecast is produced.
<code>rollmean</code>	If <code>window</code> is not <code>NULL</code> , a matrix of the rolling means of interval forecast coverage will be returned.

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1055
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5) |>
    unpack(x_lag, names_sep = "_") |>
```

```

mutate(
  # Response variable
  y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
  # Add an index to the data set
  inddd = seq(1, n)) |>
drop_na() |>
select(inddd, y, starts_with("x_lag")) |>
# Make the data set a `tsibble`
as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1050, ]

# Index variables
index.vars <- colnames(sim_data)[3:8]

# Model fitting
pprModel <- model_ppr(data = sim_train,
  yvar = "y",
  index.vars = index.vars)

# Conformal bootstrap prediction intervals (2-steps-ahead interval forecasts)
set.seed(12345)
pprModel_cb <- cb_cvforecast(object = pprModel,
  data = sim_data,
  yvar = "y",
  predictor.vars = index.vars,
  h = 2,
  ncal = 30,
  num.futures = 100,
  window = 1000)

# Mean coverage of generated 95% conformal bootstrap prediction intervals
cov_data <- avgCoverage(object = pprModel_cb)
cov_data$mean

```

avgWidth

Calculate interval forecast width

Description

This is a wrapper for the function `conformalForecast::width`. Calculates the mean width of prediction intervals on the validation set. If `window` is not `NULL`, a matrix of the rolling means of interval width is also returned. If `includemedian` is `TRUE`, the information of the median interval width will be returned.

Usage

```
avgWidth(
  object,
  level = 95,
  includemedian = FALSE,
  window = NULL,
  na.rm = FALSE
)
```

Arguments

<code>object</code>	An object of class <code>bb_cvforecast</code> or <code>cb_cvforecast</code> .
<code>level</code>	Target confidence level for prediction intervals.
<code>includemedian</code>	If TRUE, the median interval width will also be returned.
<code>window</code>	If not NULL, the rolling mean (and rolling median if applicable) matrix for interval width will also be returned.
<code>na.rm</code>	A logical indicating whether NA values should be stripped before the rolling mean and rolling median computation proceeds.

Value

A list of class width with the following components:

<code>width</code>	Forecast interval width as a multivariate time series, where the h th column holds the interval width for the forecast horizon h . The time index corresponds to the period for which the forecast is produced.
<code>mean</code>	Mean interval width across the validation set.
<code>rollmean</code>	If <code>window</code> is not NULL, a matrix of the rolling means of interval width will be returned.
<code>median</code>	Median interval width across the validation set.
<code>rollmedian</code>	If <code>window</code> is not NULL, a matrix of the rolling medians of interval width will be returned.

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1055
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
```

```

unpack(x_lag, names_sep = "_") |>
mutate(
  # Response variable
  y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
  # Add an index to the data set
  inddd = seq(1, n)) |>
drop_na() |>
select(inddd, y, starts_with("x_lag")) |>
# Make the data set a `tsibble`
as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1050, ]

# Index variables
index.vars <- colnames(sim_data)[3:8]

# Model fitting
pprModel <- model_ppr(data = sim_train,
                      yvar = "y",
                      index.vars = index.vars)

# Conformal bootstrap prediction intervals (2-steps-ahead interval forecasts)
set.seed(12345)
pprModel_cb <- cb_cvforecast(object = pprModel,
                             data = sim_data,
                             yvar = "y",
                             predictor.vars = index.vars,
                             h = 2,
                             ncal = 30,
                             num.futures = 100,
                             window = 1000)

# Mean width of generated 95% conformal bootstrap prediction intervals
width_data <- avgWidth(object = pprModel_cb)
width_data$mean

```

bb_cvforecast

Single season block bootstrap prediction intervals through time series cross-validation forecasting

Description

Compute prediction intervals by applying the single season block bootstrap method to subsets of time series data using a rolling forecast origin.

Usage

```

bb_cvforecast(
  object,
  data,
  yvar,
  neighbour = 0,
  predictor.vars,
  h = 1,
  season.period = 1,
  m = 1,
  num.futures = 1000,
  level = c(80, 95),
  forward = TRUE,
  initial = 1,
  window = NULL,
  roll.length = 1,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colNames = NULL,
  na.rm = TRUE,
  verbose = list(solver = FALSE, progress = FALSE),
  ...
)

```

Arguments

object	Fitted model object of class smimodel, backward, gaimFit or pprFit.
data	Data set. Must be a data set of class tsibble.(Make sure there are no additional date or time related variables except for the index of the tsibble). If multiple models are fitted, the grouping variable should be the key of the tsibble. If a key is not specified, a dummy key with only one level will be created.
yvar	Name of the response variable as a character string.
neighbour	If multiple models are fitted: Number of neighbours of each key (i.e. grouping variable) to be considered in model fitting to handle smoothing over the key. Should be an integer. If neighbour = x, x number of keys before the key of interest and x number of keys after the key of interest are grouped together for model fitting. The default is neighbour = 0 (i.e. no neighbours are considered for model fitting).
predictor.vars	A character vector of names of the predictor variables.
h	Forecast horizon.
season.period	Length of the seasonal period.
m	Multiplier. (Block size = NULLseason.period * m)
num.futures	Number of possible future sample paths to be generated.
level	Confidence level for prediction intervals.
forward	If TRUE, the final forecast origin for forecasting is y_T . Otherwise, the final forecast origin is y_{T-1} .

initial	Initial period of the time series where no cross-validation forecasting is performed.
window	Length of the rolling window. If NULL, a rolling window will not be used.
roll.length	Number of observations by which each rolling/expanding window should be rolled forward.
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colNames	If recursive = TRUE, a character vector giving the names of the columns in test data to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in data, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.
na.rm	logical; if TRUE (default), any NA and NaN's are removed from the sample before the quantiles are computed.
verbose	A named list controlling verbosity options. Defaults to list(solver = FALSE, progress = FALSE). solver Logical. If TRUE, prints detailed solver output when the SMI model is used. progress Logical. If TRUE, prints cross-validation progress messages (all models) and optimisation algorithm progress messages (SMI model only).
...	Other arguments not currently used.

Value

An object of class `bb_cvforecast`, which is a list that contains following elements:

x	The original time series.
method	A character string "bb_cvforecast".
fit_times	The number of times the model is fitted in cross-validation.
mean	Point forecasts as a multivariate time series, where the h^{th} column holds the point forecasts for forecast horizon h . The time index corresponds to the period for which the forecast is produced.
res	The matrix of in-sample residuals produced in cross-validation. The number of rows corresponds to <code>fit_times</code> , and the row names corresponds the time index of the forecast origin of the corresponding cross-validation iteration.
model_fit	Models fitted in cross-validation.
level	The confidence values associated with the prediction intervals.

lower	A list containing lower bounds for prediction intervals for each level. Each element within the list will be a multivariate time series with the same dimensional characteristics as mean.
upper	A list containing upper bounds for prediction intervals for each level. Each element within the list will be a multivariate time series with the same dimensional characteristics as mean.
possible_futures	A list of matrices containing future sample paths generated at each cross-validation step.

See Also[cb_cvforecast](#)**Examples**

```

if(requireNamespace("gurobi", quietly = TRUE)){
  library(dplyr)
  library(ROI)
  library(tibble)
  library(tidy)
  library(tsibble)

  # Simulate data
  n = 1105
  set.seed(123)
  sim_data <- tibble(x_lag_000 = runif(n)) |>
    mutate(
      # Add x_lags
      x_lag = lag_matrix(x_lag_000, 5) |>
        unpack(x_lag, names_sep = "_") |>
        mutate(
          # Response variable
          y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 +
            (0.35*x_lag_002 + 0.7*x_lag_005)^2 + rnorm(n, sd = 0.1),
          # Add an index to the data set
          inddd = seq(1, n)) |>
      drop_na() |>
      select(inddd, y, starts_with("x_lag")) |>
      # Make the data set a `tsibble`
      as_tsibble(index = inddd)

  # Index variables
  index.vars <- colnames(sim_data)[3:8]

  # Training set
  sim_train <- sim_data[1:1000, ]
  # Test set
  sim_test <- sim_data[1001:1100, ]

  # Model fitting
  smimodel_ppr <- model_smimodel(data = sim_train,

```

```

        yvar = "y",
        index.vars = index.vars,
        initialise = "ppr")

# Block bootstrap prediction intervals (3-steps-ahead interval forecasts)
set.seed(12345)
smimodel_ppr_bb <- bb_cvforecast(object = smimodel_ppr,
                                data = sim_data,
                                yvar = "y",
                                predictor.vars = index.vars,
                                h = 3,
                                num.futures = 50,
                                window = 1000)
}

```

blockBootstrap

Futures through single season block bootstrapping

Description

Generates possible future sample paths by applying the single season block bootstrap method.

Usage

```

blockBootstrap(
  object,
  newdata,
  resids,
  preds,
  season.period = 1,
  m = 1,
  num.futures = 1000,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL
)

```

Arguments

object	Fitted model object.
newdata	Test data set. Must be a data set of class <code>tsibble</code> .
resids	In-sample residuals from the fitted model.
preds	Predictions for the test set (i.e. data for the forecast horizon).
season.period	Length of the seasonal period.
m	Multiplier. (Block size = season.period * m)

num.futures	Number of possible future sample paths to be generated.
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string.
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, The range of column numbers in test data to be filled with forecasts.

Value

A matrix of simulated future sample paths.

cb_cvforecast	<i>Conformal bootstrap prediction intervals through time series cross-validation forecasting</i>
---------------	--

Description

Compute prediction intervals by applying the conformal bootstrap method to subsets of time series data using a rolling forecast origin.

Usage

```
cb_cvforecast(
  object,
  data,
  yvar,
  neighbour = 0,
  predictor.vars,
  h = 1,
  ncal = 100,
  num.futures = 1000,
  level = c(80, 95),
  forward = TRUE,
  initial = 1,
  window = NULL,
  roll.length = 1,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colNames = NULL,
  na.rm = TRUE,
  nacheck_frac_numerator = 2,
  nacheck_frac_denominator = 3,
  verbose = list(solver = FALSE, progress = FALSE),
  ...
)
```

Arguments

object	Fitted model object of class smimodel, backward, gaimFit or pprFit.
data	Data set. Must be a data set of class tsibble.(Make sure there are no additional date or time related variables except for the index of the tsibble). If multiple models are fitted, the grouping variable should be the key of the tsibble. If a key is not specified, a dummy key with only one level will be created.
yvar	Name of the response variable as a character string.
neighbour	If multiple models are fitted: Number of neighbours of each key (i.e. grouping variable) to be considered in model fitting to handle smoothing over the key. Should be an integer. If neighbour = x, x number of keys before the key of interest and x number of keys after the key of interest are grouped together for model fitting. The default is neighbour = 0 (i.e. no neighbours are considered for model fitting).
predictor.vars	A character vector of names of the predictor variables.
h	Forecast horizon.
ncal	Length of a calibration window.
num.futures	Number of possible future sample paths to be generated in bootstrap.
level	Confidence level for prediction intervals.
forward	If TRUE, the final forecast origin for forecasting is y_T . Otherwise, the final forecast origin is y_{T-1} .
initial	Initial period of the time series where no cross-validation forecasting is performed.
window	Length of the rolling window. If NULL, a rolling window will not be used.
roll.length	Number of observations by which each rolling/expanding window should be rolled forward.
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colNames	If recursive = TRUE, a character vector giving the names of the columns in test data to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in data, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.
na.rm	logical; if TRUE (default), any NA and NaN's are removed from the sample before the quantiles are computed.

nacheck_frac_numerator	Numerator of the fraction of non-missing values that is required in a test set.
nacheck_frac_denominator	Denominator of the fraction of non-missing values that is required in a test set.
verbose	A named list controlling verbosity options. Defaults to <code>list(solver = FALSE, progress = FALSE)</code> .
	solver Logical. If TRUE, prints detailed solver output when the SMI model is used.
	progress Logical. If TRUE, prints cross-validation progress messages (all models) and optimisation algorithm progress messages (SMI model only).
...	Other arguments not currently used.

Value

An object of class `cb_cvforecast`, which is a list that contains following elements:

<code>x</code>	The original time series.
<code>method</code>	A character string "cb_cvforecast".
<code>fit_times</code>	The number of times the model is fitted in cross-validation.
<code>mean</code>	Point forecasts as a multivariate time series, where the h^{th} column holds the point forecasts for forecast horizon h . The time index corresponds to the period for which the forecast is produced.
<code>error</code>	Forecast errors given by $e_{t+h t} = y_{t+h} - \hat{y}_{t+h t}$.
<code>res</code>	The matrix of in-sample residuals produced in cross-validation.
<code>level</code>	The confidence levels associated with the prediction intervals.
<code>cal_times</code>	The number of calibration windows considered in cross-validation.
<code>num_cal</code>	The number of non-missing multi-step forecast errors in each calibration window.
<code>skip_cal</code>	An indicator vector indicating whether a calibration window is skipped without constructing prediction intervals due to missing model or missing data in the test set.
<code>lower</code>	A list containing lower bounds for prediction intervals for each level. Each element within the list will be a multivariate time series with the same dimensional characteristics as <code>mean</code> .
<code>upper</code>	A list containing upper bounds for prediction intervals for each level. Each element within the list will be a multivariate time series with the same dimensional characteristics as <code>mean</code> .
<code>possible_futures</code>	A list of matrices containing future sample paths generated at each calibration step.

See Also

[bb_cvforecast](#)

Examples

```

if(requireNamespace("gurobi", quietly = TRUE)){
  library(dplyr)
  library(ROI)
  library(tibble)
  library(tidyr)
  library(tsibble)

  # Simulate data
  n = 1105
  set.seed(123)
  sim_data <- tibble(x_lag_000 = runif(n)) |>
    mutate(
      # Add x_lags
      x_lag = lag_matrix(x_lag_000, 5) |>
        unpack(x_lag, names_sep = "_") |>
        mutate(
          # Response variable
          y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 +
            (0.35*x_lag_002 + 0.7*x_lag_005)^2 + rnorm(n, sd = 0.1),
          # Add an index to the data set
          inddd = seq(1, n)) |>
      drop_na() |>
      select(inddd, y, starts_with("x_lag")) |>
      # Make the data set a `tsibble`
      as_tsibble(index = inddd)

  # Index variables
  index.vars <- colnames(sim_data)[3:8]

  # Training set
  sim_train <- sim_data[1:1000, ]
  # Test set
  sim_test <- sim_data[1001:1100, ]

  # Model fitting
  smimodel_ppr <- model_smimodel(data = sim_train,
                                yvar = "y",
                                index.vars = index.vars,
                                initialise = "ppr")

  # Conformal bootstrap prediction intervals (3-steps-ahead interval forecasts)
  set.seed(12345)
  smimodel_ppr_cb <- cb_cvforecast(object = smimodel_ppr,
                                   data = sim_data,
                                   yvar = "y",
                                   predictor.vars = index.vars,
                                   h = 3,
                                   ncal = 30,
                                   num.futures = 100,
                                   window = 1000)
}

```

eliminate

Eliminate a variable and fit a nonparametric additive model

Description

Eliminates a specified variable and fits a nonparametric additive model with remaining variables, and returns validation set MSE. This is an internal function of the package, and designed to be called from [model_backward](#).

Usage

```
eliminate(
  ind,
  train,
  val,
  yvar,
  family = gaussian(),
  s.vars = NULL,
  s.basedim = NULL,
  linear.vars = NULL,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL
)
```

Arguments

ind	An integer corresponding to the position of the predictor variable to be eliminated when fitting the model. (i.e. the function will combine <code>s.vars</code> and <code>linear.vars</code> in a single vector and eliminate the element corresponding to <code>ind</code> .)
train	The data set on which the model(s) will be trained. Must be a data set of class <code>tsibble</code> .
val	Validation data set. (The data set on which the model selection will be performed.) Must be a data set of class <code>tsibble</code> .
yvar	Name of the response variable as a character string.
family	A description of the error distribution and link function to be used in the model (see glm and family).
s.vars	A character vector of names of the predictor variables for which splines should be fitted (i.e. non-linear predictors).
s.basedim	Dimension of the bases used to represent the smooth terms corresponding to <code>s.vars</code> . (For more information refer <code>mgcv::s()</code> .)

linear.vars	A character vector of names of the predictor variables that should be included linearly into the model (i.e. linear predictors).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in <code>val</code> that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If <code>recursive = TRUE</code> , the range of column numbers in <code>val.data</code> to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. <code>lag_1</code> , <code>lag_2</code> , ..., <code>lag_m</code> , <code>lag_m</code> = maximum lag used) in <code>val.data</code> , with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.

Value

A numeric.

forecast.backward	<i>Forecasting using nonparametric additive models with backward elimination</i>
-------------------	--

Description

Returns forecasts and other information for nonparametric additive models with backward elimination.

Usage

```
## S3 method for class 'backward'
forecast(
  object,
  h = 1,
  level = c(80, 95),
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)
```

Arguments

object	An object of class backward. Usually the result of a call to <code>model_backward</code> .
h	Forecast horizon.
level	Confidence level for prediction intervals.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a <code>tsibble</code>).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string.
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts.
...	Other arguments not currently used.

Value

An object of class forecast. Here, it is a list containing the following elements:

method	The name of the forecasting method as a character string.
model	The fitted model.
mean	Point forecasts as a time series.
residuals	Residuals from the fitted model.
fitted	Fitted values (one-step forecasts).

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1215
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5) |>
    unpack(x_lag, names_sep = "_") |>
    mutate(
      # Response variable
      y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
      # Add an index to the data set
      inddd = seq(1, n)) |>
    drop_na() |>
    select(inddd, y, starts_with("x_lag")) |>
    # Make the data set a `tsibble`
```

```

  as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Validation set
sim_val <- sim_data[1001:1200, ]
# Test set
sim_test <- sim_data[1201:1210, ]

# Predictors taken as non-linear variables
s.vars <- colnames(sim_data)[3:8]

# Model fitting
backwardModel <- model_backward(data = sim_train,
                                val.data = sim_val,
                                yvar = "y",
                                s.vars = s.vars)
forecast(backwardModel, newdata = sim_test)

```

forecast.gaimFit

Forecasting using GAIMs

Description

Returns forecasts and other information for GAIMs.

Usage

```

## S3 method for class 'gaimFit'
forecast(
  object,
  h = 1,
  level = c(80, 95),
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)

```

Arguments

object	An object of class <code>gaimFit</code> . Usually the result of a call to <code>model_gaim</code> .
h	Forecast horizon.
level	Confidence level for prediction intervals.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a <code>tsibble</code>).

exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string.
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts.
...	Other arguments not currently used.

Value

An object of class forecast. Here, it is a list containing the following elements:

method	The name of the forecasting method as a character string.
model	The fitted model.
mean	Point forecasts as a time series.
residuals	Residuals from the fitted model.
fitted	Fitted values (one-step forecasts).

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1015
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1010, ]

# Predictors taken as index variables
index.vars <- colnames(sim_data)[3:7]
```

```

# Assign group indices for each predictor
index.ind = c(rep(1, 3), rep(2, 2))

# Predictors taken as non-linear variables not entering indices
s.vars = "x_lag_005"

# Model fitting
gaimModel <- model_gaim(data = sim_train,
                        yvar = "y",
                        index.vars = index.vars,
                        index.ind = index.ind,
                        s.vars = s.vars)

forecast(gaimModel, newdata = sim_test)

```

forecast.gamFit

Forecasting using GAMs

Description

Returns forecasts and other information for GAMs.

Usage

```

## S3 method for class 'gamFit'
forecast(
  object,
  h = 1,
  level = c(80, 95),
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)

```

Arguments

object	An object of class gamFit. Usually the result of a call to model_gam .
h	Forecast horizon.
level	Confidence level for prediction intervals.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a <code>tsibble</code>).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string.

recursive Whether to obtain recursive forecasts or not (default - FALSE).
 recursive_colRange If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts.
 ... Other arguments not currently used.

Value

An object of class forecast. Here, it is a list containing the following elements:

method The name of the forecasting method as a character string.
 model The fitted model.
 mean Point forecasts as a time series.
 residuals Residuals from the fitted model.
 fitted Fitted values (one-step forecasts).

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1015
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5) |>
    unpack(x_lag, names_sep = "_") |>
    mutate(
      # Response variable
      y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
      # Add an index to the data set
      inddd = seq(1, n)) |>
    drop_na() |>
    select(inddd, y, starts_with("x_lag")) |>
    # Make the data set a `tsibble`
    as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1010, ]

# Predictors taken as non-linear variables
s.vars <- colnames(sim_data)[3:6]

# Predictors taken as linear variables
```

```

linear.vars <- colnames(sim_data)[7:8]

# Model fitting
gamModel <- model_gam(data = sim_train,
                      yvar = "y",
                      s.vars = s.vars,
                      linear.vars = linear.vars)

forecast(gamModel, newdata = sim_test)

```

forecast.pprFit *Forecasting using PPR models*

Description

Returns forecasts and other information for PPR models.

Usage

```

## S3 method for class 'pprFit'
forecast(
  object,
  h = 1,
  level = c(80, 95),
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)

```

Arguments

object	An object of class <code>pprFit</code> . Usually the result of a call to <code>model_ppr</code> .
h	Forecast horizon.
level	Confidence level for prediction intervals.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a <code>tsibble</code>).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string.
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If <code>recursive = TRUE</code> , the range of column numbers in <code>newdata</code> to be filled with forecasts.
...	Other arguments not currently used.

Value

An object of class forecast. Here, it is a list containing the following elements:

method	The name of the forecasting method as a character string.
model	The fitted model.
mean	Point forecasts as a time series.
residuals	Residuals from the fitted model.
fitted	Fitted values (one-step forecasts).

Examples

```
library(dplyr)
library(tibble)
library(tidy)
library(tsibble)

# Simulate data
n = 1015
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1010, ]

# Index variables
index.vars <- colnames(sim_data)[3:8]

# Model fitting
pprModel <- model_ppr(data = sim_train,
                     yvar = "y",
                     index.vars = index.vars)

forecast(pprModel, newdata = sim_test)
```

forecast.smimodel	<i>Forecasting using SMI models</i>
-------------------	-------------------------------------

Description

Returns forecasts and other information for SMI models.

Usage

```
## S3 method for class 'smimodel'
forecast(
  object,
  h = 1,
  level = c(80, 95),
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)
```

Arguments

object	An object of class <code>smimodel</code> . Usually the result of a call to <code>model_smimodel</code> .
h	Forecast horizon.
level	Confidence level for prediction intervals.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a <code>tsibble</code>).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string.
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If <code>recursive = TRUE</code> , the range of column numbers in <code>newdata</code> to be filled with forecasts.
...	Other arguments not currently used.

Value

An object of class `forecast`. Here, it is a list containing the following elements:

method	The name of the forecasting method as a character string.
model	The fitted model.
mean	Point forecasts as a time series.
residuals	Residuals from the fitted model.
fitted	Fitted values (one-step forecasts).

Examples

```

if(requireNamespace("gurobi", quietly = TRUE)){
  library(dplyr)
  library(ROI)
  library(tibble)
  library(tidyr)
  library(tsibble)

  # Simulate data
  n = 1015
  set.seed(123)
  sim_data <- tibble(x_lag_000 = runif(n)) |>
    mutate(
      # Add x_lags
      x_lag = lag_matrix(x_lag_000, 5)) |>
    unpack(x_lag, names_sep = "_") |>
    mutate(
      # Response variable
      y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
      # Add an index to the data set
      inddd = seq(1, n)) |>
    drop_na() |>
    select(inddd, y, starts_with("x_lag")) |>
    # Make the data set a `tsibble`
    as_tsibble(index = inddd)

  # Training set
  sim_train <- sim_data[1:1000, ]
  # Test set
  sim_test <- sim_data[1001:1010, ]

  # Index variables
  index.vars <- colnames(sim_data)[3:8]

  # Model fitting
  smimodel_ppr <- model_smimodel(data = sim_train,
                                yvar = "y",
                                index.vars = index.vars,
                                initialise = "ppr")

  forecast(smimodel_ppr, newdata = sim_test)
}

```

 greedy.fit

Greedy search for tuning penalty parameters

Description

Function to perform a greedy search over a given grid of penalty parameter combinations (λ_0 , λ_2), and fits a single SMI model with the best (lowest validation set MSE) penalty parameter

combination. If the optimal combination lies on the edge of the grid, the penalty parameters are adjusted by $\pm 10\%$, and a second round of grid search is performed. This is a helper function designed to be called from `greedy_smimodel`.

Usage

```
greedy.fit(
  data,
  val.data,
  yvar,
  neighbour = 0,
  family = gaussian(),
  index.vars,
  initialise = c("ppr", "additive", "linear", "multiple", "userInput"),
  num_ind = 5,
  num_models = 5,
  seed = 123,
  index.ind = NULL,
  index.coefs = NULL,
  s.vars = NULL,
  linear.vars = NULL,
  nlambda = 100,
  lambda.min.ratio = 1e-04,
  refit = TRUE,
  M = 10,
  max.iter = 50,
  tol = 0.001,
  tolCoefs = 0.001,
  TimeLimit = Inf,
  MIPGap = 1e-04,
  NonConvex = -1,
  verbose = list(solver = FALSE, progress = FALSE),
  parallel = FALSE,
  workers = NULL,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL
)
```

Arguments

<code>data</code>	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>).
<code>val.data</code>	Validation data set. (The data set on which the penalty parameter selection will be performed.) Must be a data set of class <code>tsibble</code> . (Once the penalty parameter selection is completed, the best model will be re-fitted for the combined data set <code>data + val.data</code> .)

yvar	Name of the response variable as a character string.
neighbour	neighbour argument passed from the outer function.
family	A description of the error distribution and link function to be used in the model (see <code>glm</code> and <code>family</code>).
index.vars	A character vector of names of the predictor variables for which indices should be estimated.
initialise	The model structure with which the estimation process should be initialised. The default is "ppr", where the initial model is derived from projection pursuit regression. The other options are "additive" - nonparametric additive model, "linear" - linear regression model (i.e. a special case single-index model, where the initial values of the index coefficients are obtained through a linear regression), "multiple" - multiple models are fitted starting with different initial models (number of indices = num_ind; num_models random instances of the model (i.e. the predictor assignment to indices and initial index coefficients are generated randomly) are considered), and the final optimal model with the lowest loss is returned, and "userInput" - user specifies the initial model structure (i.e. the number of indices and the placement of index variables among indices) and the initial index coefficients through index.ind and index.coefs arguments respectively.
num_ind	If initialise = "ppr" or "multiple": an integer that specifies the number of indices to be used in the model(s). The default is num_ind = 5.
num_models	If initialise = "multiple": an integer that specifies the number of starting models to be checked. The default is num_models = 5.
seed	If initialise = "multiple": the seed to be set when generating random starting points.
index.ind	If initialise = "userInput": an integer vector that assigns group index for each predictor in index.vars.
index.coefs	If initialise = "userInput": a numeric vector of index coefficients.
s.vars	A character vector of names of the predictor variables for which splines should be fitted individually (rather than considering as part of an index).
linear.vars	A character vector of names of the predictor variables that should be included linearly into the model.
nlambda	The number of values for lambda0 (penalty parameter for L0 penalty) - default is 100.
lambda.min.ratio	Smallest value for lambda0, as a fraction of lambda0.max (data derived).
refit	Whether to refit the model combining training and validation sets after parameter tuning. If FALSE, the final model will be estimated only on the training set.
M	Big-M value used in MIP.
max.iter	Maximum number of MIP iterations performed to update index coefficients for a given model.
tol	Tolerance for the objective function value (loss) of MIP.
tolCoefs	Tolerance for coefficients.

TimeLimit	A limit for the total time (in seconds) expended in a single MIP iteration.
MIPGap	Relative MIP optimality gap.
NonConvex	The strategy for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.
verbose	A named list controlling verbosity options. Defaults to <code>list(solver = FALSE, progress = FALSE)</code> . solver Logical. If TRUE, print detailed solver output. progress Logical. If TRUE, print optimisation algorithm progress messages.
parallel	The option to use parallel processing in fitting SMI models for different penalty parameter combinations.
workers	If <code>parallel = TRUE</code> : Number of cores to use.
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in <code>val.data</code> that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If <code>recursive = TRUE</code> , the range of column numbers in <code>val.data</code> to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. <code>lag_1, lag_2, . . . , lag_m, lag_m = maximum lag used</code>) in <code>val.data</code> , with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.

Value

A list that contains six elements:

initial	A list of information of the model initialisation. (For descriptions of the list elements see make_smimodelFit).
best	A list of information of the final optimised model. (For descriptions of the list elements see make_smimodelFit).
best_lambdas	Selected penalty parameter combination.
lambda0_seq	Sequence of values for <code>lambda0</code> used to construct the initial grid.
lambda2_seq	Sequence of values for <code>lambda2</code> used to construct the initial grid.
searched	A tibble containing the penalty parameter combinations searched during the two-step greedy search and the corresponding validation set MSEs.

`greedy_smimodel`*SMI model estimation through a greedy search for penalty parameters*

Description

Performs a greedy search over a given grid of penalty parameter combinations (λ_0 , λ_2), and fits SMI model(s) with best (lowest validation set MSE) penalty parameter combination(s). If the optimal combination lies on the edge of the grid, the penalty parameters are adjusted by $\pm 10\%$, and a second round of grid search is performed. If a grouping variable is used, penalty parameters are tuned separately for each individual model.

Usage

```
greedy_smimodel(  
  data,  
  val.data,  
  yvar,  
  neighbour = 0,  
  family = gaussian(),  
  index.vars,  
  initialise = c("ppr", "additive", "linear", "multiple", "userInput"),  
  num_ind = 5,  
  num_models = 5,  
  seed = 123,  
  index.ind = NULL,  
  index.coefs = NULL,  
  s.vars = NULL,  
  linear.vars = NULL,  
  nlambda = 100,  
  lambda.min.ratio = 1e-04,  
  refit = TRUE,  
  M = 10,  
  max.iter = 50,  
  tol = 0.001,  
  tolCoefs = 0.001,  
  TimeLimit = Inf,  
  MIPGap = 1e-04,  
  NonConvex = -1,  
  verbose = list(solver = FALSE, progress = FALSE),  
  parallel = FALSE,  
  workers = NULL,  
  exclude.trunc = NULL,  
  recursive = FALSE,  
  recursive_colRange = NULL  
)
```

Arguments

<code>data</code>	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>). If multiple models are fitted, the grouping variable should be the key of the <code>tsibble</code> . If a key is not specified, a dummy key with only one level will be created.
<code>val.data</code>	Validation data set. (The data set on which the penalty parameter selection will be performed.) Must be a data set of class <code>tsibble</code> . (Once the penalty parameter selection is completed, the best model will be re-fitted for the combined data set <code>data + val.data</code> .)
<code>yvar</code>	Name of the response variable as a character string.
<code>neighbour</code>	If multiple models are fitted: Number of neighbours of each key (i.e. grouping variable) to be considered in model fitting to handle smoothing over the key. Should be an integer. If <code>neighbour = x</code> , <code>x</code> number of keys before the key of interest and <code>x</code> number of keys after the key of interest are grouped together for model fitting. The default is <code>neighbour = 0</code> (i.e. no neighbours are considered for model fitting).
<code>family</code>	A description of the error distribution and link function to be used in the model (see <code>glm</code> and <code>family</code>).
<code>index.vars</code>	A character vector of names of the predictor variables for which indices should be estimated.
<code>initialise</code>	The model structure with which the estimation process should be initialised. The default is <code>"ppr"</code> , where the initial model is derived from projection pursuit regression. The other options are <code>"additive"</code> - nonparametric additive model, <code>"linear"</code> - linear regression model (i.e. a special case single-index model, where the initial values of the index coefficients are obtained through a linear regression), <code>"multiple"</code> - multiple models are fitted starting with different initial models (number of indices = <code>num_ind</code> ; <code>num_models</code> random instances of the model (i.e. the predictor assignment to indices and initial index coefficients are generated randomly) are considered), and the final optimal model with the lowest loss is returned, and <code>"userInput"</code> - user specifies the initial model structure (i.e. the number of indices and the placement of index variables among indices) and the initial index coefficients through <code>index.ind</code> and <code>index.coefs</code> arguments respectively.
<code>num_ind</code>	If <code>initialise = "ppr"</code> or <code>"multiple"</code> : an integer that specifies the number of indices to be used in the model(s). The default is <code>num_ind = 5</code> .
<code>num_models</code>	If <code>initialise = "multiple"</code> : an integer that specifies the number of starting models to be checked. The default is <code>num_models = 5</code> .
<code>seed</code>	If <code>initialise = "multiple"</code> : the seed to be set when generating random starting points.
<code>index.ind</code>	If <code>initialise = "userInput"</code> : an integer vector that assigns group index for each predictor in <code>index.vars</code> .
<code>index.coefs</code>	If <code>initialise = "userInput"</code> : a numeric vector of index coefficients.
<code>s.vars</code>	A character vector of names of the predictor variables for which splines should be fitted individually (rather than considering as part of an index).

<code>linear.vars</code>	A character vector of names of the predictor variables that should be included linearly into the model.
<code>nlambda</code>	The number of values for <code>lambda0</code> (penalty parameter for L0 penalty) - default is 100.
<code>lambda.min.ratio</code>	Smallest value for <code>lambda0</code> , as a fraction of <code>lambda0.max</code> (data derived).
<code>refit</code>	Whether to refit the model combining training and validation sets after parameter tuning. If FALSE, the final model will be estimated only on the training set.
<code>M</code>	Big-M value used in MIP.
<code>max.iter</code>	Maximum number of MIP iterations performed to update index coefficients for a given model.
<code>tol</code>	Tolerance for the objective function value (loss) of MIP.
<code>tolCoefs</code>	Tolerance for coefficients.
<code>TimeLimit</code>	A limit for the total time (in seconds) expended in a single MIP iteration.
<code>MIPGap</code>	Relative MIP optimality gap.
<code>NonConvex</code>	The strategy for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.
<code>verbose</code>	A named list controlling verbosity options. Defaults to <code>list(solver = FALSE, progress = FALSE)</code> . solver Logical. If TRUE, print detailed solver output. progress Logical. If TRUE, print optimisation algorithm progress messages.
<code>parallel</code>	The option to use parallel processing in fitting SMI models for different penalty parameter combinations.
<code>workers</code>	If <code>parallel = TRUE</code> : Number of cores to use.
<code>exclude.trunc</code>	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in <code>val.data</code> that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
<code>recursive</code>	Whether to obtain recursive forecasts or not (default - FALSE).
<code>recursive_colRange</code>	If <code>recursive = TRUE</code> , the range of column numbers in <code>val.data</code> to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. <code>lag_1, lag_2, ..., lag_m, lag_m = maximum lag used</code>) in <code>val.data</code> , with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.

Value

An object of class `smimodel`. This is a tibble with two columns:

key	The level of the grouping variable (i.e. key of the training data set).
fit	Information of the fitted model corresponding to the key.

Each row of the column `fit` contains a list with six elements:

initial	A list of information of the model initialisation. (For descriptions of the list elements see make_smimodelFit).
best	A list of information of the final optimised model. (For descriptions of the list elements see make_smimodelFit).
best_lambdas	Selected penalty parameter combination.
lambda0_seq	Sequence of values for <code>lambda0</code> used to construct the initial grid.
lambda2_seq	Sequence of values for <code>lambda2</code> used to construct the initial grid.
searched	A tibble containing the penalty parameter combinations searched during the two-step greedy search and the corresponding validation set MSEs.

The number of rows of the tibble equals to the number of levels in the grouping variable.

See Also

[model_smimodel](#)

Examples

```
if(requireNamespace("gurobi", quietly = TRUE)){
  library(dplyr)
  library(ROI)
  library(tibble)
  library(tidyr)
  library(tsibble)

  # Simulate data
  n = 1205
  set.seed(123)
  sim_data <- tibble(x_lag_000 = runif(n)) |>
    mutate(
      # Add x_lags
      x_lag = lag_matrix(x_lag_000, 5) |>
      unpack(x_lag, names_sep = "_") |>
      mutate(
        # Response variable
        y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
        # Add an index to the data set
        inddd = seq(1, n)) |>
      drop_na() |>
      select(inddd, y, starts_with("x_lag")) |>
      # Make the data set a `tsibble`
      as_tsibble(index = inddd)

  # Training set
  sim_train <- sim_data[1:1000, ]
}
```

```

# Validation set
sim_val <- sim_data[1001:1200, ]

# Index variables
index.vars <- colnames(sim_data)[3:8]

# Model fitting
smi_greedy <- greedy_smimodel(data = sim_train,
                             val.data = sim_val,
                             yvar = "y",
                             index.vars = index.vars,
                             initialise = "ppr",
                             lambda.min.ratio = 0.1)

# Best (optimised) fitted model
smi_greedy$fit[[1]]$best

# Selected penalty parameter combination
smi_greedy$fit[[1]]$best_lambdas
}

```

init_alpha

Initialising index coefficients

Description

Initialises index coefficient vector through linear regression or penalised linear regression.

Usage

```

init_alpha(
  Y,
  X,
  index.ind,
  init.type = "penalisedReg",
  lambda0 = 1,
  lambda2 = 1,
  M = 10
)

```

Arguments

Y	Column matrix of response.
X	Matrix of predictors entering indices.
index.ind	An integer vector that assigns group index for each predictor.

init.type	Type of initialisation for index coefficients. ("penalisedReg" - Penalised linear regression; "reg" - Linear regression)
lambda0	If init.type = "penalisedReg", penalty parameter for L0 penalty.
lambda2	If init.type = "penalisedReg", penalty parameter for L2 penalty.
M	If init.type = "penalisedReg", the big-M value to be used in the MIP.

Value

A list containing the following components:

alpha_init	Normalised vector of index coefficients.
alpha_nonNormalised	Non-normalised (i.e. prior to normalising) vector of index coefficients.

inner_update	<i>Updating index coefficients and non-linear functions iteratively</i>
--------------	---

Description

Iteratively updates index coefficients and non-linear functions using mixed integer programming. (A helper function used within `update_smimodelFit`; users are not expected to directly call this function.)

Usage

```
inner_update(
  x,
  data,
  yvar,
  family = gaussian(),
  index.vars,
  s.vars,
  linear.vars,
  num_ind,
  dgz,
  alpha_old,
  lambda0 = 1,
  lambda2 = 1,
  M = 10,
  max.iter = 50,
  tol = 0.001,
  TimeLimit = Inf,
  MIPGap = 1e-04,
  NonConvex = -1,
  verbose = list(solver = FALSE, progress = FALSE)
)
```

Arguments

<code>x</code>	Fitted gam.
<code>data</code>	Training data set on which models will be trained. Should be a <code>tsibble</code> .
<code>yvar</code>	Name of the response variable as a character string.
<code>family</code>	A description of the error distribution and link function to be used in the model (see <code>glm</code> and <code>family</code>).
<code>index.vars</code>	A character vector of names of the predictor variables for which indices should be estimated.
<code>s.vars</code>	A character vector of names of the predictor variables for which splines should be fitted individually (rather than considering as part of an index).
<code>linear.vars</code>	A character vector of names of the predictor variables that should be included linearly into the model.
<code>num_ind</code>	Number of indices.
<code>dgz</code>	The <code>tibble</code> of derivatives of the estimated smooths.
<code>alpha_old</code>	Current vector of index coefficients.
<code>lambda0</code>	Penalty parameter for L0 penalty.
<code>lambda2</code>	Penalty parameter for L2 penalty.
<code>M</code>	Big-M value to be used in MIP.
<code>max.iter</code>	Maximum number of MIP iterations performed to update index coefficients for a given model.
<code>tol</code>	Tolerance for loss.
<code>TimeLimit</code>	A limit for the total time (in seconds) expended in a single MIP iteration.
<code>MIPGap</code>	Relative MIP optimality gap.
<code>NonConvex</code>	The strategy for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.
<code>verbose</code>	A named list controlling verbosity options. Defaults to <code>list(solver = FALSE, progress = FALSE)</code> . <code>solver</code> Logical. If TRUE, print detailed solver output. <code>progress</code> Logical. If TRUE, print optimisation algorithm progress messages.

Value

A list containing following elements:

<code>best_alpha</code>	The vector of best index coefficient estimates.
<code>min_loss</code>	Minimum value of the objective function(loss).
<code>index.ind</code>	An integer vector that assigns group index for each predictor, corresponding to <code>best_alpha</code> .
<code>ind_pos</code>	A list that indicates which predictors belong to which index, corresponding to <code>best_alpha</code> .
<code>X_new</code>	A matrix of selected predictor variables, corresponding to <code>best_alpha</code> .

lag_matrix	<i>Function for adding lags of time series variables</i>
------------	--

Description

Generates specified number of lagged variables of the given variable in the form of a tibble.

Usage

```
lag_matrix(variable, n = 10)
```

Arguments

variable	Variable to be lagged.
n	Number of lags. The default value is n = 10.

Value

A tibble.

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
# Adding lagged variables to an existing tibble
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(100)) |>
  mutate(x_lag = lag_matrix(x_lag_000, 3)) |>
  unpack(x_lag, names_sep = "_")
```

loss	<i>Calculating the loss of the MIP used to estimate a SMI model</i>
------	---

Description

Calculates the value of the objective function (loss function) of the mixed integer program used to estimate a SMI model.

Usage

```
loss(Y, Yhat, alpha, lambda0, lambda2)
```

Arguments

<code>Y</code>	Column matrix of response.
<code>Yhat</code>	Predicted value of the response.
<code>alpha</code>	Vector of index coefficients.
<code>lambda0</code>	Penalty parameter for L0 penalty.
<code>lambda2</code>	Penalty parameter for L2 penalty.

Value

A numeric.

MAE	<i>Point estimate accuracy measures</i>
-----	---

Description

Point estimate accuracy measures

Usage

```
MAE(residuals, na.rm = TRUE, ...)
```

```
MSE(residuals, na.rm = TRUE, ...)
```

```
point_measures
```

Arguments

<code>residuals</code>	A vector of residuals from either the validation or test data.
<code>na.rm</code>	If TRUE, remove the missing values before calculating the accuracy measure.
<code>...</code>	Additional arguments for each measure.

Format

An object of class `list` of length 2.

Value

For the individual functions (MAE, MSE), returns a single numeric scalar giving the requested accuracy measure.

For the exported object `point_measures`, returns a named list of functions that can be supplied to higher-level accuracy routines.

Examples

```
set.seed(123)
ytrain <- rnorm(100)
ytest  <- rnorm(30)
yhat   <- ytest + rnorm(30, sd = 0.3)
resid  <- ytest - yhat

MAE(resid)
MSE(resid)
```

make_smimodelFit	<i>Converting a fitted gam object to a smimodelFit object</i>
------------------	---

Description

Converts a given object of class gam to an object of class smimodelFit.

Usage

```
make_smimodelFit(
  x,
  data,
  yvar,
  neighbour,
  index.vars,
  index.ind,
  index.data,
  index.names,
  alpha,
  s.vars = NULL,
  linear.vars = NULL,
  lambda0 = NULL,
  lambda2 = NULL,
  M = NULL,
  max.iter = NULL,
  tol = NULL,
  tolCoefs = NULL,
  TimeLimit = NULL,
  MIPGap = NULL,
  NonConvex = NULL
)
```

Arguments

x	A fitted gam object.
data	The original training data set.

yvar	Name of the response variable as a character string.
neighbour	neighbour argument passed from the outer function.
index.vars	A character vector of names of the predictor variables for which indices are estimated.
index.ind	An integer vector that assigns group index for each predictor in index.vars.
index.data	A tibble including columns for the constructed indices.
index.names	A character vector of names of the constructed indices.
alpha	A vector of index coefficients.
s.vars	A character vector of names of the predictor variables for which splines are fitted individually (rather than considering as part of an index).
linear.vars	A character vector of names of the predictor variables that are included linearly in the model.
lambda0	Penalty parameter for L0 penalty.
lambda2	Penalty parameter for L2 penalty.
M	Big-M value to be used in MIP.
max.iter	Maximum number of MIP iterations performed to update index coefficients for a given model.
tol	Tolerance for the objective function value (loss) of MIP.
tolCoefs	Tolerance for coefficients.
TimeLimit	A limit for the total time (in seconds) expended in a single MIP iteration.
MIPGap	Relative MIP optimality gap.
NonConvex	The strategy for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.

Value

An object of class `smimodelFit`, which is a list that contains following elements:

alpha	A sparse matrix of index coefficients vectors. Each column of the matrix corresponds to the index coefficient vector of each index.
derivatives	A tibble of derivatives of the estimated smooths.
var_y	Name of the response variable.
vars_index	A character vector of names of the predictor variables for which indices are estimated.
vars_s	A character vector of names of the predictor variables for which splines are fitted individually.
vars_linear	A character vector of names of the predictor variables that are included linearly in the model.
neighbour	Number of neighbours of each key considered in model fitting.
gam	Fitted gam.
lambda0	L0 penalty parameter used for model fitting.

lambda2	L2 penalty parameter used for model fitting.
M	Big-M value used in MIP.
max.iter	Maximum number of MIP iterations for a single round of index coefficients update.
tol	Tolerance for the objective function value (loss) used in solving MIP.
tolCoefs	Tolerance for coefficients used in updating index coefficients.
TimeLimit	Limit for the total time (in seconds) expended in a single MIP iteration.
MIPGap	Relative MIP optimality gap used.
Nonconvex	The strategy used for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.

 model_backward

Nonparametric Additive Model with Backward Elimination

Description

Fits a nonparametric additive model, with simultaneous variable selection through a backward elimination procedure as proposed by Fan and Hyndman (2012).

Usage

```

model_backward(
  data,
  val.data,
  yvar,
  neighbour = 0,
  family = gaussian(),
  s.vars = NULL,
  s.basedim = NULL,
  linear.vars = NULL,
  refit = TRUE,
  tol = 0.001,
  parallel = FALSE,
  workers = NULL,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  verbose = FALSE
)

```

Arguments

data	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>). If multiple models are fitted, the grouping variable should be the key of the <code>tsibble</code> . If a key is not specified, a dummy key with only one level will be created.
val.data	Validation data set. (The data set on which the model selection will be performed.) Must be a data set of class <code>tsibble</code> .
yvar	Name of the response variable as a character string.
neighbour	If multiple models are fitted: Number of neighbours of each key (i.e. grouping variable) to be considered in model fitting to handle smoothing over the key. Should be an integer. If <code>neighbour = x</code> , <code>x</code> number of keys before the key of interest and <code>x</code> number of keys after the key of interest are grouped together for model fitting. The default is <code>neighbour = 0</code> (i.e. no neighbours are considered for model fitting).
family	A description of the error distribution and link function to be used in the model (see <code>glm</code> and <code>family</code>).
s.vars	A character vector of names of the predictor variables for which splines should be fitted (i.e. non-linear predictors).
s.basedim	Dimension of the bases used to represent the smooth terms corresponding to <code>s.vars</code> . (For more information refer <code>mgcv::s()</code> .)
linear.vars	A character vector of names of the predictor variables that should be included linearly into the model (i.e. linear predictors).
refit	Whether to refit the model combining training and validation sets after model selection. If <code>FALSE</code> , the final model will be estimated only on the training set.
tol	Tolerance for the ratio of relative change in validation set MSE, used in model selection.
parallel	Whether to use parallel computing in model selection or not.
workers	If <code>parallel = TRUE</code> , number of workers to use.
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in <code>val.data</code> that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - <code>FALSE</code>).
recursive_colRange	If <code>recursive = TRUE</code> , the range of column numbers in <code>val.data</code> to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. <code>lag_1</code> , <code>lag_2</code> , ..., <code>lag_m</code> , <code>lag_m</code> = maximum lag used) in <code>val.data</code> , with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.

verbose Logical; controls whether progress messages (model indices) are printed during fitting. Defaults to FALSE.

Details

This function fits a nonparametric additive model formulated through Backward Elimination, as proposed by Fan and Hyndman (2012). The process starts with all predictors included in an additive model, and predictors are progressively omitted until the best model is obtained based on the validation set. Once the best model is obtained, the final model is re-fitted for the data set combining training and validation sets. For more details see reference.

Value

An object of class backward. This is a tibble with two columns:

key The level of the grouping variable (i.e. key of the training data set).
fit Information of the fitted model corresponding to the key.

Each row of the column fit is an object of class gam. For details refer `mgcv::gamObject`.

References

Fan, S. & Hyndman, R.J. (2012). Short-Term Load Forecasting Based on a Semi-Parametric Additive Model. *IEEE Transactions on Power Systems*, 27(1), 134-141.[doi:10.1109/TPWRS.2011.2162082](https://doi.org/10.1109/TPWRS.2011.2162082).

See Also

[model_smimodel](#), [model_gaim](#), [model_ppr](#), [model_gam](#), [model_lm](#)

Examples

```
library(dplyr)
library(tibble)
library(tidyverse)
library(tsibble)

# Simulate data
n = 1205
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5) |>
    unpack(x_lag, names_sep = "_") |>
    mutate(
      # Response variable
      y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
      # Add an index to the data set
      inddd = seq(1, n)) |>
    drop_na() |>
    select(indddd, y, starts_with("x_lag")) |>
    # Make the data set a `tsibble`
```

```

  as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Validation set
sim_val <- sim_data[1001:1200, ]

# Predictors taken as non-linear variables
s.vars <- colnames(sim_data)[3:8]

# Model fitting
backwardModel <- model_backward(data = sim_train,
                                val.data = sim_val,
                                yvar = "y",
                                s.vars = s.vars)

# Fitted model
backwardModel$fit[[1]]

```

 model_gaim

Groupwise Additive Index Models (GAIM)

Description

A wrapper for `cgaim::cgaim()` enabling multiple GAIM models based on a grouping variable. Currently does not support Constrained GAIM (CGAIM)s.

Usage

```

model_gaim(
  data,
  yvar,
  neighbour = 0,
  index.vars,
  index.ind,
  s.vars = NULL,
  linear.vars = NULL,
  verbose = FALSE,
  ...
)

```

Arguments

data Training data set on which models will be trained. Must be a data set of class `tsibble`. (Make sure there are no additional date or time related variables except for the index of the `tsibble`). If multiple models are fitted, the grouping variable should be the key of the `tsibble`. If a key is not specified, a dummy key with only one level will be created.

yvar	Name of the response variable as a character string.
neighbour	If multiple models are fitted: Number of neighbours of each key (i.e. grouping variable) to be considered in model fitting to handle smoothing over the key. Should be an integer. If neighbour = x, x number of keys before the key of interest and x number of keys after the key of interest are grouped together for model fitting. The default is neighbour = 0 (i.e. no neighbours are considered for model fitting).
index.vars	A character vector of names of the predictor variables for which indices should be estimated.
index.ind	An integer vector that assigns group index for each predictor in index.vars.
s.vars	A character vector of names of the predictor variables for which splines should be fitted individually (rather than considering as part of an index).
linear.vars	A character vector of names of the predictor variables that should be included linearly into the model.
verbose	Logical; controls whether progress messages (model indices) are printed during fitting. Defaults to FALSE.
...	Other arguments not currently used. (Note that the arguments in cgaim::cgaim() related to constrained GAIMs are currently not supported. Furthermore, the argument subset is also not supported due to a bug in cgaim::cgaim().)

Details

Group-wise Additive Index Model (GAIM) can be written in the form

$$y_i = \sum_{j=1}^p g_j(\boldsymbol{\alpha}_j^T \mathbf{x}_{ij}) + \varepsilon_i, \quad i = 1, \dots, n,$$

where y_i is the univariate response, $\mathbf{x}_{ij} \in \mathbb{R}^{l_j}$, $j = 1, \dots, p$ are pre-specified non-overlapping subsets of \mathbf{x}_i , and $\boldsymbol{\alpha}_j$ are the corresponding index coefficients, g_j is an unknown (possibly nonlinear) component function, and ε_i is the random error, which is independent of \mathbf{x}_i .

Value

An object of class `gaimFit`. This is a tibble with two columns:

key	The level of the grouping variable (i.e. key of the training data set).
fit	Information of the fitted model corresponding to the key.

Each row of the column `fit` is an object of class `cgaim`. For details refer `cgaim::cgaim()`.

See Also

[model_smimodel](#), [model_backward](#), [model_ppr](#), [model_gam](#), [model_lm](#)

Examples

```

library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1005
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Predictors taken as index variables
index.vars <- colnames(sim_data)[3:7]

# Assign group indices for each predictor
index.ind = c(rep(1, 3), rep(2, 2))

# Predictors taken as non-linear variables not entering indices
s.vars = "x_lag_005"

# Model fitting
gaimModel <- model_gaim(data = sim_data,
                        yvar = "y",
                        index.vars = index.vars,
                        index.ind = index.ind,
                        s.vars = s.vars)

# Fitted model
gaimModel$fit[[1]]

```

model_gam

Generalised Additive Models

Description

A wrapper for `mgcv::gam()` enabling multiple GAMs based on a grouping variable.

Usage

```

model_gam(
  data,
  yvar,
  family = gaussian(),
  neighbour = 0,
  s.vars,
  s.basedim = NULL,
  linear.vars = NULL,
  verbose = FALSE,
  ...
)

```

Arguments

data	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>). If multiple models are fitted, the grouping variable should be the key of the <code>tsibble</code> . If a key is not specified, a dummy key with only one level will be created.
yvar	Name of the response variable as a character string.
family	A description of the error distribution and link function to be used in the model (see <code>glm</code> and <code>family</code>).
neighbour	If multiple models are fitted: Number of neighbours of each key (i.e. grouping variable) to be considered in model fitting to handle smoothing over the key. Should be an integer. If <code>neighbour = x</code> , <code>x</code> number of keys before the key of interest and <code>x</code> number of keys after the key of interest are grouped together for model fitting. The default is <code>neighbour = 0</code> (i.e. no neighbours are considered for model fitting).
s.vars	A character vector of names of the predictor variables for which splines should be fitted (i.e. non-linear predictors).
s.basedim	Dimension of the bases used to represent the smooth terms corresponding to <code>s.vars</code> . (For more information refer <code>mgcv::s()</code> .)
linear.vars	A character vector of names of the predictor variables that should be included linearly into the model (i.e. linear predictors).
verbose	Logical; controls whether progress messages (model indices) are printed during fitting. Defaults to <code>FALSE</code> .
...	Other arguments not currently used.

Value

An object of class `gamFit`. This is a `tibble` with two columns:

key	The level of the grouping variable (i.e. key of the training data set).
fit	Information of the fitted model corresponding to the key.

Each row of the column `fit` is an object of class `gam`. For details refer `mgcv::gamObject`.

See Also

[model_smimodel](#), [model_backward](#), [model_gaim](#), [model_ppr](#), [model_lm](#)

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1005
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Predictors taken as non-linear variables
s.vars <- colnames(sim_data)[3:6]

# Predictors taken as linear variables
linear.vars <- colnames(sim_data)[7:8]

# Model fitting
gamModel <- model_gam(data = sim_data,
                      yvar = "y",
                      s.vars = s.vars,
                      linear.vars = linear.vars)

# Fitted model
gamModel$fit[[1]]
```

model_lm

Linear Regression models

Description

A wrapper for [lm](#) enabling multiple linear models based on a grouping variable.

Usage

```
model_lm(data, yvar, neighbour = 0, linear.vars, verbose = FALSE, ...)
```

Arguments

data	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>). If multiple models are fitted, the grouping variable should be the key of the <code>tsibble</code> . If a key is not specified, a dummy key with only one level will be created.
yvar	Name of the response variable as a character string.
neighbour	If multiple models are fitted: Number of neighbours of each key (i.e. grouping variable) to be considered in model fitting to handle smoothing over the key. Should be an integer. If <code>neighbour = x</code> , <code>x</code> number of keys before the key of interest and <code>x</code> number of keys after the key of interest are grouped together for model fitting. The default is <code>neighbour = 0</code> (i.e. no neighbours are considered for model fitting).
linear.vars	A character vector of names of the predictor variables.
verbose	Logical; controls whether progress messages (model indices) are printed during fitting. Defaults to <code>FALSE</code> .
...	Other arguments not currently used.

Value

An object of class `lmFit`. This is a tibble with two columns:

key	The level of the grouping variable (i.e. key of the training data set).
fit	Information of the fitted model corresponding to the key.

Each row of the column `fit` is an object of class `lm`. For details refer `stats::lm`.

See Also

[model_smimodel](#), [model_backward](#), [model_gaim](#), [model_ppr](#), [model_gam](#)

Examples

```
library(dplyr)
library(tibble)
library(tidyverse)
library(tsibble)

# Simulate data
n = 1005
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
```

```

unpack(x_lag, names_sep = "_") |>
mutate(
  # Response variable
  y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
  # Add an index to the data set
  inddd = seq(1, n)) |>
drop_na() |>
select(inddd, y, starts_with("x_lag")) |>
# Make the data set a `tsibble`
as_tsibble(index = inddd)

# Predictor variables
linear.vars <- colnames(sim_data)[3:8]

# Model fitting
lmModel <- model_lm(data = sim_data,
                    yvar = "y",
                    linear.vars = linear.vars)

# Fitted model
lmModel$fit[[1]]

```

model_ppr

Projection Pursuit Regression (PPR) models

Description

A wrapper for `stats::ppr()` enabling multiple PPR models based on a grouping variable.

Usage

```

model_ppr(
  data,
  yvar,
  neighbour = 0,
  index.vars,
  num_ind = 5,
  verbose = FALSE,
  ...
)

```

Arguments

data	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>). If multiple models are fitted, the grouping variable should be the key of the <code>tsibble</code> . If a key is not specified, a dummy key with only one level will be created.
yvar	Name of the response variable as a character string.

neighbour	If multiple models are fitted: Number of neighbours of each key (i.e. grouping variable) to be considered in model fitting to handle smoothing over the key. Should be an integer. If neighbour = x, x number of keys before the key of interest and x number of keys after the key of interest are grouped together for model fitting. The default is neighbour = 0 (i.e. no neighbours are considered for model fitting).
index.vars	A character vector of names of the predictor variables for which indices should be estimated.
num_ind	An integer that specifies the number of indices to be used in the model(s). (Corresponds to nterms in stats::ppr().)
verbose	Logical; controls whether progress messages (model indices) are printed during fitting. Defaults to FALSE.
...	Other arguments not currently used. (For more information on other arguments that can be passed, refer stats::ppr().)

Details

A Projection Pursuit Regression (PPR) model (Friedman & Stuetzle (1981)) is given by

$$y_i = \sum_{j=1}^p g_j(\boldsymbol{\alpha}_j^T \mathbf{x}_i) + \varepsilon_i, \quad i = 1, \dots, n,$$

where y_i is the response, \mathbf{x}_i is the q -dimensional predictor vector, $\boldsymbol{\alpha}_j = (\alpha_{j1}, \dots, \alpha_{jp})^T$, $j = 1, \dots, p$ are q -dimensional projection vectors (or vectors of "index coefficients"), g_j 's are unknown nonlinear functions, and ε_i is the random error.

Value

An object of class pprFit. This is a tibble with two columns:

key	The level of the grouping variable (i.e. key of the training data set).
fit	Information of the fitted model corresponding to the key.

Each row of the column fit is an object of class c("ppr.form", "ppr"). For details refer stats::ppr().

References

Friedman, J. H. & Stuetzle, W. (1981). Projection pursuit regression. *Journal of the American Statistical Association*, 76, 817–823. doi:10.2307/2287576.

See Also

[model_smimodel](#), [model_backward](#), [model_gaim](#), [model_gam](#), [model_lm](#)

Examples

```

library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1005
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Index variables
index.vars <- colnames(sim_data)[3:8]

# Model fitting
pprModel <- model_ppr(data = sim_data,
                      yvar = "y",
                      index.vars = index.vars)

# Fitted model
pprModel$fit[[1]]

```

model_smimodel

Sparse Multiple Index (SMI) Models

Description

Fits nonparametric multiple index model(s), with simultaneous predictor selection (hence "sparse") and predictor grouping. Possible to fit multiple SMI models based on a grouping variable.

Usage

```

model_smimodel(
  data,
  yvar,

```

```

neighbour = 0,
family = gaussian(),
index.vars,
initialise = c("ppr", "additive", "linear", "multiple", "userInput"),
num_ind = 5,
num_models = 5,
seed = 123,
index.ind = NULL,
index.coefs = NULL,
s.vars = NULL,
linear.vars = NULL,
lambda0 = 1,
lambda2 = 1,
M = 10,
max.iter = 50,
tol = 0.001,
tolCoefs = 0.001,
TimeLimit = Inf,
MIPGap = 1e-04,
NonConvex = -1,
verbose = list(solver = FALSE, progress = FALSE)
)

```

Arguments

data	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>). If multiple models are fitted, the grouping variable should be the key of the <code>tsibble</code> . If a key is not specified, a dummy key with only one level will be created.
yvar	Name of the response variable as a character string.
neighbour	If multiple models are fitted: Number of neighbours of each key (i.e. grouping variable) to be considered in model fitting to handle smoothing over the key. Should be an integer. If <code>neighbour = x</code> , <code>x</code> number of keys before the key of interest and <code>x</code> number of keys after the key of interest are grouped together for model fitting. The default is <code>neighbour = 0</code> (i.e. no neighbours are considered for model fitting).
family	A description of the error distribution and link function to be used in the model (see glm and family).
index.vars	A character vector of names of the predictor variables for which indices should be estimated.
initialise	The model structure with which the estimation process should be initialised. The default is "ppr", where the initial model is derived from projection pursuit regression. The other options are "additive" - nonparametric additive model, "linear" - linear regression model (i.e. a special case single-index model, where the initial values of the index coefficients are obtained through a linear regression), "multiple" - multiple models are fitted starting with different initial models (number of indices = <code>num_ind</code> ; <code>num_models</code> random instances of

the model (i.e. the predictor assignment to indices and initial index coefficients are generated randomly) are considered), and the final optimal model with the lowest loss is returned, and "userInput" - user specifies the initial model structure (i.e. the number of indices and the placement of index variables among indices) and the initial index coefficients through `index.ind` and `index.coefs` arguments respectively.

<code>num_ind</code>	If <code>initialise = "ppr"</code> or <code>"multiple"</code> : an integer that specifies the number of indices to be used in the model(s). The default is <code>num_ind = 5</code> .
<code>num_models</code>	If <code>initialise = "multiple"</code> : an integer that specifies the number of starting models to be checked. The default is <code>num_models = 5</code> .
<code>seed</code>	If <code>initialise = "multiple"</code> : the seed to be set when generating random starting points.
<code>index.ind</code>	If <code>initialise = "userInput"</code> : an integer vector that assigns group index for each predictor in <code>index.vars</code> .
<code>index.coefs</code>	If <code>initialise = "userInput"</code> : a numeric vector of index coefficients.
<code>s.vars</code>	A character vector of names of the predictor variables for which splines should be fitted individually (rather than considering as part of an index).
<code>linear.vars</code>	A character vector of names of the predictor variables that should be included linearly into the model.
<code>lambda0</code>	Penalty parameter for L0 penalty.
<code>lambda2</code>	Penalty parameter for L2 penalty.
<code>M</code>	Big-M value to be used in MIP.
<code>max.iter</code>	Maximum number of MIP iterations performed to update index coefficients for a given model.
<code>tol</code>	Tolerance for the objective function value (loss) of MIP.
<code>tolCoefs</code>	Tolerance for coefficients.
<code>TimeLimit</code>	A limit for the total time (in seconds) expended in a single MIP iteration.
<code>MIPGap</code>	Relative MIP optimality gap.
<code>NonConvex</code>	The strategy for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.
<code>verbose</code>	A named list controlling verbosity options. Defaults to <code>list(solver = FALSE, progress = FALSE)</code> . solver Logical. If TRUE, print detailed solver output. progress Logical. If TRUE, print optimisation algorithm progress messages.

Details

Sparse Multiple Index (SMI) model is a semi-parametric model that can be written as

$$y_i = \beta_0 + \sum_{j=1}^p g_j(\boldsymbol{\alpha}_j^T \mathbf{x}_{ij}) + \sum_{k=1}^d f_k(w_{ik}) + \boldsymbol{\theta}^T \mathbf{u}_i + \varepsilon_i, \quad i = 1, \dots, n,$$

where y_i is the univariate response, β_0 is the model intercept, $\mathbf{x}_{ij} \in \mathbb{R}^{l_j}$, $j = 1, \dots, p$ are p subsets of predictors entering indices, $\boldsymbol{\alpha}_j$ is a vector of index coefficients corresponding to the index

$h_{ij} = \alpha_j^T \mathbf{x}_{ij}$, and g_j is a smooth nonlinear function (estimated by a penalised cubic regression spline). The model also allows for predictors that do not enter any indices, including covariates w_{ik} that relate to the response through nonlinear functions f_k , $k = 1, \dots, d$, and linear covariates \mathbf{u}_i .

In the model formulation related to this implementation, both the number of indices p and the predictor grouping among indices are assumed to be unknown prior to model estimation. Suppose we observe y_1, \dots, y_n , along with a set of potential predictors, $\mathbf{x}_1, \dots, \mathbf{x}_n$, with each vector \mathbf{x}_i containing q predictors. This function implements algorithmic variable selection for index variables (i.e. predictors entering indices) of the SMI model by allowing for zero index coefficients for predictors. Non-overlapping predictors among indices are assumed (i.e. no predictor enters more than one index). For algorithmic details see reference.

Value

An object of class `smimodel`. This is a tibble with two columns:

<code>key</code>	The level of the grouping variable (i.e. key of the training data set).
<code>fit</code>	Information of the fitted model corresponding to the key.

Each row of the column `fit` contains a list with two elements:

<code>initial</code>	A list of information of the model initialisation. (For descriptions of the list elements see make_smimodelFit).
<code>best</code>	A list of information of the final optimised model. (For descriptions of the list elements see make_smimodelFit).

References

Palihawadana, N.K., Hyndman, R.J. & Wang, X. (2024). Sparse Multiple Index Models for High-Dimensional Nonparametric Forecasting. (Department of Econometrics and Business Statistics Working Paper Series 16/24).

See Also

[greedy_smimodel](#)

Examples

```
if(requireNamespace("gurobi", quietly = TRUE)){
  library(dplyr)
  library(ROI)
  library(tibble)
  library(tidyr)
  library(tsibble)

  # Simulate data
  n = 1005
  set.seed(123)
  sim_data <- tibble(x_lag_000 = runif(n)) |>
    mutate(
      # Add x_lags
      x_lag = lag_matrix(x_lag_000, 5)) |>
```

```

unpack(x_lag, names_sep = "_") |>
mutate(
  # Response variable
  y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
  # Add an index to the data set
  inddd = seq(1, n)) |>
drop_na() |>
select(inddd, y, starts_with("x_lag")) |>
# Make the data set a `tsibble`
as_tsibble(index = inddd)

# Index variables
index.vars <- colnames(sim_data)[3:8]

# Model fitting
smimodel_ppr <- model_smimodel(data = sim_data,
                              yvar = "y",
                              index.vars = index.vars,
                              initialise = "ppr")

# Best (optimised) fitted model
smimodel_ppr$fit[[1]]$best
}

```

new_smimodelFit

Constructor function for the class smimodelFit

Description

Constructs an object of class `smimodelFit` using the information passed to arguments.

Usage

```

new_smimodelFit(
  data,
  yvar,
  neighbour = 0,
  family = gaussian(),
  index.vars,
  initialise = c("additive", "linear", "userInput"),
  index.ind = NULL,
  index.coefs = NULL,
  s.vars = NULL,
  linear.vars = NULL
)

```

Arguments

data	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>).
yvar	Name of the response variable as a character string.
neighbour	neighbour argument passed from the outer function.
family	A description of the error distribution and link function to be used in the model (see <code>glm</code> and <code>family</code>).
index.vars	A character vector of names of the predictor variables for which indices should be estimated.
initialise	The model structure with which the estimation process should be initialised. The default is "additive", where the initial model will be a nonparametric additive model. The other options are "linear" - linear regression model (i.e. a special case single-index model, where the initial values of the index coefficients are obtained through a linear regression), and "userInput" - user specifies the initial model structure (i.e. the number of indices and the placement of index variables among indices) and the initial index coefficients through <code>index.ind</code> and <code>index.coefs</code> arguments respectively.
index.ind	If <code>initialise = "userInput"</code> : an integer vector that assigns group index for each predictor in <code>index.vars</code> .
index.coefs	If <code>initialise = "userInput"</code> : a numeric vector of index coefficients.
s.vars	A character vector of names of the predictor variables for which splines should be fitted individually (rather than considering as part of an index).
linear.vars	A character vector of names of the predictor variables that should be included linearly into the model.

Value

A list of initial model information. For descriptions of the list elements see `make_smimodelFit`.

normalise_alpha	<i>Scaling index coefficient vectors to have unit norm</i>
-----------------	--

Description

Scales a coefficient vector of a particular index to have unit norm.

Usage

```
normalise_alpha(alpha)
```

Arguments

alpha	A vector of index coefficients.
-------	---------------------------------

Value

A numeric vector.

possibleFutures_benchmark

Possible future sample paths (multi-step) from residuals of a fitted benchmark model

Description

Generates possible future sample paths (multi-step) using residuals of a fitted benchmark model through recursive forecasting.

Usage

```
possibleFutures_benchmark(
  object,
  newdata,
  bootstraps,
  exclude.trunc = NULL,
  recursive_colRange
)
```

Arguments

object	A fitted model object of the class backward, pprFit, or gaimFit.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).
bootstraps	Generated matrix of bootstrapped residual series.
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string.
recursive_colRange	The range of column numbers in newdata to be filled with forecasts.

Value

A list containing the following components:

firstFuture	A numeric vector of 1-step-ahead simulated futures.
future_cols	A list of multi-steps-ahead simulated futures, where each list element corresponds to each 1-step-ahead simulated future in firstFuture.

`possibleFutures_smimodel`*Possible future sample paths (multi-step) from smimodel residuals*

Description

Generates possible future sample paths (multi-step) using residuals of a fitted smimodel through recursive forecasting.

Usage

```
possibleFutures_smimodel(  
  object,  
  newdata,  
  bootstraps,  
  exclude.trunc = NULL,  
  recursive_colRange  
)
```

Arguments

<code>object</code>	A smimodel object.
<code>newdata</code>	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).
<code>bootstraps</code>	Generated matrix of bootstrapped residual series.
<code>exclude.trunc</code>	The names of the predictor variables that should not be truncated for stable predictions as a character string.
<code>recursive_colRange</code>	The range of column numbers in newdata to be filled with forecasts.

Value

A list containing the following components:

<code>firstFuture</code>	A numeric vector of 1-step-ahead simulated futures.
<code>future_cols</code>	A list of multi-steps-ahead simulated futures, where each list element corresponds to each 1-step-ahead simulated future in <code>firstFuture</code> .

predict.backward *Obtaining forecasts on a test set from a fitted backward*

Description

Gives forecasts on a test set.

Usage

```
## S3 method for class 'backward'
predict(
  object,
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)
```

Arguments

object	A backward object.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in newdata that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in newdata, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.
...	Other arguments not currently used.

Value

A tsibble with forecasts on test set.

Examples

```

library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1215
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Validation set
sim_val <- sim_data[1001:1200, ]
# Test set
sim_test <- sim_data[1201:1210, ]

# Predictors taken as non-linear variables
s.vars <- colnames(sim_data)[3:8]

# Model fitting
backwardModel <- model_backward(data = sim_train,
                               val.data = sim_val,
                               yvar = "y",
                               s.vars = s.vars)
predict(object = backwardModel, newdata = sim_test)

```

predict.gaimFit

Obtaining forecasts on a test set from a fitted gaimFit

Description

Gives forecasts on a test set.

Usage

```
## S3 method for class 'gaimFit'
predict(
  object,
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)
```

Arguments

object	A gaimFit object.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in newdata that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in newdata, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.
...	Other arguments not currently used.

Value

A tsibble with forecasts on test set.

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1015
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
```

```

mutate(
  # Add x_lags
  x_lag = lag_matrix(x_lag_000, 5)) |>
unpack(x_lag, names_sep = "_") |>
mutate(
  # Response variable
  y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
  # Add an index to the data set
  inddd = seq(1, n)) |>
drop_na() |>
select(inddd, y, starts_with("x_lag")) |>
# Make the data set a `tsibble`
as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1010, ]

# Predictors taken as index variables
index.vars <- colnames(sim_data)[3:7]

# Assign group indices for each predictor
index.ind = c(rep(1, 3), rep(2, 2))

# Predictors taken as non-linear variables not entering indices
s.vars = "x_lag_005"

# Model fitting
gaimModel <- model_gaim(data = sim_train,
                        yvar = "y",
                        index.vars = index.vars,
                        index.ind = index.ind,
                        s.vars = s.vars)

predict(object = gaimModel, newdata = sim_test)

```

predict.gamFit

Obtaining forecasts on a test set from a fitted gamFit

Description

Gives forecasts on a test set.

Usage

```

## S3 method for class 'gamFit'
predict(
  object,

```

```

newdata,
exclude.trunc = NULL,
recursive = FALSE,
recursive_colRange = NULL,
...
)

```

Arguments

object	A gamFit object.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in newdata that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in newdata, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.
...	Other arguments not currently used.

Value

A tsibble with forecasts on test set.

Examples

```

library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1015
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5) |>
    unpack(x_lag, names_sep = "_") |>
    mutate(

```

```

# Response variable
y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
# Add an index to the data set
inddd = seq(1, n)) |>
drop_na() |>
select(inddd, y, starts_with("x_lag")) |>
# Make the data set a `tsibble`
as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1010, ]

# Predictors taken as non-linear variables
s.vars <- colnames(sim_data)[3:6]

# Predictors taken as linear variables
linear.vars <- colnames(sim_data)[7:8]

# Model fitting
gamModel <- model_gam(data = sim_train,
                      yvar = "y",
                      s.vars = s.vars,
                      linear.vars = linear.vars)

predict(object = gamModel, newdata = sim_test)

```

predict.lmFit

Obtaining forecasts on a test set from a fitted lmFit

Description

Gives forecasts on a test set.

Usage

```

## S3 method for class 'lmFit'
predict(object, newdata, recursive = FALSE, recursive_colRange = NULL, ...)

```

Arguments

object	A lmFit object.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).
recursive	Whether to obtain recursive forecasts or not (default - FALSE).

recursive_colRange

If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in newdata, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.

... Other arguments not currently used.

Value

A tsibble with forecasts on test set.

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1015
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1010, ]

# Predictor variables
linear.vars <- colnames(sim_data)[3:8]

# Model fitting
lmModel <- model_lm(data = sim_train,
  yvar = "y",
  linear.vars = linear.vars)
```

```
predict(object = lmModel, newdata = sim_test)
```

predict.pprFit *Obtaining forecasts on a test set from a fitted pprFit*

Description

Gives forecasts on a test set.

Usage

```
## S3 method for class 'pprFit'
predict(
  object,
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)
```

Arguments

object	A pprFit object.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in newdata that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in newdata, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.
...	Other arguments not currently used.

Value

A tsibble with forecasts on test set.

Examples

```
library(dplyr)
library(tibble)
library(tidyr)
library(tsibble)

# Simulate data
n = 1015
set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1010, ]

# Index variables
index.vars <- colnames(sim_data)[3:8]

# Model fitting
pprModel <- model_ppr(data = sim_train,
  yvar = "y",
  index.vars = index.vars)

predict(object = pprModel, newdata = sim_test)
```

predict.smimodel

Obtaining forecasts on a test set from a fitted smimodel

Description

Gives forecasts on a test set.

Usage

```
## S3 method for class 'smimodel'
predict(
  object,
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)
```

Arguments

object	A smimodel object.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in newdata that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in newdata, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.
...	Other arguments not currently used.

Value

A tsibble with forecasts on test set.

Examples

```
if(requireNamespace("gurobi", quietly = TRUE)){
  library(dplyr)
  library(ROI)
  library(tibble)
  library(tidyr)
  library(tsibble)

  # Simulate data
  n = 1015
```

```

set.seed(123)
sim_data <- tibble(x_lag_000 = runif(n)) |>
  mutate(
    # Add x_lags
    x_lag = lag_matrix(x_lag_000, 5)) |>
  unpack(x_lag, names_sep = "_") |>
  mutate(
    # Response variable
    y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
    # Add an index to the data set
    inddd = seq(1, n)) |>
  drop_na() |>
  select(inddd, y, starts_with("x_lag")) |>
  # Make the data set a `tsibble`
  as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1010, ]

# Index variables
index.vars <- colnames(sim_data)[3:8]

# Model fitting
smimodel_ppr <- model_smimodel(data = sim_train,
                               yvar = "y",
                               index.vars = index.vars,
                               initialise = "ppr")

predict(object = smimodel_ppr, newdata = sim_test)
}

```

predict.smimodelFit *Obtaining forecasts on a test set from a smimodelFit*

Description

Gives forecasts on a test set.

Usage

```

## S3 method for class 'smimodelFit'
predict(
  object,
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,

```

```
  ...
)
```

Arguments

object	A smimodelFit object.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in newdata that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in newdata, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.
...	Other arguments not currently used.

Value

A tibble with forecasts on test set.

Examples

```
if(requireNamespace("gurobi", quietly = TRUE)){
  library(dplyr)
  library(ROI)
  library(tibble)
  library(tidyr)
  library(tsibble)

  # Simulate data
  n = 1015
  set.seed(123)
  sim_data <- tibble(x_lag_000 = runif(n)) |>
    mutate(
      # Add x_lags
      x_lag = lag_matrix(x_lag_000, 5) |>
      unpack(x_lag, names_sep = "_") |>
      mutate(
        # Response variable
        y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),
```

```

    # Add an index to the data set
    inddd = seq(1, n) |>
drop_na() |>
select(inddd, y, starts_with("x_lag")) |>
# Make the data set a `tsibble`
as_tsibble(index = inddd)

# Training set
sim_train <- sim_data[1:1000, ]
# Test set
sim_test <- sim_data[1001:1010, ]

# Index variables
index.vars <- colnames(sim_data)[3:8]

# Model fitting
smimodel_ppr <- model_smimodel(data = sim_train,
                              yvar = "y",
                              index.vars = index.vars,
                              initialise = "ppr")

predict(object = smimodel_ppr$fit[[1]]$best, newdata = sim_test)
}

```

predict_gam

Obtaining recursive forecasts on a test set from a fitted mgcv::gam

Description

Gives recursive forecasts on a test set.

Usage

```

predict_gam(
  object,
  newdata,
  exclude.trunc = NULL,
  recursive = FALSE,
  recursive_colRange = NULL,
  ...
)

```

Arguments

object	A gam object.
newdata	The set of new data on for which the forecasts are required (i.e. test set; should be a tsibble).

exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in newdata that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in newdata to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in newdata, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.
...	Other arguments not currently used.

Value

A tibble with forecasts on test set.

```
prep_newdata
```

Prepare a data set for recursive forecasting

Description

Prepare a test data for recursive forecasting by appropriately removing existing (actual) values from a specified range of columns (lagged response columns) of the data set. Handles seasonal data with gaps.

Usage

```
prep_newdata(newdata, recursive_colRange)
```

Arguments

newdata	Data set to be used. Should be a tibble.
recursive_colRange	The range of column numbers (lagged response columns) in newdata from which existing values should be removed. Make sure such columns are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in newdata, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.

Value

A tibble.

print.backward	<i>Printing a backward object</i>
----------------	-----------------------------------

Description

The default print method for a backward object.

Usage

```
## S3 method for class 'backward'  
print(x, ...)
```

Arguments

x	A model object of class backward as produced by model_backward() function.
...	Other arguments not currently used.

Value

No return value; called for side effects. Prints a summary of the fitted model(s) to console.

print.gainFit	<i>Printing a gainFit object</i>
---------------	----------------------------------

Description

The default print method for a gainFit object.

Usage

```
## S3 method for class 'gainFit'  
print(x, ...)
```

Arguments

x	A model object of class gainFit as produced by model_gain() function.
...	Other arguments not currently used.

Value

No return value; called for side effects. Prints a summary of the fitted model(s) to console.

print.pprFit	<i>Printing a pprFit object</i>
--------------	---------------------------------

Description

The default print method for a pprFit object.

Usage

```
## S3 method for class 'pprFit'  
print(x, ...)
```

Arguments

x	A model object of class pprFit as produced by model_ppr() function.
...	Other arguments not currently used.

Value

No return value; called for side effects. Prints a summary of the fitted model(s) to console.

print.smimodel	<i>Printing a smimodel object</i>
----------------	-----------------------------------

Description

The default print method for a smimodel object.

Usage

```
## S3 method for class 'smimodel'  
print(x, ...)
```

Arguments

x	An object of class smimodel.
...	Other arguments not currently used.

Value

No return value; called for side effects. Prints a summary of the fitted model(s) to console.

`print.smimodelFit` *Printing a smimodelFit object*

Description

The default print method for a smimodelFit object.

Usage

```
## S3 method for class 'smimodelFit'  
print(x, ...)
```

Arguments

`x` An object of class smimodelFit.
`...` Other arguments not currently used.

Value

No return value; called for side effects. Prints a summary of the fitted model to console.

`randomBlock` *Randomly sampling a block*

Description

Samples a block of specified size from a given series starting from a random point in the series.

Usage

```
randomBlock(series, block.size)
```

Arguments

`series` A series from which a block should be sampled.
`block.size` Size of the block to be sampled.

Value

A numeric vector.

remove_lags	<i>Remove actual values from a data set for recursive forecasting</i>
-------------	---

Description

Appropriately removes existing (actual) values from the specified column range (lagged response columns) of a given data set (typically a test set for which recursive forecasting is required).

Usage

```
remove_lags(data, recursive_colRange)
```

Arguments

data	Data set (a tibble) from which the actual lagged values should be removed.
recursive_colRange	The range of column numbers in data from which lagged values should be removed.

Value

A tibble.

residBootstrap	<i>Generate multiple single season block bootstrap series</i>
----------------	---

Description

Generates multiple replications of single season block bootstrap series.

Usage

```
residBootstrap(x, season.period = 1, m = 1, num.bootstrap = 1000)
```

Arguments

x	A series of residuals from which bootstrap series to be generated.
season.period	Length of the seasonal period.
m	Multiplier. (Block size = season.period * m)
num.bootstrap	Number of bootstrap series to be generated.

Value

A matrix of bootstrapped series.

residuals.smimodel *Extract residuals from a fitted smimodel*

Description

Generates residuals from a fitted smimodel object.

Usage

```
## S3 method for class 'smimodel'  
residuals(object, ...)
```

Arguments

object A smimodel object.
... Other arguments not currently used.

Value

A numeric vector of residuals.

Examples

```
if(requireNamespace("gurobi", quietly = TRUE)){  
  library(dplyr)  
  library(ROI)  
  library(tibble)  
  library(tidyr)  
  library(tsibble)  
  
  # Simulate data  
  n = 1005  
  set.seed(123)  
  sim_data <- tibble(x_lag_000 = runif(n)) |>  
    mutate(  
      # Add x_lags  
      x_lag = lag_matrix(x_lag_000, 5)) |>  
    unpack(x_lag, names_sep = "_") |>  
    mutate(  
      # Response variable  
      y = (0.9*x_lag_000 + 0.6*x_lag_001 + 0.45*x_lag_003)^3 + rnorm(n, sd = 0.1),  
      # Add an index to the data set  
      inddd = seq(1, n)) |>  
    drop_na() |>  
    select(inddd, y, starts_with("x_lag")) |>  
  # Make the data set a `tsibble`  
  as_tsibble(index = inddd)  
  
  # Index variables
```

```
index.vars <- colnames(sim_data)[3:8]

# Model fitting
smimodel_ppr <- model_smimodel(data = sim_data,
                               yvar = "y",
                               index.vars = index.vars,
                               initialise = "ppr")

residuals(smimodel_ppr)
}
```

scaling

Scale data

Description

Scales the columns of the data corresponding to `index.vars`.

Usage

```
scaling(data, index.vars)
```

Arguments

<code>data</code>	Training data set on which models will be trained. Should be a tibble.
<code>index.vars</code>	A character vector of names of the predictor variables for which indices should be estimated.

Value

A list containing the following components:

<code>scaled_data</code>	The scaled data set of class tibble.
<code>scaled_info</code>	A named numeric vector of standard deviations of <code>index.vars</code> that were used to scale the corresponding columns of data.

seasonBootstrap	<i>Single season block bootstrap</i>
-----------------	--------------------------------------

Description

Generates a single replication of single season block bootstrap series.

Usage

```
seasonBootstrap(x, season.period = 1, m = 1)
```

Arguments

x	A series of residuals from which bootstrap series to be generated.
season.period	Length of the seasonal period.
m	Multiplier. (Block size = season.period * m)

Value

A numeric vector.

smimodel.fit	<i>SMI model estimation</i>
--------------	-----------------------------

Description

Fits a single nonparametric multiple index model to the data. This is a helper function designed to be called from user-facing wrapper functions, [model_smimodel](#) and [greedy_smimodel](#).

Usage

```
smimodel.fit(
  data,
  yvar,
  neighbour = 0,
  family = gaussian(),
  index.vars,
  initialise = c("ppr", "additive", "linear", "multiple", "userInput"),
  num_ind = 5,
  num_models = 5,
  seed = 123,
  index.ind = NULL,
  index.coefs = NULL,
  s.vars = NULL,
  linear.vars = NULL,
```

```

lambda0 = 1,
lambda2 = 1,
M = 10,
max.iter = 50,
tol = 0.001,
tolCoefs = 0.001,
TimeLimit = Inf,
MIPGap = 1e-04,
NonConvex = -1,
verbose = list(solver = FALSE, progress = FALSE)
)

```

Arguments

data	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>).
yvar	Name of the response variable as a character string.
neighbour	neighbour argument passed from the outer function.
family	A description of the error distribution and link function to be used in the model (see <code>glm</code> and <code>family</code>).
index.vars	A character vector of names of the predictor variables for which indices should be estimated.
initialise	The model structure with which the estimation process should be initialised. The default is "ppr", where the initial model is derived from projection pursuit regression. The other options are "additive" - nonparametric additive model, "linear" - linear regression model (i.e. a special case single-index model, where the initial values of the index coefficients are obtained through a linear regression), "multiple" - multiple models are fitted starting with different initial models (number of indices = <code>num_ind</code> ; <code>num_models</code> random instances of the model (i.e. the predictor assignment to indices and initial index coefficients are generated randomly) are considered), and the final optimal model with the lowest loss is returned, and "userInput" - user specifies the initial model structure (i.e. the number of indices and the placement of index variables among indices) and the initial index coefficients through <code>index.ind</code> and <code>index.coefs</code> arguments respectively.
num_ind	If <code>initialise = "ppr"</code> or <code>"multiple"</code> : an integer that specifies the number of indices to be used in the model(s). The default is <code>num_ind = 5</code> .
num_models	If <code>initialise = "multiple"</code> : an integer that specifies the number of starting models to be checked. The default is <code>num_models = 5</code> .
seed	If <code>initialise = "multiple"</code> : the seed to be set when generating random starting points.
index.ind	If <code>initialise = "userInput"</code> : an integer vector that assigns group index for each predictor in <code>index.vars</code> .
index.coefs	If <code>initialise = "userInput"</code> : a numeric vector of index coefficients.

s.vars	A character vector of names of the predictor variables for which splines should be fitted individually (rather than considering as part of an index).
linear.vars	A character vector of names of the predictor variables that should be included linearly into the model.
lambda0	Penalty parameter for L0 penalty.
lambda2	Penalty parameter for L2 penalty.
M	Big-M value to be used in MIP.
max.iter	Maximum number of MIP iterations performed to update index coefficients for a given model.
tol	Tolerance for the objective function value (loss) of MIP.
tolCoefs	Tolerance for coefficients.
TimeLimit	A limit for the total time (in seconds) expended in a single MIP iteration.
MIPGap	Relative MIP optimality gap.
NonConvex	The strategy for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.
verbose	A named list controlling verbosity options. Defaults to <code>list(solver = FALSE, progress = FALSE)</code> . solver Logical. If TRUE, print detailed solver output. progress Logical. If TRUE, print optimisation algorithm progress messages.

Value

A list with two elements:

initial	A list of information of the model initialisation. (For descriptions of the list elements see make_smimodelFit).
best	A list of information of the final optimised model. (For descriptions of the list elements see make_smimodelFit).

split_index	<i>Splitting predictors into multiple indices</i>
-------------	---

Description

Splits a given number of predictors into a given number of indices.

Usage

```
split_index(num_pred, num_ind)
```

Arguments

num_pred	Number of predictors.
num_ind	Number of indices.

Value

A list containing the following components:

- index An integer vector that assigns group indices for each predictor.
- index_positions A list of length = num_ind that indicates which predictors belong to which index.

<code>truncate_vars</code>	<i>Truncating predictors to be in the in-sample range</i>
----------------------------	---

Description

Truncates predictors to be in the in-sample range to avoid spline extrapolation.

Usage

```
truncate_vars(range.object, data, cols.trunc)
```

Arguments

- `range.object` A matrix containing range of each predictor variable. Should be a matrix with two rows for min and max, and the columns should correspond to variables.
- `data` Out-of-sample data set of which variables should be truncated.
- `cols.trunc` Column names of the variables to be truncated.

<code>tune_smimodel</code>	<i>SMI model with a given penalty parameter combination</i>
----------------------------	---

Description

Fits a nonparametric multiple index model to the data for a given combination of the penalty parameters (`lambda0`, `lambda2`), and returns the validation set mean squared error (MSE). (Used within [greedy.fit](#); users are not expected to use this function directly.)

Usage

```
tune_smimodel(
  data,
  val.data,
  yvar,
  neighbour = 0,
  family = gaussian(),
  index.vars,
  initialise = c("ppr", "additive", "linear", "multiple", "userInput"),
  num_ind = 5,
```

```

num_models = 5,
seed = 123,
index.ind = NULL,
index.coefs = NULL,
s.vars = NULL,
linear.vars = NULL,
lambda.comb = c(1, 1),
M = 10,
max.iter = 50,
tol = 0.001,
tolCoefs = 0.001,
TimeLimit = Inf,
MIPGap = 1e-04,
NonConvex = -1,
verbose = list(solver = FALSE, progress = FALSE),
exclude.trunc = NULL,
recursive = FALSE,
recursive_colRange = NULL
)

```

Arguments

<code>data</code>	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>).
<code>val.data</code>	Validation data set. (The data set on which the penalty parameter selection will be performed.) Must be a data set of class <code>tsibble</code> . (Once the penalty parameter selection is completed, the best model will be re-fitted for the combined data set <code>data + val.data</code> .)
<code>yvar</code>	Name of the response variable as a character string.
<code>neighbour</code>	<code>neighbour</code> argument passed from the outer function.
<code>family</code>	A description of the error distribution and link function to be used in the model (see glm and family).
<code>index.vars</code>	A character vector of names of the predictor variables for which indices should be estimated.
<code>initialise</code>	The model structure with which the estimation process should be initialised. The default is <code>"ppr"</code> , where the initial model is derived from projection pursuit regression. The other options are <code>"additive"</code> - nonparametric additive model, <code>"linear"</code> - linear regression model (i.e. a special case single-index model, where the initial values of the index coefficients are obtained through a linear regression), <code>"multiple"</code> - multiple models are fitted starting with different initial models (number of indices = <code>num_ind</code> ; <code>num_models</code> random instances of the model (i.e. the predictor assignment to indices and initial index coefficients are generated randomly) are considered), and the final optimal model with the lowest loss is returned, and <code>"userInput"</code> - user specifies the initial model structure (i.e. the number of indices and the placement of index variables among indices) and the initial index coefficients through <code>index.ind</code> and <code>index.coefs</code> arguments respectively.

num_ind	If initialise = "ppr" or "multiple": an integer that specifies the number of indices to be used in the model(s). The default is num_ind = 5.
num_models	If initialise = "multiple": an integer that specifies the number of starting models to be checked. The default is num_models = 5.
seed	If initialise = "multiple": the seed to be set when generating random starting points.
index.ind	If initialise = "userInput": an integer vector that assigns group index for each predictor in index.vars.
index.coefs	If initialise = "userInput": a numeric vector of index coefficients.
s.vars	A character vector of names of the predictor variables for which splines should be fitted individually (rather than considering as part of an index).
linear.vars	A character vector of names of the predictor variables that should be included linearly into the model.
lambda.comb	A numeric vector (of length two) indicating the values for the two penalty parameters lambda0 and lambda2.
M	Big-M value used in MIP.
max.iter	Maximum number of MIP iterations performed to update index coefficients for a given model.
tol	Tolerance for the objective function value (loss) of MIP.
tolCoefs	Tolerance for coefficients.
TimeLimit	A limit for the total time (in seconds) expended in a single MIP iteration.
MIPGap	Relative MIP optimality gap.
NonConvex	The strategy for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.
verbose	A named list controlling verbosity options. Defaults to list(solver = FALSE, progress = FALSE). solver Logical. If TRUE, print detailed solver output. progress Logical. If TRUE, print optimisation algorithm progress messages.
exclude.trunc	The names of the predictor variables that should not be truncated for stable predictions as a character string. (Since the nonlinear functions are estimated using splines, extrapolation is not desirable. Hence, if any predictor variable in val.data that is treated non-linearly in the estimated model, will be truncated to be in the in-sample range before obtaining predictions. If any variables are listed here will be excluded from such truncation.)
recursive	Whether to obtain recursive forecasts or not (default - FALSE).
recursive_colRange	If recursive = TRUE, the range of column numbers in val.data to be filled with forecasts. Recursive/autoregressive forecasting is required when the lags of the response variable itself are used as predictor variables into the model. Make sure such lagged variables are positioned together in increasing lag order (i.e. lag_1, lag_2, ..., lag_m, lag_m = maximum lag used) in val.data, with no break in the lagged variable sequence even if some of the intermediate lags are not used as predictors.

Value

A numeric.

unscaling	<i>Unscale a fitted smimodel</i>
-----------	----------------------------------

Description

Transforms back the index coefficients to suit original-scale index variables if the same were scaled when estimating the smimodel (happens in `initialise = "ppr"` in `model_smimodel` or `greedy_smimodel`). Users are not expected to directly use this function; usually called within `smimodel.fit`.

Usage

```
unscaling(object, scaledInfo)
```

Arguments

object	A smimodel object.
scaledInfo	The list returned from a call of the function <code>scaling</code> .

Value

A smimodel object.

update_alpha	<i>Updating index coefficients using MIP</i>
--------------	--

Description

Updates index coefficients by solving a mixed integer program.

Usage

```
update_alpha(
  Y,
  X,
  num_pred,
  num_ind,
  index.ind,
  dgz,
  alpha_old,
  lambda0 = 1,
  lambda2 = 1,
  M = 10,
```

```

    TimeLimit = Inf,
    MIPGap = 1e-04,
    NonConvex = -1,
    verbose = FALSE
  )

```

Arguments

Y	Column matrix of response.
X	Matrix of predictors (size adjusted to number of indices).
num_pred	Number of predictors.
num_ind	Number of indices.
index.ind	An integer vector that assigns group index for each predictor.
dgz	The tibble of derivatives of the estimated smooths from previous iteration.
alpha_old	Vector of index coefficients from previous iteration.
lambda0	Penalty parameter for L0 penalty.
lambda2	Penalty parameter for L2 penalty.
M	Big-M value to be used in MIP.
TimeLimit	A limit for the total time (in seconds) expended in a single MIP iteration.
MIPGap	Relative MIP optimality gap.
NonConvex	The strategy for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.
verbose	The option to print detailed solver output.

Value

A vector of normalised index coefficients.

update_smimodelFit	<i>Updating a smimodelFit</i>
--------------------	-------------------------------

Description

Optimises and updates a given smimodelFit.

Usage

```

update_smimodelFit(
  object,
  data,
  lambda0 = 1,
  lambda2 = 1,
  M = 10,

```

```

max.iter = 50,
tol = 0.001,
tolCoefs = 0.001,
TimeLimit = Inf,
MIPGap = 1e-04,
NonConvex = -1,
verbose = list(solver = FALSE, progress = FALSE),
...
)

```

Arguments

object	A smimodelFit object.
data	Training data set on which models will be trained. Must be a data set of class <code>tsibble</code> . (Make sure there are no additional date or time related variables except for the index of the <code>tsibble</code>).
lambda0	Penalty parameter for L0 penalty.
lambda2	Penalty parameter for L2 penalty.
M	Big-M value to be used in MIP.
max.iter	Maximum number of MIP iterations performed to update index coefficients for a given model.
tol	Tolerance for the objective function value (loss) of MIP.
tolCoefs	Tolerance for coefficients.
TimeLimit	A limit for the total time (in seconds) expended in a single MIP iteration.
MIPGap	Relative MIP optimality gap.
NonConvex	The strategy for handling non-convex quadratic objectives or non-convex quadratic constraints in Gurobi solver.
verbose	A named list controlling verbosity options. Defaults to <code>list(solver = FALSE, progress = FALSE)</code> .
	solver Logical. If TRUE, print detailed solver output.
	progress Logical. If TRUE, print optimisation algorithm progress messages.
...	Other arguments not currently used.

Value

A list of optimised model information. For descriptions of the list elements see [make_smimodelFit](#).

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