Package 'fastTS'

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Type Package

Title Fast Time Series Modeling for Seasonal Series with Exogenous Variables

Version 1.0.2

Description An implementation of sparsity-ranked lasso and related methods for time series data. This methodology is especially useful for large time series with exogenous features and/or complex seasonality. Originally described in Peterson and Cavanaugh (2022) <doi:10.1007/s10182-021-00431-7> in the context of variable selection with interactions and/or polynomials, ranked sparsity is a philosophy with methods useful for variable selection in the presence of prior informational asymmetry. This situation exists for time series data with complex seasonality, as shown in Peterson and Cavanaugh (2024) <doi:10.1177/1471082X231225307>, which also describes this package in greater detail. The sparsity-ranked penalization methods for time series implemented in 'fastTS' can fit large/complex/high-frequency time series quickly, even with a high-dimensional exogenous feature set. The method is considerably faster than its competitors, while often producing more accurate predictions. Also included is a long hourly series of arrivals into the University of Iowa Emergency Department with concurrent local temperature.

Suggests covr, kableExtra, knitr, magrittr, rmarkdown, testthat (>= 3.0.0), tibble

Imports dplyr, methods, ncvreg, RcppRoll, rlang, yardstick

Depends R (>= 3.5)

License GPL (>= 3)

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RoxygenNote 7.3.1

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VignetteBuilder knitr

https://github.com/petersonR/fastTS/

BugReports https://github.com/petersonR/fastTS/issues

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Author Ryan Andrew Peterson [aut, cre, cph] (<https://orcid.org/0000-0002-4650-5798>)

Maintainer Ryan Andrew Peterson <ryan.a.peterson@cuanschutz.edu>

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AICc

internal AICc function for lasso models

Description

internal AICc function for lasso models

Internal function for obtaining oos results

Internal function for converting time series into model matrix of lags

Usage

```
AICc(fit, eps = 1)
get_oos_results(fits, ytest, Xtest)
get_model_matrix(y, X = NULL, n_lags_max)
```

fastTS

Arguments

fit	an object with logLik method,
eps	minimum df used in computation
fits	a list of fits with different tuning parameters
ytest	validation data
Xtest	new X data, including lags
У	time series vector
Х	Additional exogenous features
n_lags_max	Maximum number of lags to add

fastTS

Fast time series modeling with ranked sparsity

Description

Uses penalized regression to quickly fit time series models with potentially complex seasonal patterns and exogenous variables. Based on methods described in Peterson & Cavanaugh (2024).

Usage

```
fastTS(
  у,
 X = NULL,
  n_lags_max,
  gamma = c(0, 2^{(-2:4)}),
  ptrain = 0.8,
 pf_{eps} = 0.01,
 w_endo,
 w_exo,
 weight_type = c("pacf", "parametric"),
 m = NULL,
  r = c(rep(0.1, length(m)), 0.01),
 plot = FALSE,
 ncvreg_args = list(penalty = "lasso", returnX = FALSE, lambda.min = 0.001)
)
## S3 method for class 'fastTS'
plot(x, log.l = TRUE, ...)
## S3 method for class 'fastTS'
coef(object, choose = c("AICc", "BIC"), ...)
## S3 method for class 'fastTS'
print(x, ...)
```

```
## S3 method for class 'fastTS'
summary(object, choose = c("AICc", "BIC"), ...)
```

Arguments

У	univariate time series outcome
Х	matrix of predictors (no intercept)
n_lags_max	maximum number of lags to consider
gamma	vector of exponent for weights
ptrain	prop. to leave out for test data
pf_eps	penalty factors below this will be set to zero
w_endo	optional pre-specified weights for endogenous terms
w_exo	optional pre-specified weights for exogenous terms (details)
weight_type	type of weights to use for endogenous terms
m	<pre>mode(s) for seasonal lags (used if weight_type = "parametric")</pre>
r	<pre>penalty factors for seasonal + local scaling functions (used if weight_type = "parametric")</pre>
plot	logical; whether to plot the penalty functions
ncvreg_args	additional args to pass through to nevreg
x	a fastTS object
log.l	Should the x-axis (lambda) be logged?
	passed to downstream functions
object	a fastTS object
choose	which criterion to use for lambda selection (AICc or BIC)

Details

The default weights for exogenous features will be chosen based on a similar approach to the adaptive lasso (using bivariate OLS estimates). For lower dimensional X, it's advised to set w_exo="unpenalized", because this allows for statistical inference on exogenous variable coefficients via the summary function.

By default, a seasonal frequency m must not be specified and the PACF is used to estimate the weights for endogenous terms. A parametric version is also available, which allows for a penalty scaling function that penalizes seasonal and recent lags less according to the penalty scaling functions described in Peterson & Cavanaugh (2024). See the penalty_scaler function for more details, and to plot the penalty function for various values of m and r.

Value

A list of class fastTS with elements

fits a list of lasso fits

fastTS

ncvreg_args	arguments passed to nevreg
gamma	the (negative) exponent on the penalty weights, one for each fit
n_lags_max	the maximum number of lags
У	the time series
Х	the utilized matrix of exogenous features
oos_results	results on test data using best of fits
train_idx	index of observations used in training data
weight_type	the type of weights used for endogenous terms
m	the mode(s) for seasonal lags (used if weight_type = "parametric")
r	penalty factors for seasonal + local scaling functions
ptrain	the proportion used to train the model

x invisibly

a vector of model coefficients

x (invisibly)

the summary object produced by novreg evaluated at the best tuning parameter combination (best AICc).

References

Breheny, P. and Huang, J. (2011) Coordinate descent algorithms for nonconvex penalized regression, with applications to biological feature selection. Ann. Appl. Statist., 5: 232-253.

Peterson, R.A., Cavanaugh, J.E. (2022) Ranked sparsity: a cogent regularization framework for selecting and estimating feature interactions and polynomials. AStA Adv Stat Anal. https://doi.org/10.1007/s10182-021-00431-7

Peterson, R.A., Cavanaugh, J.E. (2024). Fast, effective, and coherent time series modeling using the sparsity-ranked lasso. Statistical Modelling (accepted). DOI: https://doi.org/10.48550/arXiv.2211.01492

See Also

predict.fastTS

Examples

```
data("LakeHuron")
fit_LH <- fastTS(LakeHuron)
fit_LH
coef(fit_LH)
plot(fit_LH)</pre>
```

penalty_scaler

Description

Penalty Scaling Function for parametric penalty weights

Usage

penalty_scaler(lag, m, r, plot = TRUE, log = TRUE)

Arguments

lag	a vector of lags for which to calculate the penalty function
m	a vector of seasonality modes
r	a vector of dim $(m + 1)$ for the factor penalties on $c(m, time)$
plot	logical; whether to plot the penalty function
log	logical; whether to return the log of the penalty function

predict.fastTS	Predict function for fastTS object
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Description

Predict function for fastTS object

Usage

```
## S3 method for class 'fastTS'
predict(
   object,
   n_ahead = 1,
   X_test,
   y_test,
   cumulative = FALSE,
   forecast_ahead = FALSE,
   return_intermediate = FALSE,
   ...
)
```

Arguments

object	an fastTS object	
n_ahead	the look-ahead period for predictions	
X_test	a matrix exogenous features for future predictions (optional)	
y_test	the test series for future predictions (optional)	
cumulative	cumulative (rolling) sums of 1-, 2-, 3-,, k-step-ahead predictions.	
forecast_ahead	returns forecasted values for end of training series	
return_intermediate		
	if TRUE, returns the intermediate predictions between the 1st and n_ahead pre-	
	dictions, as data frame.	
	currently unused	

Details

The 'y_test' argument must be supplied if predictions are desired or if 'n_ahead' < 'nrow(X_test)'. This is because in order to obtain 1-step forecast for, say, the 10th observation in the test data set, the 9th observation of 'y_test' is required.

Forecasts for the first 'n_ahead' observations after the training set can be obtained by setting 'forecast_ahead' to TRUE, which will return the forecasted values at the end of the training data. it produces the 1-step-ahead prediction, the 2-step-ahead prediction, ... through the 'n_ahead'-step prediction. The 'cumulative' argument is similar but will return the cumulative (rolling) sums of 1-, 2-, 3=, ..., 'n_ahead'-step-ahead predictions.

Value

a vector of predictions, or a matrix of 1- through n_ahead predictions.

Examples

```
data("LakeHuron")
fit_LH <- fastTS(LakeHuron)
predict(fit_LH)</pre>
```

uihc_ed_arrivals	Hourly arrivals into the University of Iowa Hospital Emergency De-
	partment

Description

A data set containing the 17 columns described below. There are 41640 observations running from 2013 to 2018. Data set are already sorted by time.

Usage

uihc_ed_arrivals

Format

a data frame with 17 columns and 41640 rows:

Year Calendar year Quarter Fiscal year quarter Month Integer for month of year Day Integer for day of month Hour Integer for hour of day Arrivals Number of arrivals into the ED (outcome) Date Date Weekday Indicator for day of week temp hourly concurrent temperature xmas Christmas day indicator xmas2 Day after Christmas nye New Years Eve indicator nyd New Years Day indicator thx Thanksgiving day indicator thx Thanksgiving day (after) indicator ind Independence day indicator game_Day Hawkeye football game day indicator

Source

UIHC Emergency Department.

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