Package ‘Rlgt’

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Type Package

Title Bayesian Exponential Smoothing Models with Trend Modifications

Version 0.1-4

URL https://github.com/cbergmeir/Rlgt

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Description An implementation of a number of Global Trend models for time series forecasting that are Bayesian generalizations and extensions of some Exponential Smoothing models. The main differences/additions include 1) nonlinear global trend, 2) Student-t error distribution, and 3) a function for the error size, so heteroscedasticity. The methods are particularly useful for short time series. When tested on the well-known M3 dataset, they are able to outperform all classical time series algorithms. The models are fitted with MCMC using the ‘rstan’ package.

License GPL-3

Encoding UTF-8

LazyData true

ByteCompile true

Depends R (>= 3.4.0), Rcpp (>= 0.12.0), methods, rstantools, forecast

Imports rstan (>= 2.18.1), sn

LinkingTo StanHeaders (>= 2.18.0), rstan (>= 2.18.1), BH (>= 1.66.0), Rcpp (>= 0.12.0), RcppEigen (>= 0.3.3.3.0), RcppParallel (>= 5.0.2)

SystemRequirements GNU make

NeedsCompilation yes

RoxygenNote 7.1.2

Suggests knitr, rmarkdown

VignetteBuilder knitr

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Rlgt-package

Getting started with the Rlgt package

Description

An implementation of Bayesian ETS models named LGT (for non-seasonal time series data) and SGT (for seasonal time series data). These models have been tested on the M3 competition dataset in which they outperform all of the models originally participating in the competition.

Getting started

The best way to get started with the package is to have a look at the vignettes and the various demos that ship with the package. There is a vignette with examples of how to use the various methods included in the package, and a vignette that discusses some of the theoretical background.

As to the demos, you can find their source code in the "demo" subfolder in the package sources (available on CRAN). There are some basic demos and other more advanced ones that run on subsets of the M3 dataset and run potentially for hours.

The package contains models for seasonal and non-seasonal data, allows for external regressors, and different error distributions. In the following, we briefly also present some of the theoretical background of the methods.
LGT (Local and Global Trend)

The LGT model is constructed based on Holt’s linear trend method. The model is designed to allow for a more general term of error by allowing for heteroscedasticity and an addition of constant "global" trend in the model.

Model Equations:
In terms of mathematical notation, the model can be fully represented as follows:

\[ y_{t+1} \sim \text{Student}(\nu, \hat{y}_{t+1}, \sigma_{t+1}) \quad (eq.1.1) \]
\[ \hat{y}_{t+1} = l_t + \gamma l_t^p + \lambda b_t \quad (eq.1.2) \]
\[ l_{t+1} = \alpha y_{t+1} + (1 - \alpha) (l_t) \quad (eq.1.3) \]
\[ b_{t+1} = \beta (l_{t+1} - l_t) + (1 - \beta) b_t \quad (eq.1.4) \]
\[ \hat{\sigma}_{t+1} = \sigma l_t^\tau + \xi \quad (eq.1.5) \]

Notations:
- \( y_t \): value of the dependent variable of interest at time \( t \)
- \( \hat{y}_{t+1} \): forecasted value of \( y \) at time \( t+1 \) given information up to time \( t \)
- \( \hat{\sigma}_{t+1} \): forecasted deviation at time \( t+1 \) given information up to time \( t \)
- \( l_t \): level at time \( t \)
- \( b_t \): local trend at time \( t \)

Parameters:
- \( \nu \): degrees of freedom of the t-distribution
- \( \gamma \): coefficient of the global trend
- \( \rho \): power coefficient of the global trend
- \( \lambda \): damping coefficient of the local trend
- \( \alpha \): smoothing parameter for the level term
- \( \beta \): smoothing parameter for the local trend term
- \( \sigma \): coefficient of the size of error function
- \( \tau \): power coefficient of the size of error function
- \( \xi \): base or minimum value of the size of error function

SGT (Seasonal, Global Trend)

The SGT model was designed as a seasonal counterpart to the LGT model. Similar to LGT, this model is devised to allow for a global trend term and heteroscedastic error.

Model Equations:

\[ y_{t+1} \sim \text{Student}(\nu, \hat{y}_{t+1}, \sigma_{t+1}) \quad (eq.2.1) \]
\[ \hat{y}_{t+1} = (l_t + \gamma l_t^p) s_{t+1} \quad (eq.2.2) \]
\[ l_{t+1} = \alpha \frac{y_{t+1}}{s_{t+1}} + (1 - \alpha) (l_t) \quad (eq.2.3) \]
\[ s_{t+m+1} = \zeta \frac{y_{t+1}}{l_{t+1}} + (1 - \zeta) s_{t+1} \quad (eq.2.4) \]
\[ \hat{\sigma}_{t+1} = \sigma \hat{y}_{t+1}^\tau + \xi \quad (eq.2.5) \]
Additional Notations:

$s_t$ seasonality factor at time $t$
$m$ number of seasons in the data (e.g. 12 for monthly, 4 for quarterly)

Additional Parameters:

$\zeta$ smoothing parameter for the seasonality terms

**S2GT (Double Seasonal, Global Trend)**

S2GT is designed as an extension to SGT for time series data which exhibit two seasonality patterns.

**Model Equations:**

\[
y_{t+1} \sim \text{Student} (\nu, \hat{y}_{t+1}, \sigma_{t+1}) \quad (eq.3.1)\\
\hat{y}_{t+1} = (l_t + \gamma l_t^d) s_{t+1} w_{t+1} \quad (eq.3.2)\\
l_t = \alpha \frac{y_t}{s_t w_t} + (1 - \alpha) (l_{t-1}) \quad (eq.3.3)\\
s_{t+m} = \zeta \frac{y_t}{l_t w_t} + (1 - \zeta) s_t \quad (eq.3.4)\\
w_{t+d} = \delta \frac{y_t}{l_t s_t} + (1 - \delta) w_t \quad (eq.3.5)\\
\hat{\sigma}_{t+1} = \sigma y_{t+1} + \xi \quad (eq.3.6)
\]

Additional Notations:

$w_t$ second seasonality factor prevailing at time $t$
$d$ number of (second) seasons in a complete period (e.g. 12 for monthly, 4 for quarterly)

Additional Parameters:

$\delta$ smoothing parameters for the second seasonality factors

NA

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As to the demos, you can find their source code in the "demo" subfolder in the package sources (available on CRAN). There are some basic demos and other more advanced ones that run on subsets of the M3 dataset and run potentially for hours.

The package contains models for seasonal and non-seasonal data, allows for external regressors, and different error distributions. In the following, we briefly also present some of the theoretical background of the methods.
forecast.rlgtfit

**Description**

produce forecasts from an `rlgtfit` object

**Usage**

```r
## S3 method for class 'rlgtfit'
forecast(
  object,
  xreg = NULL,
  h = ifelse(frequency(object$x) > 1, 2 * frequency(object$x), 10),
  level = c(80, 95),
  NUM_OF_TRIALS = 2000,
  ...
)
```

**Arguments**

- `object`: `rlgtfit` object
- `xreg`: input regression matrix
- `h`: forecasting horizon (the default is 10 for annual and 2*periods otherwise)
- `level`: confidence levels for prediction intervals a.k.a. coverage percentiles. Must be between 0 and 100.
- `NUM_OF_TRIALS`: number of simulations to run. Suggested range is between (1000,5000), but it needs to be higher for good coverage for very high levels, e.g. 99.8.
- `...`: currently not used

**Value**

returns a forecast object compatible with the forecast package in R

**Examples**

```r
# The following is a toy example that runs within a few seconds. To get good fitting results the number of iterations should be set to at least 2000, and 4 chains should be used (the default). To speed up computation the number of cores should also be adjusted (default is 4).
rlgt_model <- rlgt(lynx,
                   control=rlgt.control(MAX_NUM_OF_REPEATS=1, NUM_OF_ITER=50, NUM_OF_CHAINS = 1, NUM_OF_CORES = 1), verbose=TRUE)

# print the model details
print(rlgt_model)
```
# Produce Forecasts for the next 10 years
forecast_result <- forecast(rlgt_model, h = 10, level=c(80, 95, 98))

plot(forecast_result, main="Forecasting lynx dataset with LGT model")

---

iclaims.example  
**Weekly Initial Claims of US Unemployment Benefits & Google Trends Queries**

---

**Description**

A dataset containing the weekly initial claims for US unemployment benefits against a few related Google trend queries from Jan 2010 - June 2018. This aims to mimick the dataset from Scott and Varian (2014).

**Usage**

data("iclaims.example")

**Format**

A data frame with 443 rows and 5 variables with log-transformation

- **week** date of records starting by Mondays with US calendar format
- **claims** weekly initial claims of unemployment benefits in thousands
- **trend.unemploy** normalized trend queries retrieved from gtrendsR API
- **trend.filling** normalized trend queries retrieved from gtrendsR API
- **trend.job** normalized trend queries retrieved from gtrendsR API

**References**

U.S. Employment and Training Administration, Initial Claims [ICNSA], retrieved from FRED, Federal Reserve Bank of St. Louis; [https://fred.stlouisfed.org/series/ICNSA](https://fred.stlouisfed.org/series/ICNSA), October 27, 2018.


An interface for retrieving and displaying the information returned online by Google Trends is provided. Trends (number of hits) over the time as well as geographic representation of the results can be displayed. [https://CRAN.R-project.org/package=gtrendsR](https://CRAN.R-project.org/package=gtrendsR)

initModel

.Initialize a model from the Rlgt family

Description

This is an internal function that usually won’t be called by users directly. It validates the model type and generates the corresponding list of parameters for the model.

Usage

initModel(
  model.type = NULL,
  use.regression = FALSE,
  seasonalityMethodId = 0,
  levelMethodId = 0,
  useSmoothingMethodForError = FALSE
)

Arguments

model.type type of the forecasting model selected, a character object
use.regression binary parameter indicating whether additional regressors will be used for forecasting in multivariate settings.
seasonalityMethodId Seasonality method Id (0- HW, 1- generalized).
levelMethodId Level method Id.
useSmoothingMethodForError
  if the non-standard function for error size should be used, one based on smoothed innovations or surprises

Value

an Rlgt skeleton model

posterior_interval.rlgtfit

rlgtfit posterior interval

Description

This is a method of the link{rlgtfit} class to produce posterior intervals

Usage

## S3 method for class 'rlgtfit'
posterior_interval(object, prob = 0.9, type = "central", ...)
Arguments

- **object**: an object of class rlgtfit
- **prob**: percentile level to be generated (multiple values can be accepted as a vector)
- **type**: currently only central is available
  ... currently not in use

Value

confidence interval

Examples

# The following is a toy example that runs within a few seconds. To get good
# fitting results the number of iterations should be set to at least 2000, and
# 4 chains should be used (the default). To speed up computation the number of
# cores should also be adjusted (default is 4).

rlgt_model <- rlgt(lynx,
  control=rlgt.control(MAX_NUM_OF_REPEATS=1, NUM_OF_ITER=50, NUM_OF_CHAINS = 1,
          NUM_OF_CORES = 1), verbose=TRUE)

# print the model details
posterior_interval(rlgt_model)

print.rlgtfit

Generic print function for rlgtfit models

Description

Print out some characteristics of an rlgtfit model.

Usage

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

Arguments

- **x**: an rlgtfit object
- **...**: additional function parameters (currently not used)
Fit an Rlgt model

Description

The main function to fit an rlgt model. It fits the parameter values with MCMC.

Usage

```r
rlgt(
  y,
  seasonality = 1,
  seasonality2 = 1,
  seasonality.type = c("multiplicative", "generalized"),
  error.size.method = c("std", "innov"),
  level.method = c("HW", "seasAvg", "HW_sAvg"),
  xreg = NULL,
  control = rlgt.control(),
  verbose = FALSE
)
```

Arguments

- `y` - time-series data for training (provided as a numeric vector, or a ts, or msts object).
- `seasonality` - This specification of seasonality will be overridden by frequency of `y`, if `y` is of ts or msts class. 1 by default, i.e. no seasonality.
- `seasonality2` - Second seasonality. If larger than 1, a dual seasonality model will be used. However, this is experimental. If not specified and multiple seasonality time series (of msts class) is used, a single seasonality model will be applied, one with seasonality equal to the largest of seasonalities of the time series. 1 by default, i.e. no seasonality or single seasonality.
- `seasonality.type` - Either "multiplicative" (default) or "generalized". The latter seasonality generalizes additive and multiplicative seasonality types.
- `error.size.method` - Function providing size of the error. Either "std" (monotonically, but slower than proportionally, growing with the series values) or "innov" (proportional to a smoothed abs size of innovations, i.e. surprises).
- `level.method` - "HW", "seasAvg", "HW_sAvg". Here, "HW" follows Holt-Winters approach. "seasAvg" calculates level as a smoothed average of the last seasonality number of points (or seasonality2 of them for the dual seasonality model), and HW_sAvg is an weighted average of HW and seasAvg methods.
- `xreg` - Optionally, a vector or matrix of external regressors, which must have the same number of rows as `y`.
control  list of control parameters, e.g. hyperparameter values for the model’s prior distributions, number of fitting iterations etc.

verbose  whether verbose information should be printed (Boolean value only), default FALSE.

Value

rlgtfit object

Examples

# The following is a toy example that runs within a few seconds. To get good
# fitting results the number of iterations should be set to at least 2000, and
# 4 chains should be used (the default). To speed up computation the number of
# cores should also be adjusted (default is 4).

rlgt_model <- rlgt(lynx,
    control=rlgt.control(MAX_NUM_OF_REPEATS=1, NUM_OF_ITER=50, NUM_OF_CHAINS = 1,
                        NUM_OF_CORES = 1), verbose=TRUE)

# print the model details
print(rlgt_model)

## Not run: demo(exampleScript)
MAX_RHAT_ALLOWED = 1.006,
NUM_OF_SEASON_INIT_CYCLES = 3,
MIN_NU = 2,
MAX_NU = 20,
MIN_POW_TREND = -0.5,
MAX_POW_TREND = 1,
POW_TREND_ALPHA = 1,
POW_TREND_BETA = 1,
POW_SEASON_ALPHA = 1,
POW_SEASON_BETA = 1,
MIN_SIGMA = 1e-10,
MIN_VAL = 1e-30,
MAX_VAL = 1e+38
)

Arguments

ADAPT_DELTA Target Metropolis acceptance rate. See Stan manual. Suggested range is between (0.85-0.97).

MAX_TREE_DEPTH NUTS maximum tree depth. See Stan manual for more details. Suggested range is between (10-15), default is 12.

NUM_OF_CHAINS Number of MCMC chains. Suggested range is 3 to 4. Default is 4.

NUM_OF_CORES Number of cores used for calculations. It can be smaller than NUM_OF_CHAINS, but for best computational speed, it should be equal to NUM_OF_CHAINS. Default is 4.

ADD_JITTER Whether to add a very small amount (sd=min(y)*0.0001) of jitter to the input series. It is sometimes useful in cases of series with some perfectly flat sections. Default is TRUE.

CAUCHY_SD_DIV Cauchy distribution is used for some parameters with non-obvious range. The error size hyperparameter of this distribution is calculated by dividing the max value of the time series by this constant. Suggested range is between (100,300). Default 150.

NUM_OF_ITER Starting number of iterations for each chain. Suggested range is between (2000,10000). Default is 5000. Generally, the longer the series, the smaller is the value to reach convergence. Some models e.g. those with "innov" error size method are more difficult to fit and require more iterations.

MAX_NUM_OF_REPEATS Maximum number of the sampling procedure repeats if the fit is unsatisfactorily, i.e. avgRhat>MAX_RHAT_ALLOWED. Each round will double the number of iterations which could potentially double the running time. Suggested range is between (2,4). Default is 2.

MAX_RHAT_ALLOWED Maximum average value of Rhat’s that suggests a good fit, i.e. the threshold below which the fit is considered as acceptable. Consult Stan’s manual for more details on Rhat. Suggested range is between (1.005,1.02). Default is 1.006.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>NUM_OF_SEASON_INIT_CYCLES</td>
<td>For seasonal models, number of seasonality periods used for establishing initial seasonality coefficients. Default is 3.</td>
</tr>
<tr>
<td>MIN_NU</td>
<td>Minimum degrees of freedom of the Student’s distribution that is used in most models. Suggested range(1.2, 5). Default 2.</td>
</tr>
<tr>
<td>MAX_NU</td>
<td>Maximum degrees of freedom of the Student’s distribution. Suggested range is between (15,30). Default 20.</td>
</tr>
<tr>
<td>MIN_POW_TREND</td>
<td>Minimum value of the global trend power coefficient. Suggested range is between (-1,0). Default -.5</td>
</tr>
<tr>
<td>MAX_POW_TREND</td>
<td>Maximum value of the global trend power coefficient. It should be 1 to allow the model to approach exponential growth when needed. Default is 1.</td>
</tr>
<tr>
<td>POW_TREND_ALPHA</td>
<td>Alpha parameter of Beta prior distribution. To make the forecast more upward curved, so to nudge it towards larger values, make the parameter larger. Suggested range is between (1,6) Default 1.</td>
</tr>
<tr>
<td>POW_TREND_BETA</td>
<td>Beta parameter of Beta prior distribution for the global trend power coefficient. 1 by default, see also above.</td>
</tr>
<tr>
<td>POW_SEASON_ALPHA</td>
<td>Alpha parameter of Beta distribution that is the prior of the power coefficient in the formula of the generalized seasonality in gSGT model. 1 by default, increasing it (say, to 3 or 5) will push the seasonality towards multiplicative behavior.</td>
</tr>
<tr>
<td>POW_SEASON_BETA</td>
<td>Beta parameter of Beta distribution that is the prior of the power coefficient in the formula of the generalized seasonality in gSGT model. 1 by default.</td>
</tr>
<tr>
<td>MIN_SIGMA</td>
<td>Minimum size of the fitted sigma, applied for numerical stability. Must be positive. 1e-10 by default.</td>
</tr>
<tr>
<td>MIN_VAL</td>
<td>Minimum value that forecast can take. Must be positive. 1e-30 by default.</td>
</tr>
<tr>
<td>MAX_VAL</td>
<td>Maximum value the forecast can take. 1e38 by default.</td>
</tr>
</tbody>
</table>

**Value**

list of control parameters

---

**rlgtfit**

**rlgtfit class**

**Description**

A constructor function for objects of class `rlgtfit`, the main class of the package. Objects of this class are output from the `rlgt` function. This constructor will usually not be called by users directly.
Usage

rlgtfit(
    y,
    model.type,
    use.regression,
    seasonalityMethodId,
    levelMethodId,
    useSmoothingMethodForError = FALSE,
    seasonality,
    seasonality2,
    rlgtmodel,
    params,
    control,
    samples
)

Arguments

y time series data for training (provided as a vector or a ts object).
model.type the type of rlgt model, one of: "LGT", "SGT", "S2GT"
use.regression whether the data has any additional variables to be used with forecasting, i.e. multivariate time-series.
seasonalityMethodId Seasonality method Id (0- HW, 1- generalized).
levelMethodId Level method Id.
useSmoothingMethodForError if the non-standard function for error size should be used, one based on smoothed innovations or surprises
seasonality This specification of seasonality will be overridden by frequency of y, if y is of ts or msts class. 1 by default, i.e. no seasonality.
seasonality2 Second seasonality. If larger than 1, a dual seasonality model will be used. This specification of seasonality will be overridden by the second seasonality of y, if y is of msts class. 1 by default, i.e. no seasonality or single seasonality.
rlgtmodel an rlgt model.
params list of parameters of the model (to be fitted).
control list of control parameters, i.e. hyperparameter values for the model’s prior distribution. See rlgt.control
samples stanfit object representing the MCMC samples

Value

an rlgtfit instance
umcsent.example

University of Michigan Monthly Survey of Consumer Sentiment & Google Trends Queries

Description
A dataset containing monthly University of Michigan survey of Consumer Sentiment along a few related google trend queries Jan from 2014 - June 2018. This aims to mimick the dataset from Scott and Varian (2014).

Usage

data("umcsent.example")

Format
A data frame with 174 rows and 8 variables with log-transformation

date  first date of each month in US calendar format
consumer.sent  monthly initial claims of University of Michigan: Consumer Sentiment
search.engine  normalized trend queries retrieved from gtrendsR API
financial.planning  normalized trend queries retrieved from gtrendsR API
bus.news  normalized trend queries retrieved from gtrendsR API
investing  normalized trend queries retrieved from gtrendsR API
energy.utilities  normalized trend queries retrieved from gtrendsR API

References
University of Michigan, University of Michigan: Consumer Sentiment [UMCSENT], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UMCSENT, November 17, 2018.
An interface for retrieving and displaying the information returned online by Google Trends is provided. Trends (number of hits) over the time as well as geographic representation of the results can be displayed. https://CRAN.R-project.org/package=gtrendsR
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