# Package 'scoringRules'

August 21, 2019

Title Scoring Rules for Parametric and Simulated Distribution

Type Package

Forecasts

Version 1.0.0
<b>Date</b> 2019-08-19
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<b>Description</b> Dictionary-like reference for computing scoring rules in a wide range of situations. Covers both parametric forecast distributions (such as mixtures of Gaussians) and distributions generated via simulation.
<pre>URL https://github.com/FK83/scoringRules</pre>
License GPL (>= 2)
Imports Rcpp (>= 0.12.0), methods, MASS, knitr
<b>Depends</b> R (>= 3.00)
Suggests gsl (>= 1.8-3), hypergeo(>= 1.0), rmarkdown, testthat, crch
LinkingTo Rcpp, RcppArmadillo
RoxygenNote 6.1.1
VignetteBuilder knitr
Encoding UTF-8
NeedsCompilation yes
Repository CRAN
<b>Date/Publication</b> 2019-08-20 22:10:02 UTC
R topics documented:
ar_ms

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# Description

Bayesian analysis of a Markov Switching autoregressive model

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### Usage

```
ar_ms(y, nlag = 1, beta_switch = FALSE, variance_switch = TRUE,
identification_constraint = "variance", n_burn = 5000,
n_rep = 20000, forecast_periods = 5, printout = FALSE,
Hm1_delta = 25, mu_delta = 0, s_ = 0.3, nu_ = 3,
R = matrix(c(8, 2, 2, 8), nrow = 2))
```

### **Arguments**

y numeric vector (time series to be analyzed).

nlag integer, number of autoregressive lags (defaults to one).

beta\_switch, variance\_switch

logicals, indicating whether there should be Markovian state dependence in regression parameters and residual variance, respectively. Defaults to beta\_switch = FALSE, variance\_switch = TRUE.

identification\_constraint

character, indicating how to identify latent states. Possible values: "variance", "mean" and "persistence". Defaults to "variance".

n\_burn, n\_rep integers, number of MCMC iterations for burn-in and main analysis. forecast\_periods

number of future periods for which forecasts are computed.

printout logical, whether to print progress report during MCMC (defaults to FALSE). Hm1\_delta, mu\_delta, s\_, nu\_, R

prior parameters as described in KLTG (2019, Appendix E and Table 4).

### **Details**

The default parameters are as set by KLTG (2019, Section 5). The output matrices fcMeans and fcSds can be used to construct the mixture-of-parameters estimator analyzed by KLTG. While many of the model features can be changed as described above, the number of Markov regimes is always fixed at two.

ar\_ms is an R/C++ implementation of Matlab code kindly shared by Gianni Amisano via his website (https://sites.google.com/site/gianniamisanowebsite/). See Amisano and Giacomini (2007) who analyze a similar model.

### Value

List containing parameter estimates and forecasts, with the following elements:

- pars, matrix of posterior draws for parameters (rows are MCMC iterations, columns are parameters)
- fcMeans and fcSds, matrices of forecast means and standard deviations (rows are MCMC iterations, columns are forecast horizons)
- probs, matrix of filtered probabilities for first latent state (rows are MCMC iterations, columns are time periods, excluding the first nlag values for initialization).
- count, integer, counter for the number of states that were relabeled based on identification\_constraint.

### Author(s)

Fabian Krueger, based on Matlab code by Gianni Amisano (see details section)

#### References

Amisano, G. and R. Giacomini (2007), 'Comparing density forecasts via weighted likelihood ratio tests', Journal of Business and Economic Statistics 25, 177-190.

Krueger, F., Lerch, S., Thorarinsdottir, T.L. and T. Gneiting (2019): 'Predictive inference based on Markov chain Monte Carlo output', working paper, Heidelberg Institute for Theoretical Studies, available at http://arxiv.org/abs/1608.06802.

### See Also

run\_casestudy uses ar\_ms to replicate the results of KLTG (2019, Section 5).

### **Examples**

```
## Not run:
# Use GDP data from 2014Q4 edition
data(gdp)
dat \leftarrow subset(gdp, vint == "2014Q4")
y <- dat$val[order(dat$dt)]</pre>
# Fit model, using the default settings
set.seed(816)
fit <- ar_ms(y)</pre>
# Histograms of parameter draws
par(mfrow = c(2, 2))
hist(fit$pars[,1], main = "Intercept (state-invariant)", xlab = "")
hist(fit$pars[,2], main = "AR(1) term (state-invariant)", xlab = "")
hist(1/fit$pars[,3], main = "Residual variance in 1st state", xlab = "")
hist(1/fit$pars[,4], main = "Residual variance in 2nd state", xlab = "")
# By construction, the residual variance is smaller in the 1st than in the 2nd state:
print(mean(1/fit$pars[,3] < 1/fit$pars[,4]))</pre>
## End(Not run)
```

crps.numeric

Continuous Ranked Probability Score for Parametric Forecast Distributions

# Description

Calculate the Continuous Ranked Probability Score (CRPS) given observations and parameters of a family of distributions.

### Usage

```
## S3 method for class 'numeric'
crps(y, family, ...)
```

### **Arguments**

y vector of realized values.

family string which specifies the parametric family; current options: "2pexp", "2pnorm", "beta", "binom", "cl vectors of parameter values; expected input depends on the chosen family. See details below.

# **Details**

Mathematical details are available in Appendix A of the vignette *Evaluating probabilistic forecasts* with scoringRules that accompanies the package.

The parameters supplied to each of the functions are numeric vectors:

- 1. Distributions defined on the real line:
  - "laplace" or "lapl": location (real-valued location parameter), scale (positive scale parameter); see crps\_lapl
  - "logistic" or "logis": location (real-valued location parameter), scale (positive scale parameter); see crps\_logis
  - "normal" or "norm": mean, sd (mean and standard deviation); see crps\_norm
  - "normal-mixture" or "mixture-normal" or "mixnorm": m (mean parameters), s (standard deviations), w (weights); see crps\_mixnorm; note: matrix-input for parameters
  - "t": df (degrees of freedom), location (real-valued location parameter), scale (positive scale parameter); see crps\_t
  - "two-piece-exponential" or "2pexp": location (real-valued location parameter), scale1, scale2 (positive scale parameters); see crps\_2pexp
  - "two-piece-normal" or "2pnorm": location (real-valued location parameter), scale1, scale2 (positive scale parameters); see crps\_2pnorm
- 2. Distributions for non-negative random variables:
  - "exponential" or "exp": rate (positive rate parameter); see crps\_exp
  - "gamma": shape (positive shape parameter), rate (positive rate parameter), scale (alternative to rate); see crps\_gamma
  - "log-laplace" or "llapl": locationlog (real-valued location parameter), scalelog (positive scale parameter); see crps\_llapl
  - "log-logistic" or "llogis": locationlog (real-valued location parameter), scalelog (positive scale parameter); see crps\_llogis
  - "log-normal" or "lnorm": locationlog (real-valued location parameter), scalelog (positive scale parameter); see crps\_lnorm
- 3. Distributions with flexible support and/or point masses:
  - "beta": shape1, shape2 (positive shape parameters), lower, upper (lower and upper limits); see crps\_beta

• "uniform" or "unif": min, max (lower and upper limits), lmass, umass (point mass in lower or upper limit); see crps\_unif

- "expM": location (real-valued location parameter), scale (positive scale parameter), mass (point mass in location); see crps\_expM
- "gev": location (real-valued location parameter), scale (positive scale parameter), shape (real-valued shape parameter); see crps\_gev
- "gpd": location (real-valued location parameter), scale (positive scale parameter), shape (real-valued shape parameter), mass (point mass in location); see <a href="mailto:crps\_gpd">crps\_gpd</a>
- "tlogis": location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); see crps\_tlogis
- "clogis": location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); see crps\_clogis
- "gtclogis": location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); lmass, umass (point mass in lower or upper limit); see crps\_gtclogis
- "tnorm": location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); see crps\_tnorm
- "cnorm": location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); see crps\_cnorm
- "gtcnorm": location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); lmass, umass (point mass in lower or upper limit); see crps\_gtcnorm
- "tt": df (degrees of freedom), location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); see crps\_tt
- "ct": df (degrees of freedom), location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); see crps\_ct
- "gtct": df (degrees of freedom), location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); lmass, umass (point mass in lower or upper limit); see crps\_gtct
- 4. Distributions of discrete variables:
  - "binom": size (number of trials (zero or more)), prob (probability of success on each trial); see crps\_binom
  - "hyper": m (the number of white balls in the urn), n (the number of black balls in the urn), k (the number of balls drawn from the urn); see crps\_hyper
  - "negative-binomial" or "nbinom": size (positive dispersion parameter), prob (success probability), mu (mean, alternative to prob); see <a href="mailto:crps\_nbinom">crps\_nbinom</a>
  - "poisson" or "pois": lambda (positive mean); see crps\_pois

All numerical arguments should be of the same length. An exception are scalars of length 1, which will be recycled.

### Value

Vector of score values. A lower score indicates a better forecast.

### Author(s)

Alexander Jordan, Fabian Krueger, Sebastian Lerch

#### References

Closed form expressions of the CRPS for specific distributions:

Baran, S. and S. Lerch (2015): 'Log-normal distribution based Ensemble Model Output Statistics models for probabilistic wind-speed forecasting', Quarterly Journal of the Royal Meteorological Society 141, 2289-2299. (*Log-normal*)

Friederichs, P. and T.L. Thorarinsdottir (2012): 'Forecast verification for extreme value distributions with an application to probabilistic peak wind prediction', Environmetrics 23, 579-594. (Generalized Extreme Value, Generalized Pareto)

Gneiting, T., Larson, K., Westvelt III, A.H. and T. Goldman (2005): 'Calibrated probabilistic fore-casting using ensemble model output statistics and minimum CRPS estimation', Monthly Weather Review 133, 1098-1118. (*Normal*)

Gneiting, T., Larson, K., Westrick, K., Genton, M.G. and E. Aldrich (2006): 'Calibrated probabilistic forecasting at the stateline wind energy center: The regime-switching space-time method', Journal of the American Statistical Association 101, 968-979. (*Censored normal*)

Gneiting, T. and T.L. Thorarinsdottir (2010): 'Predicting inflation: Professional experts versus no-change forecasts', arXiv preprint arXiv:1010.2318. (Two-piece normal)

Grimit, E.P., Gneiting, T., Berrocal, V.J. and N.A. Johnson (2006): 'The continuous ranked probability score for circular variables and its application to mesoscale forecast ensemble verification', Quarterly Journal of the Royal Meteorological Society 132, 2925-2942. (*Mixture of normals*)

Scheuerer, M. and D. Moeller (2015): 'Probabilistic wind speed forecasting on a grid based on ensemble model output statistics', Annals of Applied Statistics 9, 1328-1349. (*Gamma*)

Thorarinsdottir, T.L. and T. Gneiting (2010): 'Probabilistic forecasts of wind speed: ensemble model output statistics by using heteroscedastic censored regression', Journal of the Royal Statistical Society (Series A) 173, 371-388. (*Truncated normal*)

Wei, W. and L. Held (2014): 'Calibration tests for count data', TEST 23, 787-205. (Poisson, Negative Binomial)

*Independent listing of closed-form solutions for the CRPS:* 

Taillardat, M., Mestre, O., Zamo, M. and P. Naveau (2016): 'Calibrated ensemble forecasts using quantile regression forests and ensemble model output statistics', Monthly Weather Review 144, 2375-2393.

### See Also

```
logs.numeric
```

# **Examples**

```
crps(y = 1, family = "normal", mean = 0, sd = 2)
crps(y = rnorm(20), family = "normal", mean = 1:20, sd = sqrt(1:20))

## Arguments can have different lengths:
crps(y = rnorm(20), family = "normal", mean = 0, sd = 2)
crps(y = 1, family = "normal", mean = 1:20, sd = sqrt(1:20))

## Mixture of normal distributions requires matrix input for parameters:
mval <- matrix(rnorm(20*50), nrow = 20)</pre>
```

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```
sdval <- matrix(runif(20*50, min = 0, max = 2), nrow = 20)
weights <- matrix(rep(1/50, 20*50), nrow = 20)
crps(y = rnorm(20), family = "mixnorm", m = mval, s = sdval, w = weights)</pre>
```

GDP data

Data and forecasts for US GDP growth

### Description

Historical data and forecast distributions for the growth rate of US gross domestic product (GDP). The forecasts are generated from a Bayesian Markov Switching model as described in Section 5 of Krueger et al (2016).

#### **Format**

gdp is a data frame which contains the real-time data set used in Section 5 of KLTG (2019), with the following columns:

- dt date in question (e.g., "2013Q2" for the second quarter of 2013)
- vint data vintage (i.e., the date at which the realization was recorded); same format as dt
- val value of the GDP growth rate

gdp\_mcmc is a list, whereby each element is a data frame. gdp\_mcmc\$forecasts contains the simulated forecast distributions. There are 20 columns (corresponding to quarters 2008:Q1 to 2012:Q4) and 5.000 rows (corresponding to simulation draws). gdp\_mcmc\$actuals contains the actual observations. There are 20 columns (again corresponding to quarterly dates) and a single row.

### **Details**

The realizations in gdp\_mcmc\$actuals are also contained in gdp, based on the second available vintage for each date. For example, gdp\_mcmc\$actuals\$X2008Q1 is the entry in gdp for which dt == "2008Q1" and vint == "2008Q3".

#### Source

The GDP growth rate is computed from real-time data provided by the Federal Reserve Bank of Philadelphia, https://www.phil.frb.org/research-and-data/real-time-center/(series code "ROUTPUT", second-vintage data). The same data also enters the model which is used to generate the forecast distribution. Disclaimer: The provider of the raw data takes no responsibility for the accuracy of the data posted here. Furthermore, the raw data may be revised over time, and the website linked above should be consulted for the official, most recent version.

The model from which the forecast draws are generated is described in Section 5 of KLTG (2019). Forecasts are one quarter ahead (that is, they are based on data until the previous quarter).

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### References

Krueger, F., Lerch, S., Thorarinsdottir, T.L. and T. Gneiting (2019): 'Predictive inference based on Markov Chain Monte Carlo output', working paper, Heidelberg Institute for Theoretical Studies, available at http://arxiv.org/abs/1608.06802.

### **Examples**

```
## Not run:

# Load data
data(gdp_mcmc)

# Histogram of forecast draws for 2012Q4
fc_draws <- gdp_mcmc$forecasts[, "X2012Q4"]
hist(fc_draws, main = "Forecast draws for 2012:Q4", xlab = "Value")

# Add vertical line at realizing value
rlz <- gdp_mcmc$actuals[, "X2012Q4"]
abline(v = rlz, lwd = 3)

# Compute CRPS for this forecast case
crps_sample(y = rlz, dat = fc_draws)

## End(Not run)</pre>
```

logs.numeric

Logarithmic Score for Parametric Forecast Distributions

### **Description**

Calculate the logarithmic score (LogS) given observations and parameters of a family of distributions.

# Usage

```
## S3 method for class 'numeric'
logs(y, family, ...)
```

# **Arguments**

y Vector of realized values.

family String which specifies the parametric family; current options: "2pexp", "2pnorm", "beta", "binom", "ex

Vectors of parameter values; expected input depends on the chosen family. See
details below.

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### **Details**

The parameters supplied to each of the functions are numeric vectors:

- 1. Distributions defined on the real line:
  - "laplace" or "lapl": location (real-valued location parameter), scale (positive scale parameter); see logs\_lapl
  - "logistic" or "logis": location (real-valued location parameter), scale (positive scale parameter); see logs\_logis
  - "normal" or "norm": mean, sd (mean and standard deviation); see logs\_norm
  - "normal-mixture" or "mixture-normal" or "mixnorm": m (mean parameters), s (standard deviations), w (weights); see <a href="logs\_mixnorm">logs\_mixnorm</a>; note: matrix-input for parameters
  - "t": df (degrees of freedom), location (real-valued location parameter), scale (positive scale parameter); see logs\_t
  - "two-piece-exponential" or "2pexp": location (real-valued location parameter), scale1, scale2 (positive scale parameters); see logs\_2pexp
  - "two-piece-normal" or "2pnorm": location (real-valued location parameter), scale1, scale2 (positive scale parameters); see logs\_2pnorm
- 2. Distributions for non-negative random variables:
  - "exponential" or "exp": rate (positive rate parameter); see logs\_exp
  - "gamma": shape (positive shape parameter), rate (positive rate parameter), scale (alternative to rate); see logs\_gamma
  - "log-laplace" or "llapl": locationlog (real-valued location parameter), scalelog (positive scale parameter); see logs\_llapl
  - "log-logistic" or "llogis": locationlog (real-valued location parameter), scalelog (positive scale parameter); see logs\_llogis
  - "log-normal" or "lnorm": locationlog (real-valued location parameter), scalelog (positive scale parameter); see logs\_lnorm
- 3. Distributions with flexible support and/or point masses:
  - "beta": shape1, shape2 (positive shape parameters), lower, upper (lower and upper limits); see logs\_beta
  - "uniform" or "unif": min, max (lower and upper limits); see logs\_unif
  - "exp2": location (real-valued location parameter), scale (positive scale parameter); see logs\_exp2
  - "gev": location (real-valued location parameter), scale (positive scale parameter), shape (real-valued shape parameter); see logs\_gev
  - "gpd": location (real-valued location parameter), scale (positive scale parameter), shape (real-valued shape parameter); see logs\_gpd
  - "tlogis": location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); see logs\_tlogis
  - "tnorm": location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); see logs\_tnorm
  - "tt": df (degrees of freedom), location (location parameter), scale (scale parameter), lower, upper (lower and upper limits); see logs\_tt
- 4. Distributions of discrete variables:

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• "binom": size (number of trials (zero or more)), prob (probability of success on each trial); see crps\_binom

- "hyper": m (the number of white balls in the urn), n (the number of black balls in the urn), k (the number of balls drawn from the urn); see <a href="mailto:crps\_hyper">crps\_hyper</a>
- "negative-binomial" or "nbinom": size (positive dispersion parameter), prob (success probability), mu (mean, alternative to prob); see logs\_nbinom
- "poisson" or "pois": lambda (positive mean); see logs\_pois

All numerical arguments should be of the same length. An exception are scalars of length 1, which will be recycled.

### Value

Vector of score values. A lower score indicates a better forecast.

### Author(s)

Alexander Jordan, Fabian Krueger, Sebastian Lerch

### See Also

```
crps.numeric
```

# **Examples**

```
logs(y = 1, family = "normal", mean = 0, sd = 2)
logs(y = rnorm(20), family = "normal", mean = 1:20, sd = sqrt(1:20))

## Arguments can have different lengths:
logs(y = rnorm(20), family = "normal", mean = 0, sd = 2)
logs(y = 1, family = "normal", mean = 1:20, sd = sqrt(1:20))

## Mixture of normal distributions requires matrix input for parameters:
mval <- matrix(rnorm(20*50), nrow = 20)
sdval <- matrix(runif(20*50, min = 0, max = 2), nrow = 20)
weights <- matrix(rep(1/50, 20*50), nrow = 20)
logs(y = rnorm(20), family = "mixnorm", m = mval, s = sdval, w = weights)</pre>
```

plot.casestudy

*Plot the output of run\_casestudy* 

### Description

Plot the output of run\_casestudy

#### Usage

```
## S3 method for class 'casestudy' plot(x, ...)
```

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### **Arguments**

x object of class casestudy, generated by run\_casestudy
... additional parameters, see details below.

### **Details**

The plot is in the same format as Figure 5 in KLTG (2019). Its content (nr of MCMC chains, maximal sample size, etc) depends on the parameters used to generate run\_casestudy. In terms of additional inputs (...), the following are currently implemented:

- scoring\_rule, the scoring rule for which results are to be plotted, either "crps" or "logs". Defaults to "crps".
- add\_main\_title, logical, whether to add main title to plot. Defaults to TRUE.

### Value

none, used for the effect of drawing a plot.

### Author(s)

Fabian Krueger

### References

Krueger, F., Lerch, S., Thorarinsdottir, T.L. and T. Gneiting (2019): 'Predictive inference based on Markov chain Monte Carlo output', working paper, Heidelberg Institute for Theoretical Studies, available at http://arxiv.org/abs/1608.06802.

### See Also

run\_casestudy produces the forecast results summarized by plot.casestudy

plot.mcstudy

*Plot the output of run\_mcstudy* 

### **Description**

Plot the output of run\_mcstudy

# Usage

```
## S3 method for class 'mcstudy' plot(x, \ldots)
```

### **Arguments**

x object of class mostudy, generated by run\_mostudy

... additional parameters, see details below.

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### **Details**

The plot is in the same format as Figure 1 or 2 in KLTG (2019), depending on the parameters set when running run\_mcstudy. These parameters also determine the plot content (nr of MCMC chains, maximal sample size, etc). In terms of additional inputs (...), the following are currently implemented:

- scoring\_rule, the scoring rule for which results are to be plotted, either "crps" or "logs". Defaults to "crps".
- add\_main\_title, logical, whether to add main title to plot. Defaults to TRUE.

### Value

none, used for the effect of drawing a plot.

### Author(s)

Fabian Krueger

### References

Krueger, F., Lerch, S., Thorarinsdottir, T.L. and T. Gneiting (2019): 'Predictive inference based on Markov chain Monte Carlo output', working paper, Heidelberg Institute for Theoretical Studies, available at http://arxiv.org/abs/1608.06802.

### See Also

run\_mcstudy produces the simulation results summarized by plot.mcstudy

print.casestudy

Simple print method for object of class casestudy

# **Description**

Simple print method for object of class casestudy

### **Usage**

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

### **Arguments**

x Object of class casestudy, generated via run\_casestudy

... Additional specifications (presently not in use)

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print.mcstudy

Simple print function for object of class mcstudy

### **Description**

Simple print function for object of class mestudy

# Usage

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

# Arguments

x Object of class mcstudy, generated via run\_mcstudy
... Additional specifications (presently not in use)

run\_casestudy

Run the case study in KLTG (2019), or a smaller version thereof

### **Description**

Run the case study in KLTG (2019), or a smaller version thereof

### **Usage**

```
run_casestudy(data_df, burnin_size = 5000, max_mcmc_sample_size = 5000,
    nr_of_chains = 3, first_vint = "1996Q2", last_vint = "2014Q3",
    forecast_horizon = 1, random_seed = 816)
```

### **Arguments**

data\_df data frame in the same format as the gdp data set in this package.

burnin\_size length of the burn-in period used for each forecast.

max\_mcmc\_sample\_size maximal number of MCMC draws to consider (integer, must equal either 1000, 5000, 10000, 20000 or 40000). Defaults to 5000.

pr\_of\_chains number of parallel MCMC for each forecast date (integer\_defaults to 3)

nr\_of\_chains number of parallel MCMC for each forecast date (integer, defaults to 3). first\_vint, last\_vint

first and last data vintage (= time point at which forecasts are made). Default to "19962Q2" and "2014Q3", respectively.

forecast\_horizon

forecast horizon to be analyzed (integer, defaults to 1).

random\_seed seed for random numbers used during the MCMC sampling process. Defaults to 816.

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### **Details**

The full results in Section 5 of KLTG (2019) are based on the following setup:  $burnin\_size = 10000$ ,  $max\_mcmc\_sample\_size = 50000$ ,  $nr\_of\_chains = 16$ ,  $data\_df = gdp$ ,  $first\_vint = "1996Q2"$ ,  $last\_vint = "2014Q3"$ , and  $forecast\_horizon = 1$ . Since running this full configuration is very time consuming, the default setup offers the possibility to run a small-scale study which reproduces the qualitative outcomes of the analysis. Running the small-scale study implied by the defaults of run\\_study as well as the GDP data ( $data\_df = gdp$ ) takes about 40 minutes on an Intel i7 processor.

### Value

Object of class "casestudy", containing the results of the analysis. This object can be passed to plot for plotting, see the documentation for plot.casestudy.

### Author(s)

Fabian Krueger

### References

Krueger, F., Lerch, S., Thorarinsdottir, T.L. and T. Gneiting (2019): 'Predictive inference based on Markov chain Monte Carlo output', working paper, Heidelberg Institute for Theoretical Studies, available at http://arxiv.org/abs/1608.06802.

### See Also

plot.casestudy produces a summary plot of the results generated by run\_casestudy run\_casestudy uses ar\_ms to fit a Bayesian Markov Switching model, recursively for several time periods.

### **Examples**

```
## Not run:
data(gdp)
cs <- run_casestudy(data_df = gdp, last_vint = "1999Q4")
plot(cs)
## End(Not run)</pre>
```

run\_mcstudy

Run the Monte Carlo study by KLTG (2019), or a smaller version thereof

### **Description**

Run the Monte Carlo study by KLTG (2019), or a smaller version thereof

run\_mcstudy

### Usage

```
run_mcstudy(s = 2, a = 0.5, n = 12, nr_iterations = 50,
zoom = FALSE, random_seed = 816)
```

# **Arguments**

s, a, n parameters characterizing the process from which data are simulated (see Sec-

tion 4 and Table 4 of KLTG, 2019). Defaults to the values reported in the main

text of the paper.

nr\_iterations number of Monte Carlo iterations (defaults to 50).

zoom set to TRUE to produce results for a fine grid of small (MCMC) sample sizes, as

in Figure 2 of KLTG (2019).

random\_seed seed used for running the simulation experiment. Defaults to 816.

### **Details**

The full results in Section 4 of KLTG (2019) are based on s = 2, a = 0.5, n = 12 and  $nr_iterations = 1000$ . Producing these results takes about 140 minutes on an Intel i7 processor.

### Value

Object of class "mcstudy", containing the results of the analysis. This object can be passed to plot for plotting, see the documentation for plot.mcstudy.

# Author(s)

Fabian Krueger

### References

Krueger, F., Lerch, S., Thorarinsdottir, T.L. and T. Gneiting (2019): 'Predictive inference based on Markov chain Monte Carlo output', working paper, Heidelberg Institute for Theoretical Studies, available at http://arxiv.org/abs/1608.06802.

### See Also

plot.mcstudy produces a summary plot of the results generated by run\_mcstudy

scores 17

scores

Generic Scoring Rule Calculation

# **Description**

Generic functions for calculating the Continuous Ranked Probability Score and the Logarithmic Score of R objects.

scoringRules provides default methods (crps.numeric, logs.numeric) to calculate scores of forecasts that are members of families of parametric distributions.

# Usage

```
crps(y, ...)
logs(y, ...)
```

# Arguments

y an object for which the score is to be calculated
... further arguments passed to or from other methods

# Details

The mean logarithmic score corresponds to the negative of the log-likelihood logLik.

### Value

Returns a vector of scores. One for each forecast-observation pair.

#### References

General background and further references on scoring rules:

Gneiting, T. and A.E. Raftery (2007): 'Strictly proper scoring rules, prediction and estimation', Journal of the American Statistical Association 102, 359-378.

Gneiting, T. and M. Katzfuss (2014): 'Probabilistic forecasting', Annual Review of Statistics and Its Application 1, 125-151.

# See Also

```
crps.numeric, logs.numeric
```

scores\_2pnorm

scores\_2pexp

Calculating scores for the two-piece-exponential distribution

# **Description**

Calculating scores for the two-piece-exponential distribution

# Usage

```
crps_2pexp(y, scale1, scale2, location = 0)
logs_2pexp(y, scale1, scale2, location = 0)
```

# **Arguments**

y vector of observations.

scale1, scale2 vectors of positive scale parameters. location vector of location parameters.

# Value

A vector of score values.

scores\_2pnorm

Calculating scores for the two-piece-normal distribution

# **Description**

Calculating scores for the two-piece-normal distribution

# Usage

```
crps_2pnorm(y, scale1, scale2, location = 0)
logs_2pnorm(y, scale1, scale2, location = 0)
```

# Arguments

y vector of observations.

scale1, scale2 vectors of positive scale parameters. location vector of location parameters.

### Value

A vector of score values.

scores\_beta 19

scores\_beta

Calculating scores for the beta distribution

# **Description**

Calculating scores for the beta distribution

# Usage

```
crps_beta(y, shape1, shape2, lower = 0, upper = 1)
logs_beta(y, shape1, shape2, lower = 0, upper = 1)
dss_beta(y, shape1, shape2, lower = 0, upper = 1)
```

# **Arguments**

```
y vector of observations.
```

shape1, shape2 vectors of positive shape parameters.

lower, upper vectors of lower and upper limits of the distribution. Must be finite.

### Value

A vector of score values.

scores\_binom

Calculating scores for the binomial distribution

# **Description**

Calculating scores for the binomial distribution

# Usage

```
crps_binom(y, size, prob)
logs_binom(y, size, prob)
```

# **Arguments**

y vector of observations.

size number of trials (zero or more).
prob probability of success on each trial.

# Value

A vector of score values.

20 scores\_gamma

scores\_exp

Calculating scores for the exponential distribution

# **Description**

Calculating scores (CRPS, LogS, DSS) for the exponential distribution, and the exponential distribution with location-scale transformation and point mass in location.

# Usage

```
crps_exp(y, rate = 1)

crps_expM(y, location = 0, scale = 1, mass = 0)

logs_exp(y, rate = 1)

logs_exp2(y, location = 0, scale = 1)

dss_exp(y, rate = 1)
```

# **Arguments**

y vector of observations.

rate vector of rates.

location vector of location parameters.
scale vector of positive scale parameters.
mass vector of point masses in location.

### Value

A vector of score values.

scores\_gamma

Calculating scores for the gamma distribution

# **Description**

Calculating scores for the gamma distribution

# Usage

```
crps_gamma(y, shape, rate = 1, scale = 1/rate)
logs_gamma(y, shape, rate = 1, scale = 1/rate)
dss_gamma(y, shape, rate = 1, scale = 1/rate)
```

scores\_gev 21

# **Arguments**

y vector of observations.

shape vector of positive shape parameters.

rate an alternative way to specify the scale.

scale vector of positive scale parameters.

# Value

A vector of score values.

scores\_gev

Calculating scores for the generalized extreme value distribution

# Description

Calculating scores for the generalized extreme value distribution

# Usage

```
crps_gev(y, shape, location = 0, scale = 1)
logs_gev(y, shape, location = 0, scale = 1)
dss_gev(y, shape, location = 0, scale = 1)
```

# Arguments

y vector of observations.

shape vector of positive shape parameters.

location vector of location parameters.

scale vector of positive scale parameters.

# Value

A vector of score values.

22 scores\_hyper

scores\_gpd

Calculating scores for the generalized Pareto distribution

# Description

Calculating scores for the generalized Pareto distribution

# Usage

```
crps_gpd(y, shape, location = 0, scale = 1, mass = 0)
logs_gpd(y, shape, location = 0, scale = 1)
dss_gpd(y, shape, location = 0, scale = 1)
```

# **Arguments**

y vector of observations.

shape vector of positive shape parameters.

location vector of location parameters.

scale vector of positive scale parameters.

mass vector of point masses in location.

### Value

A vector of score values.

scores\_hyper

Calculating scores for the hypergeometric distribution

# Description

Calculating scores for the hypergeometric distribution

# Usage

```
crps_hyper(y, m, n, k)
logs_hyper(y, m, n, k)
```

scores\_lapl 23

# Arguments

У	vector of observations / numbers of white balls drawn without replacement from an urn which contains both black and white balls.
m	the number of white balls in the urn.
n	the number of black balls in the urn.
k	the number of balls drawn from the urn.

# Value

A vector of score values.

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Calculating scores for the Laplace distribution

# Description

Calculating scores for the Laplace distribution

# Usage

```
crps_lapl(y, location = 0, scale = 1)
logs_lapl(y, location = 0, scale = 1)
dss_lapl(y, location = 0, scale = 1)
```

# Arguments

y vector of observations.

location vector of location parameters.

scale vector of positive scale parameters.

### Value

A vector of score values.

24 scores\_llogis

scores	llanl	
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Calculating scores for the log-Laplace distribution

# Description

Calculating scores for the log-Laplace distribution

# Usage

```
crps_llapl(y, locationlog, scalelog)
logs_llapl(y, locationlog, scalelog)
dss_llapl(y, locationlog, scalelog)
```

# **Arguments**

y vector of observations.

locationlog vector of location parameters on the log scale.
scalelog vector of positive scale parameters on the log scale.

# Value

A vector of score values.

scores\_llogis

Calculating scores for the log-logistic distribution

# Description

Calculating scores for the log-logistic distribution

# Usage

```
crps_llogis(y, locationlog, scalelog)
logs_llogis(y, locationlog, scalelog)
dss_llogis(y, locationlog, scalelog)
```

# Arguments

y vector of observations.

locationlog vector of location parameters on the log scale.
scalelog vector of positive scale parameters on the log scale.

scores\_lnorm 25

### Value

A vector of score values.

scores\_lnorm

Calculating scores for the log-normal distribution

# Description

Calculating scores for the log-normal distribution

# Usage

```
crps_lnorm(y, meanlog = 0, sdlog = 1, locationlog = meanlog,
    scalelog = sdlog)

logs_lnorm(y, meanlog = 0, sdlog = 1, locationlog = meanlog,
    scalelog = sdlog)

dss_lnorm(y, meanlog = 0, sdlog = 1, locationlog = meanlog,
    scalelog = sdlog)
```

# Arguments

y vector of observations.

meanlog an alternative way to specify locationlog.

sdlog an alternative way to specify scalelog.

locationlog vector of location parameters on the log scale.

scalelog vector of positive scale parameters on the log scale.

### Value

A vector of score values.

scores\_logis

Calculating scores for the logistic distribution

# **Description**

These functions calculate scores (CRPS, logarithmic score) and its gradient and Hessian with respect to the parameters of a location-scale transformed logistic distribution. Furthermore, the censoring transformation and the truncation transformation may be introduced on top of the location-scale transformed logistic distribution.

26 scores\_mixnorm

### Usage

```
## score functions
crps_logis(y, location = 0, scale = 1)
crps_clogis(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
crps_tlogis(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
crps_gtclogis(y, location = 0, scale = 1, lower = -Inf, upper = Inf, lmass = 0, umass = 0)
logs_logis(y, location = 0, scale = 1)
logs_tlogis(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
dss_logis(y, location = 0, scale = 1)
## gradient (location, scale) functions
gradcrps_logis(y, location = 0, scale = 1)
gradcrps_clogis(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
gradcrps_tlogis(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
## Hessian (location, scale) functions
hesscrps_logis(y, location = 0, scale = 1)
hesscrps_clogis(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
hesscrps_tlogis(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
```

### **Arguments**

y vector of observations.

location vector of location parameters.

scale vector of scale paramters.

lower, upper lower and upper truncation/censoring bounds.

lmass, umass vectors of point masses in lower and upper respectively.

### Value

For the score functions: a vector of score values.

For the gradient and Hessian functions: a matrix with column names corresponding to the respective partial derivatives.

scores\_mixnorm

Calculating scores for a mixture of normal distributions.

### **Description**

Calculating scores for a mixture of normal distributions.

scores\_mixnorm 27

# Usage

```
crps_mixnorm(y, m, s, w = NULL)
crps_mixnorm_int(y, m, s, w = NULL, rel_tol = 1e-06)
logs_mixnorm(y, m, s, w = NULL)
dss_mixnorm(y, m, s, w = NULL)
```

### **Arguments**

У	vector of observations.
m	matrix of mean parameters; rows represent observations, columns represent mixture components.
S	matrix of scale parameters; same structure as m.
W	optional; matrix of non-negative weights; same structure as m.
rel_tol	relative accuracy for numerical integration.

### **Details**

logs\_mixnorm and crps\_mixnorm calculate scores via analytical formulas. crps\_mixnorm\_int uses numerical integration for the CRPS; this can be faster if there are many mixture components (i.e., if m, s and w have many columns). See examples below.

### Value

A vector of score values.

### **Examples**

```
# Example 1: 100 observations, 15 mixture components
mval \leftarrow matrix(rnorm(100*15), nrow = 100)
sdval \leftarrow matrix(rgamma(100*15, shape = 2), nrow = 100)
weights <- matrix(rep(1/15, 100*15), nrow = 100)
y <- rnorm(100)
crps1 <- crps_mixnorm(y = y, m = mval, s = sdval, w = weights)</pre>
crps2 <- crps_mixnorm_int(y = y, m = mval, s = sdval, w = weights)</pre>
## Not run:
# Example 2: 2 observations, 10000 mixture components
mval <- matrix(rnorm(2*10000), nrow = 2)</pre>
sdval <- matrix(rgamma(2*10000, shape = 2), nrow = 2)</pre>
weights <- matrix(rep(1/10000, 2*10000), nrow = 2)
y <- rnorm(2)
# With many mixture components, numerical integration is much faster
system.time(crps1 <- crps_mixnorm(y = y, m = mval, s = sdval, w = weights))</pre>
system.time(crps2 <- crps_mixnorm_int(y = y, m = mval, s = sdval, w = weights))</pre>
## End(Not run)
```

28 scores\_moments

scores\_moments

Scoring Rules for a Vector of Moments

### **Description**

Calculate scores (DSS, ESS) given observations and moments of the predictive distributions.

# Usage

```
dss_moments(y, mean = 0, var = 1)
ess_moments(y, mean = 0, var = 1, skew = 0)
```

# Arguments

y vector of realized values.
mean vector of mean values.
var vector of variance values.
skew vector of skewness values.

### **Details**

The skewness of a random variable X is the third standardized moment

$$E[(\frac{X - \text{mean}}{\sqrt{\text{var}}})^3].$$

### Value

Value of the score. A lower score indicates a better forecast.

### Author(s)

Alexander Jordan, Sebastian Lerch

### References

Dawid-Sebastiani score:

Dawid, A.P. and P. Sebastiani (1999): 'Coherent dispersion criteria for optimal experimental design' The Annals of Statistics, 27, 65-81.

Error-spread score:

Christensen, H.M., I.M. Moroz, and T.N. Palmer (2015): 'Evaluation of ensemble forecast uncertainty using a new proper score: Application to medium-range and seasonal forecasts', Quarterly Journal of the Royal Meteorological Society, 141, 538-549.

scores\_nbinom 29

scores_nbinom	Calculating scores for the negative binomial distribution	

# **Description**

Calculating scores for the negative binomial distribution

### Usage

```
crps_nbinom(y, size, prob, mu)
logs_nbinom(y, size, prob, mu)
dss_nbinom(y, size, prob, mu)
```

# Arguments

У	vector of observations.
size	target for number of successful trials, or dispersion parameter (the shape param-
	eter of the gamma mixing distribution). Must be strictly positive need not be

eter of the gamma mixing distribution). Must be strictly positive, need not be

integer.

probability of success in each trial. 0 < prob <= 1. prob alternative parametrization via mean: see 'Details'. mu

### **Details**

The mean of the negative binomial distribution is given by mu = size\*(1-prob)/prob.

### Value

A vector of score values.

scores_norm	Calculating scores for the normal distribution	

# Description

These functions calculate scores (CRPS, LogS, DSS) and their gradient and Hessian with respect to the parameters of a location-scale transformed normal distribution. Furthermore, the censoring transformation and the truncation transformation may be introduced on top of the location-scale transformed normal distribution.

30 scores\_pois

### Usage

```
## score functions
crps_norm(y, mean = 0, sd = 1, location = mean, scale = sd)
crps_cnorm(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
crps_tnorm(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
crps_gtcnorm(y, location = 0, scale = 1, lower = -Inf, upper = Inf, lmass = 0, umass = 0)
logs_norm(y, mean = 0, sd = 1, location = mean, scale = sd)
logs_tnorm(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
dss_norm(y, mean = 0, sd = 1, location = mean, scale = sd)
## gradient (location, scale) functions
gradcrps_norm(y, location = 0, scale = 1)
gradcrps_cnorm(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
gradcrps_tnorm(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
## Hessian (location, scale) functions
hesscrps_norm(y, location = 0, scale = 1)
hesscrps_cnorm(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
hesscrps_tnorm(y, location = 0, scale = 1, lower = -Inf, upper = Inf)
```

# Arguments

У	vector of observations.

mean an alternative way to specify location.
sd an alternative way to specify scale.

location vector of location parameters.
scale vector of scale parameters.

lower, upper lower and upper truncation/censoring bounds.

lmass, umass vectors of point masses in lower and upper respectively.

### Value

For the score functions: a vector of score values.

For the gradient and Hessian functions: a matrix with column names corresponding to the respective partial derivatives.

scores\_pois Calculating scores for the Poisson distribution

### Description

Calculating scores for the Poisson distribution

scores\_sample\_multiv 31

### Usage

```
crps_pois(y, lambda)
logs_pois(y, lambda)
dss_pois(y, lambda)
```

### Arguments

y vector of observations.

lambda vector of (non-negative) means.

### Value

A vector of score values.

# **Description**

Compute multivariate scores of the form S(y, dat), where S is a proper scoring rule, y is a d-dimensional realization vector and dat is a simulated sample of multivariate forecasts. Available are the energy score and the variogram score of order p.

### Usage

```
es_sample(y, dat)
vs_sample(y, dat, w = NULL, p = 0.5)
```

# Arguments

y rea	lized va	lues (numeri	c vector of	length d).
-------	----------	--------------	-------------	------------

dat numeric matrix of data (columns are simulation draws from multivariate forecast

distribution).

w numeric matrix of weights for dat used in the variogram score. If no weights

are specified, constant weights with w=1 are used.

p order of variogram score. Standard choices include p = 1 and p = 0.5.

### **Details**

In the input matrix dat each column is expected to represent a sample from the multivariate forecast distribution, the number of rows of dat thus has to match the length of the observation vector y, and the number of columns of dat is the number of simulated samples.

In vs\_sample it is possible to specify a matrix w of non-negative weights that allow to emphasize or downweight pairs of component combinations based on subjective expert decisions. w is a square matrix with dimensions equal to the length of the input vector y, and the entry in the i-th row and j-th column of w corresponds to the weight assigned to the combination of the corresponding i-th and j-th component. For details and examples, see Scheuerer and Hamill (2015).

### Value

Value of the score. A lower score indicates a better forecast.

### Author(s)

Maximiliane Graeter, Sebastian Lerch, Fabian Krueger

### References

Energy score

Gneiting, T., Stanberry, L.I., Grimit, E.P., Held, L. and N.A. Johnson (2008): 'Assessing probabilistic forecasts of multivariate quantities, with an application to ensemble predictions of surface winds', TEST, 17, 211-235.

Variogram-based proper scoring rules

Scheuerer, M. and T.M. Hamill (2015): 'Variogram-based proper scoring rules for probabilistic forecasts of multivariate quantities', Monthly Weather Review, 143, 1321-1334.

### **Examples**

```
d <- 10  # number of dimensions
m <- 50  # number of samples from multivariate forecast distribution
mu0 <- rep(0, d)
mu <- rep(1, d)
S0 <- S <- diag(d)
S[S==0] <- 0.1
S0[S0==0] <- 0.2

# generate samples from multivariate normal distributions
obs <- drop(mu0 + rnorm(d) \%*\% chol(S0))
fc_sample <- replicate(m, drop(mu + rnorm(d) \%*\% chol(S)))
es_sample(y = obs, dat = fc_sample)

# weighting matrix for variogram score
w_vs <- matrix(NA, nrow = d, ncol = d)
for(d1 in 1:d){for(d2 in 1:d){w_vs[d1,d2] <- 0.5^abs(d1-d2)}}</pre>
```

scores\_sample\_univ 33

```
vs_sample(y = obs, dat = fc_sample)
vs_sample(y = obs, dat = fc_sample, w = w_vs)
vs_sample(y = obs, dat = fc_sample, w = w_vs, p = 1)
```

scores\_sample\_univ

Scoring Rules for Simulated Forecast Distributions

### **Description**

Calculate scores (CRPS, LogS, DSS) given observations and draws from the predictive distributions.

### Usage

```
crps_sample(y, dat, method = "edf", w = NULL, bw = NULL,
   num_int = FALSE, show_messages = TRUE)

logs_sample(y, dat, bw = NULL, show_messages = FALSE)

dss_sample(y, dat, w = NULL)
```

### **Arguments**

y vector of realized values.

dat vector or matrix (depending on y; see details) of simulation draws from forecast

distribution.

method string; approximation method. Options: "edf" (empirical distribution function)

and "kde" (kernel density estimation).

w optional; vector or matrix (matching dat) of weights for method "edf".

bw optional; vector (matching y) of bandwidths for kernel density estimation; see

details.

num\_int logical; if TRUE numerical integration is used for method "kde". show\_messages logical; display of messages (does not affect warnings and errors).

### **Details**

For a vector y of length n, dat should be given as a matrix with n rows. If y has length 1, then dat may be a vector.

crps\_sample employs an empirical version of the quantile decomposition of the CRPS (Laio and Tamea, 2007) when using method = "edf". For method = "kde", it uses kernel density estimation using a Gaussian kernel. The logarithmic score always uses kernel density estimation.

The bandwidth (bw) for kernel density estimation can be specified manually, in which case it must be a positive number. If bw == NULL, the bandwidth is selected using the core function bw.nrd. Numerical integration may speed up computation for crps\_sample in case of large samples dat.

34 scores\_sample\_univ

### Value

Value of the score. A lower score indicates a better forecast.

### Author(s)

Alexander Jordan, Fabian Krueger, Sebastian Lerch

### References

Evaluating simulation based forecast distributions:

Krueger, F., Lerch, S., Thorarinsdottir, T.L. and T. Gneiting (2019): 'Predictive inference based on Markov Chain Monte Carlo output', working paper, Heidelberg Institute for Theoretical Studies, available at http://arxiv.org/abs/1608.06802.

Empirical quantile decomposition of the CRPS:

Laio, F. and S. Tamea (2007): 'Verification tools for probabilistic forecasts of continuous hydrological variables', Hydrology and Earth System Sciences, 11, 1267-1277.

# **Examples**

```
## Not run:
# y has length greater than 1
v <- 1:2
sample <- matrix(rnorm(20), nrow = 2)</pre>
crps_sample(y = y, dat = sample)
logs_sample(y = y, dat = sample)
y < -1:2
sample <- rnorm(10)</pre>
crps_sample(y = y, dat = sample) # error
# y has length 1
y <- 1
sample <- rnorm(10)</pre>
crps_sample(y = y, dat = sample)
sample <- matrix(rnorm(10), nrow = 1)</pre>
crps_sample(y = y, dat = sample)
sample <- matrix(rnorm(20), nrow = 2)</pre>
crps_sample(y = y, dat = sample) # error
## End(Not run)
```

scores\_t 35

scores\_t

Calculating scores for Student's t-distribution

### **Description**

These functions calculate scores (CRPS, logarithmic score) and their gradient and Hessian with respect to the parameters of a location-scale transformed Student's *t*-distribution. Furthermore, the censoring transformation and the truncation transformation may be introduced on top of the location-scale transformed normal distribution.

### Usage

```
## score functions
crps_t(y, df, location = 0, scale = 1)
crps_ct(y, df, location = 0, scale = 1, lower = -Inf, upper = Inf)
crps_tt(y, df, location = 0, scale = 1, lower = -Inf, upper = Inf)
crps_gtct(y, df, location = 0, scale = 1, lower = -Inf, upper = Inf, lmass = 0, umass = 0)
logs_t(y, df, location = 0, scale = 1)
logs_tt(y, df, location = 0, scale = 1, lower = -Inf, upper = Inf)
dss_t(y, df, location = 0, scale = 1)
## gradient (location, scale) functions
gradcrps_t(y, df, location = 0, scale = 1)
gradcrps_ct(y, df, location = 0, scale = 1, lower = -Inf, upper = Inf)
gradcrps_tt(y, df, location = 0, scale = 1, lower = -Inf, upper = Inf)
## Hessian (location, scale) functions
hesscrps_t(y, df, location = 0, scale = 1)
hesscrps_ct(y, df, location = 0, scale = 1, lower = -Inf, upper = Inf)
hesscrps_tt(y, df, location = 0, scale = 1, lower = -Inf, upper = Inf)
```

### **Arguments**

y vector of observations.

df vector of degrees of freedom.

location vector of location parameters.

scale vector of scale parameters.

lower, upper lower and upper truncation/censoring bounds.

lmass, umass vectors of point masses in lower and upper respectively.

#### Value

For the CRPS functions: a vector of score values.

For the gradient and Hessian functions: a matrix with column names corresponding to the respective partial derivatives.

36 summary.casestudy

scores\_unif

Calculating scores for the uniform distribution

# Description

Calculating scores for the uniform distribution

# Usage

```
crps_unif(y, min = 0, max = 1, lmass = 0, umass = 0)
logs_unif(y, min = 0, max = 1)
dss_unif(y, min = 0, max = 1)
```

# **Arguments**

y vector of observations.

min, max lower and upper limits of the distribution. Must be finite.

lmass, umass vectors of point masses in min and max respectively.

# Value

A vector of score values.

summary.casestudy

Summary method for class casestudy

# **Description**

Summary method for class casestudy

# Usage

```
## S3 method for class 'casestudy'
summary(object, ...)
```

# Arguments

object Object of class casestudy, generated via run\_casestudy

... Additional specifications (presently not in use)

summary.mcstudy 37

summary.mcstudy	Simple summary method for class mcstudy
Janimar y incocaay	Simple summerly member for etass mestilay

### **Description**

Simple summary method for class mestudy

# Usage

```
## S3 method for class 'mcstudy'
summary(object, ...)
```

# **Arguments**

object Object of class mcstudy, generated via run\_mcstudy
... Additional specifications (presently not in use)

```
{\bf Supplementary\ distributions:\ Positive\ real\ line}
```

Supplementary distributions (not in base R) supported on the positive real line.

# Description

We include the probability density functions of some distributions which are part of scoringRules, but are not part of base R. The parametrizations used here are identical to the ones used when calling crps and logs.

Here we document distributions on the positive real line: fllapl - log-Laplace distribution; fllogis - log-logistic distribution.

### Usage

```
fllapl(x, locationlog, scalelog)
fllogis(x, locationlog, scalelog)
```

### Arguments

x vector of quantiles

locationlog vector of location parameters on the log scale scalelog vector of scale parameters on the log scale

### **Details**

To be added.

### Value

Probability density function of the relevant distribution, evaluated at x.

### Author(s)

Alexander Jordan

### See Also

The documentation for crps.numeric contains the full list of distributions supported by scoringRules (includes the ones documented here, as well as many others).

```
Supplementary distributions: Real line
```

Supplementary distributions (not in base R) supported on the real line.

# **Description**

We include the probability density functions of some distributions which are part of scoringRules, but are not part of base R. The parametrizations used here are identical to the ones used when calling crps and logs.

Here we document distributions with support on the real line: flapl - Laplace distribution; f2pexp - two-piece exponential distribution; fmixnorm - mixture of normal distributions; f2pnorm - two-piece normal distribution.

# Usage

```
flapl(x, location, scale)
f2pexp(x, location, scale1, scale2)
f2pnorm(x, location, scale1, scale2)
fmixnorm(x, m, s, w)
```

### **Arguments**

```
x vector of quantiles
```

location vector of location parameters

scale, scale1, scale2

vector of scale parameters

m matrix of means (rows correspond to observations, columns correspond to mix-

ture components)

s matrix of standard deviations (same structure as m)

w matrix of weights (same structure as m)

### **Details**

The Laplace distribution (flap1) is described on https://en.wikipedia.org/wiki/Laplace\_distribution. It is a special case of the two-piece exponential distribution (f2pexp), which allows for different scale parameters to the left and right of location.

The density function of a mixture of normal distributions (fmixnorm) is given by the weighted sum over the mixture components,

$$f(x) = \sum w_i / s_i \phi((x - m_i) / s_i),$$

where  $\phi$  is the pdf of the standard normal distribution.

For details on the two-piece normal distribution (f2pnorm), see Box A of Wallis (2004, "An Assessment of Bank of England and National Institute Inflation Forecast Uncertainties", National Institute Economic Review).

### Value

Probability density function of the relevant distribution, evaluated at x.

### Author(s)

Alexander Jordan

#### See Also

The documentation for crps.numeric contains the full list of distributions supported by scoringRules (includes the ones documented here, as well as many others).

```
fnorm, flogis, ft
```

### **Examples**

Supplementary distributions: Variable support

Supplementary distributions (not in base R) with variable support.

# **Description**

We include the probability density functions of some distributions which are part of scoringRules, but are not part of base R. The parametrizations used here are identical to the ones used when calling crps and logs.

Here we document distributions with variable support: fexp - location-scale exponential distribution with a point mass on the lower boundary; fgdp - generalized Pareto distribution with a point mass on the lower boundary; fgev - generalized extreme value distribution; fnorm, flogis, ft - (normal/logistic/Student's t)-distribution with flexible domain and point masses on the boundaries.

### Usage

```
fexp(x, location, scale, mass = 0, log = FALSE)
fgpd(x, location, scale, shape, mass = 0, log = FALSE)

fgev(x, location, scale, shape)

fnorm(x, location, scale, lower = -Inf, upper = Inf, lmass = 0, umass = 0, log = FALSE)
ft(x, df, location, scale, lower = -Inf, upper = Inf, lmass = 0, umass = 0, log = FALSE)
flogis(x, location, scale, lower = -Inf, upper = Inf, lmass = 0, umass = 0, log = FALSE)
```

### Arguments

X	vector of quantiles
df	vector of degrees of freedom parameters
location	vector of location parameters
scale	vector of scale parameters (positive)
shape	vector of shape parameters
mass	vector of point masses in location
lower	vector of lower bounds
upper	vector of upper bounds

lmass vector of point masses in lower, or strings "trunc" / "cens" umass vector of point masses in upper, or strings "trunc" / "cens"

logical; if TRUE, the log of the density is returned

### **Details**

For details on generalized extreme value and generalized Pareto distributions, see Friederichs, F. and T.L. Thorarinsdottir (2012, "Forecast verification for extreme value distributions with an application to probabilistic peak wind prediction", Environmetrics 23, 579-594). Note that the support of both distributions depends on the input parameters; see https://en.wikipedia.org/wiki/Generalized\_extreme\_value\_distribution and https://en.wikipedia.org/wiki/Generalized\_Pareto\_distribution.

Sometimes truncated or censored versions of the normal distribution are used to model variables with a restricted domain (e.g. precipitation). We allow the flexible specification of lower and upper boundaries and point masses in those boundaries. The truncated normal distribution assumes no point masses (i.e. redistributes the cut-off) and can be specified using the string "trunc" instead of a numerical probability. In contrast, the censored distribution introduces a point mass at the bound in the amount of the cut-off. Here, the string "cens" may be used for lmass or umass. The most common use in practice lies in the context of non-negative quantities. For example, a truncated standard normal distribution (left truncation at zero) has pdf  $f(x) = \phi(x)/(1 - \Phi(0))$ , for  $x \ge 0$  and 0 otherwise. A censored standard normal distribution (left censoring at zero) has point mass  $\Phi(0)$  at zero, and density  $\phi(x)$  for x > 0.

The location-scale family based on Student's t-distribution (ft) has mean location for df>1 and variance  $df/(df-2)*scale^2$  for df>2. Note that the crps exists only for df>1. For details, see https://en.wikipedia.org/wiki/Student's\_t-distribution#Non-standardized\_Student. 27s\_t-distribution.

# Value

Density function of the relevant distribution, evaluated at x. NOTE: For distributions involving a point mass (e.g., when lmass = "cens" in fnorm), the density functions do not integrate to one.

# Author(s)

Alexander Jordan

# See Also

The documentation for crps.numeric contains the full list of distributions supported by scoringRules (includes the ones documented here, as well as many others).

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