Package ‘scoringutils’

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Title Utilities for Scoring and Assessing Predictions

Version 2.0.0

Language en-GB

Description Facilitate the evaluation of forecasts in a convenient framework based on data.table. It allows user to to check their forecasts and diagnose issues, to visualise forecasts and missing data, to transform data before scoring, to handle missing forecasts, to aggregate scores, and to visualise the results of the evaluation. The package mostly focuses on the evaluation of probabilistic forecasts and allows evaluating several different forecast types and input formats. Find more information about the package in the Vignettes as well as in the accompanying paper, <doi:10.48550/arXiv.2205.07090>.

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Contents

`add_relative_skill` *Add relative skill scores based on pairwise comparisons*

Description

Adds a columns with relative skills computed by running pairwise comparisons on the scores. For more information on the computation of relative skill, see `get_pairwise_comparisons()`. Relative skill will be calculated for the aggregation level specified in `by`.

Usage

```
add_relative_skill(
  scores,
  compare = "model",
  by = NULL,
  metric = intersect(c("wis", "crps", "brier_score"), names(scores)),
  baseline = NULL
)
```

Arguments

`scores` An object of class `scores` (a data.table with scores and an additional attribute `metrics` as produced by `score()`).

`compare` Character vector with a single colum name that defines the elements for the pairwise comparison. For example, if this is set to "model" (the default), then elements of the "model" column will be compared.

`by` Character vector with column names that define further grouping levels for the pairwise comparisons. By default this is `NULL` and there will be one relative skill score per distinct entry of the column selected in `compare`. If further columns are given here, for example, `by = "location"` with `compare = "model"`, then one separate relative skill score is calculated for every model in every location.

`metric` A string with the name of the metric for which a relative skill shall be computed. By default this is either "crps", "wis" or "brier_score" if any of these are available.

`baseline` A string with the name of a model. If a baseline is given, then a scaled relative skill with respect to the baseline will be returned. By default (`NULL`), relative skill will not be scaled with respect to a baseline model.

`ae_median_quantile` *Absolute error of the median (quantile-based version)*

Description

Compute the absolute error of the median calculated as

$$|\text{observed} - \text{median prediction}|$$

The median prediction is the predicted value for which quantile_level == 0.5. The function requires 0.5 to be among the quantile levels in `quantile_level`.

Usage

```
ae_median_quantile(observed, predicted, quantile_level)
```

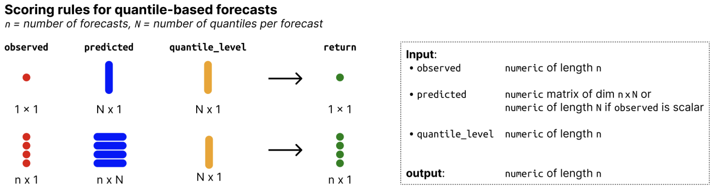
Arguments

`observed`	Numeric vector of size n with the observed values.
`predicted`	Numeric nxN matrix of predictive quantiles, n (number of rows) being the number of forecasts (corresponding to the number of observed values) and N (number of columns) the number of quantiles per forecast. If `observed` is just a single number, then predicted can just be a vector of size N.
`quantile_level`	Vector of of size N with the quantile levels for which predictions were made.

Value

Numeric vector of length N with the absolute error of the median.

Input format


Scoring rules for quantile-based forecasts
n = number of forecasts, N = number of quantiles per forecast
observed
predicted
quantile_level
return
1 × 1
N x 1
N x 1
1 × 1
n x 1
n x N
N x 1
n x 1

Input:
- `observed` — `numeric` of length `n`
- `predicted` — `numeric` matrix of dim `n x N` or `numeric` of length `N` if `observed` is scalar
- `quantile_level` — `numeric` of length `n`

output: `numeric` of length `n`

See Also

`ae_median_sample()`

Examples

```
observed <- rnorm(30, mean = 1:30)
predicted_values <- replicate(3, rnorm(30, mean = 1:30))
ae_median_quantile(
  observed, predicted_values, quantile_level = c(0.2, 0.5, 0.8)
)
```

`ae_median_sample` *Absolute error of the median (sample-based version)*

Description

Absolute error of the median calculated as

$$|\text{observed} - \text{median prediction}|$$

where the median prediction is calculated as the median of the predictive samples.

Usage

```
ae_median_sample(observed, predicted)
```

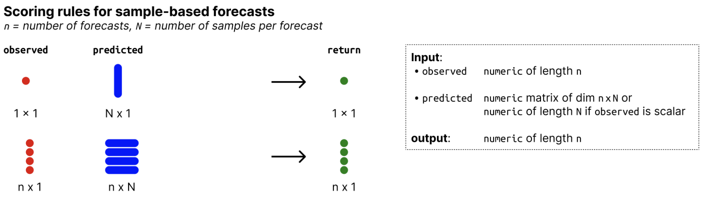
Arguments

`observed`	A vector with observed values of size n
`predicted`	nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of Monte Carlo samples. Alternatively, `predicted` can just be a vector of size n.

Value

Numeric vector of length n with the absolute errors of the median.

Input format



Scoring rules for sample-based forecasts

n = number of forecasts, N = number of samples per forecast

Input:
- `observed` `numeric` of length `n`
- `predicted` `numeric` matrix of dim `n x N` or `numeric` of length `N` if `observed` is scalar

output: `numeric` of length `n`

See Also

`ae_median_quantile()`

Examples

```
observed <- rnorm(30, mean = 1:30)
predicted_values <- matrix(rnorm(30, mean = 1:30))
ae_median_sample(observed, predicted_values)
```

---

assert_dims_ok_point *Assert Inputs Have Matching Dimensions*

Description

Function assesses whether input dimensions match. In the following, n is the number of observations / forecasts. Scalar values may be repeated to match the length of the other input. Allowed options are therefore:

- `observed` is vector of length 1 or length n
- `predicted` is:
  - a vector of of length 1 or length n
  - a matrix with n rows and 1 column

Usage

```
assert_dims_ok_point(observed, predicted)
```

Arguments

`observed` Input to be checked. Should be a factor of length n with exactly two levels, holding the observed values. The highest factor level is assumed to be the reference level. This means that `predicted` represents the probability that the observed value is equal to the highest factor level.

`predicted` Input to be checked. `predicted` should be a vector of length n, holding probabilities. Alternatively, `predicted` can be a matrix of size n x 1. Values represent the probability that the corresponding value in `observed` will be equal to the highest available factor level.

Value

Returns NULL invisibly if the assertion was successful and throws an error otherwise.

assert_forecast.forecast_binary

Assert that input is a forecast object and passes validations

Description

Assert that an object is a forecast object (i.e. a `data.table` with a class `forecast` and an additional class `forecast_<type>` corresponding to the forecast type).

See the corresponding `assert_forecast_<type>` functions for more details on the required input formats.

Usage

```
## S3 method for class 'forecast_binary'
assert_forecast(forecast, forecast_type = NULL, verbose = TRUE, ...)

## S3 method for class 'forecast_point'
assert_forecast(forecast, forecast_type = NULL, verbose = TRUE, ...)

## S3 method for class 'forecast_quantile'
assert_forecast(forecast, forecast_type = NULL, verbose = TRUE, ...)

## S3 method for class 'forecast_sample'
assert_forecast(forecast, forecast_type = NULL, verbose = TRUE, ...)

assert_forecast(forecast, forecast_type = NULL, verbose = TRUE, ...)

## Default S3 method:
assert_forecast(forecast, forecast_type = NULL, verbose = TRUE, ...)
```

Arguments

`forecast`	A forecast object (a validated data.table with predicted and observed values).
`forecast_type`	(optional) The forecast type you expect the forecasts to have. If the forecast type as determined by `scoringutils` based on the input does not match this, an error will be thrown. If `NULL` (the default), the forecast type will be inferred from the data.
`verbose`	Logical. If `FALSE` (default is `TRUE`), no messages and warnings will be created.
`...`	Currently unused. You *cannot* pass additional arguments to scoring functions via `...`. See the *Customising metrics* section below for details on how to use `purrr::partial()` to pass arguments to individual metrics.

Value

Returns `NULL` invisibly.

Examples

```
forecast <- as_forecast_binary(example_binary)
assert_forecast(forecast)
```

---

assert_forecast_generic *Validation common to all forecast types*

Description

The function runs input checks that apply to all input data, regardless of forecast type. The function

- asserts that the forecast is a data.table which has columns `observed` and `predicted`
- checks the forecast type and forecast unit
- checks there are no duplicate forecasts
- if appropriate, checks the number of samples / quantiles is the same for all forecasts.

Usage

```
assert_forecast_generic(data, verbose = TRUE)
```

Arguments

`data`	A data.table with forecasts and observed values that should be validated.
`verbose`	Logical. If `FALSE` (default is `TRUE`), no messages and warnings will be created.

Value

returns the input

---

assert_forecast_type *Assert that forecast type is as expected*

Description

Assert that forecast type is as expected

Usage

```
assert_forecast_type(data, actual = get_forecast_type(data), desired = NULL)
```

Arguments

`data`	A forecast object.
`actual`	The actual forecast type of the data
`desired`	The desired forecast type of the data

Value

Returns NULL invisibly if the assertion was successful and throws an error otherwise.

assert_input_binary *Assert that inputs are correct for binary forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring binary forecasts.

Usage

```
assert_input_binary(observed, predicted)
```

Arguments

`observed`	Input to be checked. Should be a factor of length n with exactly two levels, holding the observed values. The highest factor level is assumed to be the reference level. This means that `predicted` represents the probability that the observed value is equal to the highest factor level.
`predicted`	Input to be checked. `predicted` should be a vector of length n, holding probabilities. Alternatively, `predicted` can be a matrix of size n x 1. Values represent the probability that the corresponding value in `observed` will be equal to the highest available factor level.

Value

Returns NULL invisibly if the assertion was successful and throws an error otherwise.

assert_input_interval *Assert that inputs are correct for interval-based forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring interval-based forecasts.

Usage

```
assert_input_interval(observed, lower, upper, interval_range)
```

Arguments

`observed` Input to be checked. Should be a numeric vector with the observed values of size n.

`lower` Input to be checked. Should be a numeric vector of size n that holds the predicted value for the lower bounds of the prediction intervals.

`upper` Input to be checked. Should be a numeric vector of size n that holds the predicted value for the upper bounds of the prediction intervals.

`interval_range` Input to be checked. Should be a vector of size n that denotes the interval range in percent. E.g. a value of 50 denotes a (25%, 75%) prediction interval.

Value

Returns NULL invisibly if the assertion was successful and throws an error otherwise.

`assert_input_nominal` *Assert that inputs are correct for nominal forecasts*

Description

Function assesses whether the inputs correspond to the requirements for scoring nominal forecasts.

Usage

```
assert_input_nominal(observed, predicted, predicted_label)
```

Arguments

`observed` Input to be checked. Should be a factor of length n with N levels holding the observed values. n is the number of observations and N is the number of possible outcomes the observed values can assume. output)

`predicted` Input to be checked. `predicted` should be a vector of length n, holding probabilities. Alternatively, `predicted` can be a matrix of size n x 1. Values represent the probability that the corresponding value in `observed` will be equal to the highest available factor level.

`predicted_label`
Factor of length N with N levels, where N is the number of possible outcomes the observed values can assume.

Value

Returns NULL invisibly if the assertion was successful and throws an error otherwise.

assert_input_point *Assert that inputs are correct for point forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring point forecasts.

Usage

```
assert_input_point(observed, predicted)
```

Arguments

observed	Input to be checked. Should be a numeric vector with the observed values of size n.
predicted	Input to be checked. Should be a numeric vector with the predicted values of size n.

Value

Returns NULL invisibly if the assertion was successful and throws an error otherwise.

assert_input_quantile *Assert that inputs are correct for quantile-based forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring quantile-based forecasts.

Usage

```
assert_input_quantile(
  observed,
  predicted,
  quantile_level,
  unique_quantile_levels = TRUE
)
```

Arguments

`observed`	Input to be checked. Should be a numeric vector with the observed values of size n.
`predicted`	Input to be checked. Should be nxN matrix of predictive quantiles, n (number of rows) being the number of data points and N (number of columns) the number of quantiles per forecast. If `observed` is just a single number, then predicted can just be a vector of size N.
`quantile_level`	Input to be checked. Should be a vector of size N that denotes the quantile levels corresponding to the columns of the prediction matrix.
`unique_quantile_levels`	Whether the quantile levels are required to be unique (`TRUE`, the default) or not (`FALSE`).

Value

Returns NULL invisibly if the assertion was successful and throws an error otherwise.

`assert_input_sample` *Assert that inputs are correct for sample-based forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring sample-based forecasts.

Usage

```
assert_input_sample(observed, predicted)
```

Arguments

`observed`	Input to be checked. Should be a numeric vector with the observed values of size n.
`predicted`	Input to be checked. Should be a numeric nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of samples per forecast. If `observed` is just a single number, then predicted values can just be a vector of size N.

Value

Returns NULL invisibly if the assertion was successful and throws an error otherwise.

as_forecast_binary *Create a* forecast *object for binary forecasts*

Description

Process and validate a data.frame (or similar) or similar with forecasts and observations. If the input passes all input checks, those functions will be converted to a `forecast` object. A forecast object is a `data.table` with a class `forecast` and an additional class that depends on the forecast type.

The arguments `observed`, `predicted`, etc. make it possible to rename existing columns of the input data to match the required columns for a forecast object. Using the argument `forecast_unit`, you can specify the columns that uniquely identify a single forecast (and thereby removing other, unneeded columns. See section "Forecast Unit" below for details).

Usage

```
as_forecast_binary(
  data,
  forecast_unit = NULL,
  observed = NULL,
  predicted = NULL
)
```

Arguments

`data` A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.

`forecast_unit` (optional) Name of the columns in `data` (after any renaming of columns) that denote the unit of a single forecast. See `get_forecast_unit()` for details. If `NULL` (the default), all columns that are not required columns are assumed to form the unit of a single forecast. If specified, all columns that are not part of the forecast unit (or required columns) will be removed.

`observed` (optional) Name of the column in `data` that contains the observed values. This column will be renamed to "observed".

`predicted` (optional) Name of the column in `data` that contains the predicted values. This column will be renamed to "predicted".

Value

A `forecast` object of class `forecast_binary`

Required input

The input needs to be a data.frame or similar with the following columns:

- observed: factor with exactly two levels representing the observed values. The highest factor level is assumed to be the reference level. This means that corresponding value in predicted represent the probability that the observed value is equal to the highest factor level.
- predicted: numeric with predicted probabilities, representing the probability that the corresponding value in observed is equal to the highest available factor level.

For convenience, we recommend an additional column model holding the name of the forecaster or model that produced a prediction, but this is not strictly necessary.

See the example_binary data set for an example.

Forecast unit

In order to score forecasts, scoringutils needs to know which of the rows of the data belong together and jointly form a single forecasts. This is easy e.g. for point forecast, where there is one row per forecast. For quantile or sample-based forecasts, however, there are multiple rows that belong to a single forecast.

The *forecast unit* or *unit of a single forecast* is then described by the combination of columns that uniquely identify a single forecast. For example, we could have forecasts made by different models in various locations at different time points, each for several weeks into the future. The forecast unit could then be described as forecast_unit = c("model", "location", "forecast_date", "forecast_horizon"). scoringutils automatically tries to determine the unit of a single forecast. It uses all existing columns for this, which means that no columns must be present that are unrelated to the forecast unit. As a very simplistic example, if you had an additional row, "even", that is one if the row number is even and zero otherwise, then this would mess up scoring as scoringutils then thinks that this column was relevant in defining the forecast unit.

In order to avoid issues, we recommend setting the forecast unit explicitly, using the forecast_unit argument. This will simply drop unneeded columns, while making sure that all necessary, 'protected columns' like "predicted" or "observed" are retained.

See Also

Other functions to create forecast objects: as_forecast_nominal(), as_forecast_point(), as_forecast_quantile(), as_forecast_sample()

Examples

```
as_forecast_binary(
  example_binary,
  predicted = "predicted",
  forecast_unit = c("model", "target_type", "target_end_date",
                    "horizon", "location")
)
```

as_forecast_doc_template *General information on creating a `forecast` object*

Description

Process and validate a data.frame (or similar) or similar with forecasts and observations. If the input passes all input checks, those functions will be converted to a `forecast` object. A forecast object is a `data.table` with a class `forecast` and an additional class that depends on the forecast type.

The arguments `observed`, `predicted`, etc. make it possible to rename existing columns of the input data to match the required columns for a forecast object. Using the argument `forecast_unit`, you can specify the columns that uniquely identify a single forecast (and thereby removing other, unneeded columns. See section "Forecast Unit" below for details).

Arguments

`data` A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.

`forecast_unit` (optional) Name of the columns in `data` (after any renaming of columns) that denote the unit of a single forecast. See `get_forecast_unit()` for details. If `NULL` (the default), all columns that are not required columns are assumed to form the unit of a single forecast. If specified, all columns that are not part of the forecast unit (or required columns) will be removed.

`observed` (optional) Name of the column in `data` that contains the observed values. This column will be renamed to "observed".

`predicted` (optional) Name of the column in `data` that contains the predicted values. This column will be renamed to "predicted".

Forecast unit

In order to score forecasts, `scoringutils` needs to know which of the rows of the data belong together and jointly form a single forecasts. This is easy e.g. for point forecast, where there is one row per forecast. For quantile or sample-based forecasts, however, there are multiple rows that belong to a single forecast.

The *forecast unit* or *unit of a single forecast* is then described by the combination of columns that uniquely identify a single forecast. For example, we could have forecasts made by different models in various locations at different time points, each for several weeks into the future. The forecast unit could then be described as `forecast_unit = c("model", "location", "forecast_date", "forecast_horizon")`. `scoringutils` automatically tries to determine the unit of a single forecast. It uses all existing columns for this, which means that no columns must be present that are unrelated to the forecast unit. As a very simplistic example, if you had an additional row, "even", that is one if the row number is even and zero otherwise, then this would mess up scoring as `scoringutils` then thinks that this column was relevant in defining the forecast unit.

In order to avoid issues, we recommend setting the forecast unit explicitly, using the `forecast_unit` argument. This will simply drop unneeded columns, while making sure that all necessary, 'protected columns' like "predicted" or "observed" are retained.

as_forecast_generic *Common functionality for* as_forecast_<type> *functions*

Description

Common functionality for as_forecast_<type> functions

Usage

```
as_forecast_generic(
  data,
  forecast_unit = NULL,
  observed = NULL,
  predicted = NULL
)
```

Arguments

data	A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.
forecast_unit	(optional) Name of the columns in data (after any renaming of columns) that denote the unit of a single forecast. See get_forecast_unit() for details. If NULL (the default), all columns that are not required columns are assumed to form the unit of a single forecast. If specified, all columns that are not part of the forecast unit (or required columns) will be removed.
observed	(optional) Name of the column in data that contains the observed values. This column will be renamed to "observed".
predicted	(optional) Name of the column in data that contains the predicted values. This column will be renamed to "predicted".

Details

This function splits out part of the functionality of as_forecast_<type> that is the same for all as_forecast_<type> functions. It renames the required columns, where appropriate, and sets the forecast unit.

as_forecast_nominal *Create a* forecast *object for nominal forecasts*

Description

Process and validate a data.frame (or similar) or similar with forecasts and observations. If the input passes all input checks, those functions will be converted to a `forecast` object. A forecast object is a `data.table` with a class `forecast` and an additional class that depends on the forecast type.

The arguments `observed`, `predicted`, etc. make it possible to rename existing columns of the input data to match the required columns for a forecast object. Using the argument `forecast_unit`, you can specify the columns that uniquely identify a single forecast (and thereby removing other, unneeded columns. See section "Forecast Unit" below for details).

Usage

```
as_forecast_nominal(
  data,
  forecast_unit = NULL,
  observed = NULL,
  predicted = NULL,
  predicted_label = NULL
)
```

Arguments

`data`	A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.
`forecast_unit`	(optional) Name of the columns in `data` (after any renaming of columns) that denote the unit of a single forecast. See `get_forecast_unit()` for details. If `NULL` (the default), all columns that are not required columns are assumed to form the unit of a single forecast. If specified, all columns that are not part of the forecast unit (or required columns) will be removed.
`observed`	(optional) Name of the column in `data` that contains the observed values. This column will be renamed to "observed".
`predicted`	(optional) Name of the column in `data` that contains the predicted values. This column will be renamed to "predicted".
`predicted_label`	(optional) Name of the column in `data` that denotes the outcome to which a predicted probability corresponds to. This column will be renamed to "predicted_label".

Details

Nominal forecasts are a form of categorical forecasts and represent a generalisation of binary forecasts to multiple outcomes. The possible outcomes that the observed values can assume are not ordered.

Value

A `forecast` object of class `forecast_nominal`

Required input

The input needs to be a data.frame or similar with the following columns:

- `observed`: Column with observed values of type `factor` with N levels, where N is the number of possible outcomes. The levels of the factor represent the possible outcomes that the observed values can assume.
- `predicted`: `numeric` column with predicted probabilities. The values represent the probability that the observed value is equal to the factor level denoted in `predicted_label`. Note that forecasts must be complete, i.e. there must be a probability assigned to every possible outcome and those probabilities must sum to one.
- `predicted_label`: `factor` with N levels, denoting the outcome that the probabilities in `predicted` correspond to.

For convenience, we recommend an additional column `model` holding the name of the forecaster or model that produced a prediction, but this is not strictly necessary.

See the example_nominal data set for an example.

Forecast unit

In order to score forecasts, `scoringutils` needs to know which of the rows of the data belong together and jointly form a single forecasts. This is easy e.g. for point forecast, where there is one row per forecast. For quantile or sample-based forecasts, however, there are multiple rows that belong to a single forecast.

The *forecast unit* or *unit of a single forecast* is then described by the combination of columns that uniquely identify a single forecast. For example, we could have forecasts made by different models in various locations at different time points, each for several weeks into the future. The forecast unit could then be described as `forecast_unit = c("model", "location", "forecast_date", "forecast_horizon")`. `scoringutils` automatically tries to determine the unit of a single forecast. It uses all existing columns for this, which means that no columns must be present that are unrelated to the forecast unit. As a very simplistic example, if you had an additional row, "even", that is one if the row number is even and zero otherwise, then this would mess up scoring as `scoringutils` then thinks that this column was relevant in defining the forecast unit.

In order to avoid issues, we recommend setting the forecast unit explicitly, using the `forecast_unit` argument. This will simply drop unneeded columns, while making sure that all necessary, 'protected columns' like "predicted" or "observed" are retained.

See Also

Other functions to create forecast objects: `as_forecast_binary()`, `as_forecast_point()`, `as_forecast_quantile()`, `as_forecast_sample()`

Examples

```
as_forecast_nominal(
  na.omit(example_nominal),
  predicted = "predicted",
  forecast_unit = c("model", "target_type", "target_end_date",
                    "horizon", "location")
)
```

as_forecast_point *Create a* forecast *object for point forecasts*

Description

When converting a forecast_quantile object into a forecast_point object, the 0.5 quantile is extracted and returned as the point forecast.

Usage

```
as_forecast_point(data, ...)

## Default S3 method:
as_forecast_point(
  data,
  forecast_unit = NULL,
  observed = NULL,
  predicted = NULL,
  ...
)

## S3 method for class 'forecast_quantile'
as_forecast_point(data, ...)
```

Arguments

data	A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.
...	Unused
forecast_unit	(optional) Name of the columns in data (after any renaming of columns) that denote the unit of a single forecast. See get_forecast_unit() for details. If NULL (the default), all columns that are not required columns are assumed to form the unit of a single forecast. If specified, all columns that are not part of the forecast unit (or required columns) will be removed.
observed	(optional) Name of the column in data that contains the observed values. This column will be renamed to "observed".
predicted	(optional) Name of the column in data that contains the predicted values. This column will be renamed to "predicted".

Value

A forecast object of class forecast_point

Required input

The input needs to be a data.frame or similar with the following columns:

- `observed`: Column of type `numeric` with observed values.
- `predicted`: Column of type `numeric` with predicted values.

For convenience, we recommend an additional column `model` holding the name of the forecaster or model that produced a prediction, but this is not strictly necessary.

See the example_point data set for an example.

See Also

Other functions to create forecast objects: `as_forecast_binary()`, `as_forecast_nominal()`, `as_forecast_quantile()`, `as_forecast_sample()`

---

as_forecast_quantile *Create a* forecast *object for quantile-based forecasts*

Description

Process and validate a data.frame (or similar) or similar with forecasts and observations. If the input passes all input checks, those functions will be converted to a `forecast` object. A forecast object is a `data.table` with a class `forecast` and an additional class that depends on the forecast type.

The arguments `observed`, `predicted`, etc. make it possible to rename existing columns of the input data to match the required columns for a forecast object. Using the argument `forecast_unit`, you can specify the columns that uniquely identify a single forecast (and thereby removing other, unneeded columns. See section "Forecast Unit" below for details).

Usage

```
as_forecast_quantile(data, ...)

## Default S3 method:
as_forecast_quantile(
  data,
  forecast_unit = NULL,
  observed = NULL,
  predicted = NULL,
  quantile_level = NULL,
  ...
)

## S3 method for class 'forecast_sample'
as_forecast_quantile(
  data,
  probs = c(0.05, 0.25, 0.5, 0.75, 0.95),
  type = 7,
  ...
)
```

Arguments

`data` A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.

`...` Unused

`forecast_unit` (optional) Name of the columns in `data` (after any renaming of columns) that denote the unit of a single forecast. See `get_forecast_unit()` for details. If `NULL` (the default), all columns that are not required columns are assumed to form the unit of a single forecast. If specified, all columns that are not part of the forecast unit (or required columns) will be removed.

`observed` (optional) Name of the column in `data` that contains the observed values. This column will be renamed to "observed".

`predicted` (optional) Name of the column in `data` that contains the predicted values. This column will be renamed to "predicted".

`quantile_level` (optional) Name of the column in `data` that contains the quantile level of the predicted values. This column will be renamed to "quantile_level". Only applicable to quantile-based forecasts.

`probs` A numeric vector of quantile levels for which quantiles will be computed. Corresponds to the `probs` argument in `quantile()`.

`type` Type argument passed down to the quantile function. For more information, see `quantile()`.

Value

A `forecast` object of class `forecast_quantile`

Required input

The input needs to be a data.frame or similar with the following columns:

- `observed`: Column of type `numeric` with observed values.
- `predicted`: Column of type `numeric` with predicted values. Predicted values represent quantiles of the predictive distribution.
- `quantile_level`: Column of type `numeric`, denoting the quantile level of the corresponding predicted value. Quantile levels must be between 0 and 1.

For convenience, we recommend an additional column `model` holding the name of the forecaster or model that produced a prediction, but this is not strictly necessary.

See the example_quantile data set for an example.

Converting from `forecast_sample` to `forecast_quantile`

When creating a `forecast_quantile` object from a `forecast_sample` object, the quantiles are estimated by computing empircal quantiles from the samples via `quantile()`. Note that empirical quantiles are a biased estimator for the true quantiles in particular in the tails of the distribution and when the number of available samples is low.

Forecast unit

In order to score forecasts, `scoringutils` needs to know which of the rows of the data belong together and jointly form a single forecasts. This is easy e.g. for point forecast, where there is one row per forecast. For quantile or sample-based forecasts, however, there are multiple rows that belong to a single forecast.

The *forecast unit* or *unit of a single forecast* is then described by the combination of columns that uniquely identify a single forecast. For example, we could have forecasts made by different models in various locations at different time points, each for several weeks into the future. The forecast unit could then be described as `forecast_unit = c("model", "location", "forecast_date", "forecast_horizon")`. `scoringutils` automatically tries to determine the unit of a single forecast. It uses all existing columns for this, which means that no columns must be present that are unrelated to the forecast unit. As a very simplistic example, if you had an additional row, "even", that is one if the row number is even and zero otherwise, then this would mess up scoring as `scoringutils` then thinks that this column was relevant in defining the forecast unit.

In order to avoid issues, we recommend setting the forecast unit explicitly, using the `forecast_unit` argument. This will simply drop unneeded columns, while making sure that all necessary, 'protected columns' like "predicted" or "observed" are retained.

See Also

Other functions to create forecast objects: `as_forecast_binary()`, `as_forecast_nominal()`, `as_forecast_point()`, `as_forecast_sample()`

Examples

```
as_forecast_quantile(
  example_quantile,
  predicted = "predicted",
  forecast_unit = c("model", "target_type", "target_end_date",
                    "horizon", "location")
)
```

`as_forecast_sample` *Create a `forecast` object for sample-based forecasts*

Description

Process and validate a data.frame (or similar) or similar with forecasts and observations. If the input passes all input checks, those functions will be converted to a `forecast` object. A forecast object is a `data.table` with a class `forecast` and an additional class that depends on the forecast type.

The arguments `observed`, `predicted`, etc. make it possible to rename existing columns of the input data to match the required columns for a forecast object. Using the argument `forecast_unit`, you can specify the columns that uniquely identify a single forecast (and thereby removing other, unneeded columns. See section "Forecast Unit" below for details).

Usage

```
as_forecast_sample(
  data,
  forecast_unit = NULL,
  observed = NULL,
  predicted = NULL,
  sample_id = NULL
)
```

Arguments

`data` A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.

`forecast_unit` (optional) Name of the columns in `data` (after any renaming of columns) that denote the unit of a single forecast. See `get_forecast_unit()` for details. If `NULL` (the default), all columns that are not required columns are assumed to form the unit of a single forecast. If specified, all columns that are not part of the forecast unit (or required columns) will be removed.

`observed` (optional) Name of the column in `data` that contains the observed values. This column will be renamed to "observed".

`predicted` (optional) Name of the column in `data` that contains the predicted values. This column will be renamed to "predicted".

`sample_id` (optional) Name of the column in `data` that contains the sample id. This column will be renamed to "sample_id".

Value

A `forecast` object of class `forecast_sample`

Required input

The input needs to be a data.frame or similar with the following columns:

- `observed`: Column of type `numeric` with observed values.
- `predicted`: Column of type `numeric` with predicted values. Predicted values represent random samples from the predictive distribution.

- `sample_id`: Column of any type with unique identifiers (unique within a single forecast) for each sample.

For convenience, we recommend an additional column `model` holding the name of the forecaster or model that produced a prediction, but this is not strictly necessary.

See the example_sample_continuous and example_sample_discrete data set for an example

Forecast unit

In order to score forecasts, `scoringutils` needs to know which of the rows of the data belong together and jointly form a single forecasts. This is easy e.g. for point forecast, where there is one row per forecast. For quantile or sample-based forecasts, however, there are multiple rows that belong to a single forecast.

The *forecast unit* or *unit of a single forecast* is then described by the combination of columns that uniquely identify a single forecast. For example, we could have forecasts made by different models in various locations at different time points, each for several weeks into the future. The forecast unit could then be described as `forecast_unit = c("model", "location", "forecast_date", "forecast_horizon")`. `scoringutils` automatically tries to determine the unit of a single forecast. It uses all existing columns for this, which means that no columns must be present that are unrelated to the forecast unit. As a very simplistic example, if you had an additional row, "even", that is one if the row number is even and zero otherwise, then this would mess up scoring as `scoringutils` then thinks that this column was relevant in defining the forecast unit.

In order to avoid issues, we recommend setting the forecast unit explicitly, using the `forecast_unit` argument. This will simply drop unneeded columns, while making sure that all necessary, 'protected columns' like "predicted" or "observed" are retained.

See Also

Other functions to create forecast objects: `as_forecast_binary()`, `as_forecast_nominal()`, `as_forecast_point()`, `as_forecast_quantile()`

`bias_quantile` *Determines bias of quantile forecasts*

Description

Determines bias from quantile forecasts. For an increasing number of quantiles this measure converges against the sample based bias version for integer and continuous forecasts.

Usage

```
bias_quantile(observed, predicted, quantile_level, na.rm = TRUE)
```

Arguments

`observed` Numeric vector of size n with the observed values.

`predicted` Numeric nxN matrix of predictive quantiles, n (number of rows) being the number of forecasts (corresponding to the number of observed values) and N (number of columns) the number of quantiles per forecast. If `observed` is just a single number, then predicted can just be a vector of size N.

`quantile_level` Vector of of size N with the quantile levels for which predictions were made. Note that if this does not contain the median (0.5) then the median is imputed as being the mean of the two innermost quantiles.

`na.rm` Logical. Should missing values be removed?

Details

For quantile forecasts, bias is measured as

$$B_t = (1 - 2 \cdot \max\{i | q_{t,i} \in Q_t \land q_{t,i} \leq x_t\})\mathbf{1}(x_t \leq q_{t,0.5}) + (1 - 2 \cdot \min\{i | q_{t,i} \in Q_t \land q_{t,i} \geq x_t\})1(x_t \geq q_{t,0.5}),$$

where Q_t is the set of quantiles that form the predictive distribution at time t and x_t is the observed value. For consistency, we define Q_t such that it always includes the element $q_{t,0} = -\infty$ and $q_{t,1} = \infty$. $1()$ is the indicator function that is 1 if the condition is satisfied and 0 otherwise.

In clearer terms, bias B_t is:

- $1 - 2\cdot$ the maximum percentile rank for which the corresponding quantile is still smaller than or equal to the observed value, *if the observed value is smaller than the median of the predictive distribution.*
- $1 - 2\cdot$ the minimum percentile rank for which the corresponding quantile is still larger than or equal to the observed value *if the observed value is larger than the median of the predictive distribution..*
- 0 *if the observed value is exactly the median* (both terms cancel out)

Bias can assume values between -1 and 1 and is 0 ideally (i.e. unbiased).

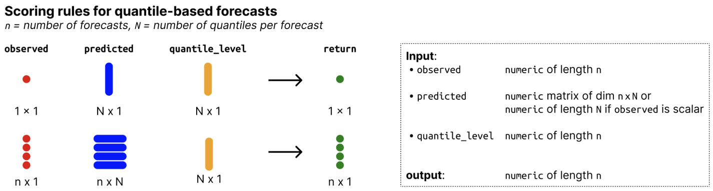
Note that if the given quantiles do not contain the median, the median is imputed as a linear interpolation of the two innermost quantiles. If the median is not available and cannot be imputed, an error will be thrown. Note that in order to compute bias, quantiles must be non-decreasing with increasing quantile levels.

For a large enough number of quantiles, the percentile rank will equal the proportion of predictive samples below the observed value, and the bias metric coincides with the one for continuous forecasts (see `bias_sample()`).

Value

scalar with the quantile bias for a single quantile prediction

Input format



Examples

```
predicted <- matrix(c(1.5:23.5, 3.3:25.3), nrow = 2, byrow = TRUE)
quantile_level <- c(0.01, 0.025, seq(0.05, 0.95, 0.05), 0.975, 0.99)
observed <- c(15, 12.4)
bias_quantile(observed, predicted, quantile_level)
```

`bias_sample` *Determine bias of forecasts*

Description

Determines bias from predictive Monte-Carlo samples. The function automatically recognises whether forecasts are continuous or integer valued and adapts the Bias function accordingly.

Usage

```
bias_sample(observed, predicted)
```

Arguments

`observed`	A vector with observed values of size n
`predicted`	nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of Monte Carlo samples. Alternatively, `predicted` can just be a vector of size n.

Details

For continuous forecasts, Bias is measured as

$$B_t(P_t, x_t) = 1 - 2 * (P_t(x_t))$$

where P_t is the empirical cumulative distribution function of the prediction for the observed value x_t. Computationally, $P_t(x_t)$ is just calculated as the fraction of predictive samples for x_t that are smaller than x_t.

For integer valued forecasts, Bias is measured as

$$B_t(P_t, x_t) = 1 - (P_t(x_t) + P_t(x_t + 1))$$

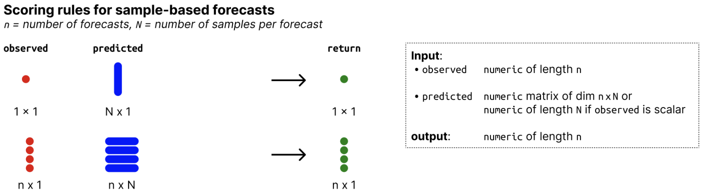
to adjust for the integer nature of the forecasts.

In both cases, Bias can assume values between -1 and 1 and is 0 ideally.

Value

Numeric vector of length n with the biases of the predictive samples with respect to the observed values.

Input format



Scoring rules for sample-based forecasts
n = number of forecasts, N = number of samples per forecast

Input:
- `observed` `numeric` of length `n`
- `predicted` `numeric` matrix of dim `n x N` or `numeric` of length `N` if `observed` is scalar

output: `numeric` of length `n`

References

The integer valued Bias function is discussed in Assessing the performance of real-time epidemic forecasts: A case study of Ebola in the Western Area region of Sierra Leone, 2014-15 Funk S, Camacho A, Kucharski AJ, Lowe R, Eggo RM, et al. (2019) Assessing the performance of real-time epidemic forecasts: A case study of Ebola in the Western Area region of Sierra Leone, 2014-15. PLOS Computational Biology 15(2): e1006785. doi:10.1371/journal.pcbi.1006785

Examples

```
## integer valued forecasts
observed <- rpois(30, lambda = 1:30)
predicted <- replicate(200, rpois(n = 30, lambda = 1:30))
bias_sample(observed, predicted)

## continuous forecasts
observed <- rnorm(30, mean = 1:30)
predicted <- replicate(200, rnorm(30, mean = 1:30))
bias_sample(observed, predicted)
```

`check_columns_present` *Check column names are present in a data.frame*

Description

The functions loops over the column names and checks whether they are present. If an issue is encountered, the function immediately stops and returns a message with the first issue encountered.

Usage

```
check_columns_present(data, columns)
```

Arguments

`data`	A data.frame or similar to be checked
`columns`	A character vector of column names to check

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`check_dims_ok_point` *Check Inputs Have Matching Dimensions*

Description

Function assesses whether input dimensions match. In the following, n is the number of observations / forecasts. Scalar values may be repeated to match the length of the other input. Allowed options are therefore:

- `observed` is vector of length 1 or length n
- `predicted` is:
  - a vector of of length 1 or length n
  - a matrix with n rows and 1 column

Usage

```
check_dims_ok_point(observed, predicted)
```

Arguments

`observed`	Input to be checked. Should be a factor of length n with exactly two levels, holding the observed values. The highest factor level is assumed to be the reference level. This means that `predicted` represents the probability that the observed value is equal to the highest factor level.
`predicted`	Input to be checked. `predicted` should be a vector of length n, holding probabilities. Alternatively, `predicted` can be a matrix of size n x 1. Values represent the probability that the corresponding value in `observed` will be equal to the highest available factor level.

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`check_duplicates` *Check that there are no duplicate forecasts*

Description

Runs `get_duplicate_forecasts()` and returns a message if an issue is encountered

Usage

```
check_duplicates(data)
```

Arguments

`data` A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`check_input_binary` *Check that inputs are correct for binary forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring binary forecasts.

Usage

```
check_input_binary(observed, predicted)
```

Arguments

`observed` Input to be checked. Should be a factor of length n with exactly two levels, holding the observed values. The highest factor level is assumed to be the reference level. This means that `predicted` represents the probability that the observed value is equal to the highest factor level.

`predicted` Input to be checked. `predicted` should be a vector of length n, holding probabilities. Alternatively, `predicted` can be a matrix of size n x 1. Values represent the probability that the corresponding value in `observed` will be equal to the highest available factor level.

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`check_input_interval` *Check that inputs are correct for interval-based forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring interval-based forecasts.

Usage

```
check_input_interval(observed, lower, upper, interval_range)
```

Arguments

`observed`	Input to be checked. Should be a numeric vector with the observed values of size n.
`lower`	Input to be checked. Should be a numeric vector of size n that holds the predicted value for the lower bounds of the prediction intervals.
`upper`	Input to be checked. Should be a numeric vector of size n that holds the predicted value for the upper bounds of the prediction intervals.
`interval_range`	Input to be checked. Should be a vector of size n that denotes the interval range in percent. E.g. a value of 50 denotes a (25%, 75%) prediction interval.

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`check_input_point` *Check that inputs are correct for point forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring point forecasts.

Usage

```
check_input_point(observed, predicted)
```

Arguments

`observed`	Input to be checked. Should be a numeric vector with the observed values of size n.
`predicted`	Input to be checked. Should be a numeric vector with the predicted values of size n.

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`check_input_quantile` *Check that inputs are correct for quantile-based forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring quantile-based forecasts.

Usage

```
check_input_quantile(observed, predicted, quantile_level)
```

Arguments

`observed` Input to be checked. Should be a numeric vector with the observed values of size n.

`predicted` Input to be checked. Should be nxN matrix of predictive quantiles, n (number of rows) being the number of data points and N (number of columns) the number of quantiles per forecast. If `observed` is just a single number, then predicted can just be a vector of size N.

`quantile_level` Input to be checked. Should be a vector of size N that denotes the quantile levels corresponding to the columns of the prediction matrix.

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`check_input_sample` *Check that inputs are correct for sample-based forecast*

Description

Function assesses whether the inputs correspond to the requirements for scoring sample-based forecasts.

Usage

```
check_input_sample(observed, predicted)
```

Arguments

`observed`	Input to be checked. Should be a numeric vector with the observed values of size n.
`predicted`	Input to be checked. Should be a numeric nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of samples per forecast. If `observed` is just a single number, then predicted values can just be a vector of size N.

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`check_number_per_forecast`

Check that all forecasts have the same number of rows

Description

Helper function that checks the number of rows (corresponding e.g to quantiles or samples) per forecast. If the number of quantiles or samples is the same for all forecasts, it returns TRUE and a string with an error message otherwise.

Usage

```
check_number_per_forecast(data, forecast_unit)
```

Arguments

`data`	A data.frame or similar to be checked
`forecast_unit`	Character vector denoting the unit of a single forecast.

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

check_numeric_vector *Check whether an input is an atomic vector of mode 'numeric'*

Description

Helper function to check whether an input is a numeric vector.

Usage

```
check_numeric_vector(x, ...)
```

Arguments

x	input to check
...	Arguments passed on to checkmate::check_numeric lower [numeric(1)] Lower value all elements of x must be greater than or equal to. upper [numeric(1)] Upper value all elements of x must be lower than or equal to. finite [logical(1)] Check for only finite values? Default is FALSE. any.missing [logical(1)] Are vectors with missing values allowed? Default is TRUE. all.missing [logical(1)] Are vectors with no non-missing values allowed? Default is TRUE. Note that empty vectors do not have non-missing values. len [integer(1)] Exact expected length of x. min.len [integer(1)] Minimal length of x. max.len [integer(1)] Maximal length of x. unique [logical(1)] Must all values be unique? Default is FALSE. sorted [logical(1)] Elements must be sorted in ascending order. Missing values are ignored. names [character(1)] Check for names. See checkNamed for possible values. Default is “any” which performs no check at all. Note that you can use checkSubset to check for a specific set of names. typed.missing [logical(1)] If set to FALSE (default), all types of missing values (NA, NA_integer_, NA_real_, NA_character_ or NA_character_) as well as empty vectors are allowed while type-checking atomic input. Set to TRUE to enable strict type checking.

`null.ok [logical(1)]`
If set to `TRUE`, `x` may also be `NULL`. In this case only a type check of `x` is performed, all additional checks are disabled.

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`check_try` *Helper function to convert assert statements into checks*

Description

Tries to execute an expression. Internally, this is used to see whether assertions fail when checking inputs (i.e. to convert an `assert_*()` statement into a check). If the expression fails, the error message is returned. If the expression succeeds, `TRUE` is returned.

Usage

```
check_try(expr)
```

Arguments

`expr`	an expression to be evaluated

Value

Returns TRUE if the check was successful and a string with an error message otherwise.

`crps_sample` *(Continuous) ranked probability score*

Description

Wrapper around the `crps_sample()` function from the **scoringRules** package. Can be used for continuous as well as integer valued forecasts

The Continuous ranked probability score (CRPS) can be interpreted as the sum of three components: overprediction, underprediction and dispersion. "Dispersion" is defined as the CRPS of the median forecast $m$. If an observation $y$ is greater than $m$ then overpredictoin is defined as the CRPS of the forecast for $y$ minus the dispersion component, and underprediction is zero. If, on the other hand, $y<m$ then underprediction is defined as the CRPS of the forecast for $y$ minus the dispersion component, and overprediction is zero.

The overprediction, underprediction and dispersion components correspond to those of the `wis()`.

Usage

```
crps_sample(observed, predicted, separate_results = FALSE, ...)

dispersion_sample(observed, predicted, ...)

overprediction_sample(observed, predicted, ...)

underprediction_sample(observed, predicted, ...)
```

Arguments

`observed` A vector with observed values of size n

`predicted` nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of Monte Carlo samples. Alternatively, `predicted` can just be a vector of size n.

`separate_results`
Logical. If `TRUE` (default is `FALSE`), then the separate parts of the CRPS (dispersion penalty, penalties for over- and under-prediction) get returned as separate elements of a list. If you want a `data.frame` instead, simply call `as.data.frame()` on the output.

`...` Additional arguments passed on to `crps_sample()` from functions `overprediction_sample()`, `underprediction_sample()` and `dispersion_sample()`.

Value

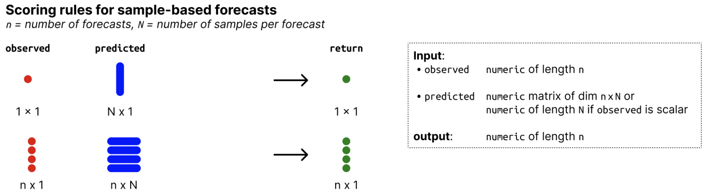
Vector with scores.

`dispersion_sample()`: a numeric vector with dispersion values (one per observation).

`overprediction_quantile()`: a numeric vector with overprediction values (one per observation).

`underprediction_quantile()`: a numeric vector with underprediction values (one per observation).

Input format


Scoring rules for sample-based forecasts
n = number of forecasts, N = number of samples per forecast
observed
predicted
return
1 × 1
N x 1
1 × 1
n x 1
n x N
n x 1
Input:
• observed numeric of length n
• predicted numeric matrix of dim n x N or
numeric of length N if observed is scalar
output: numeric of length n

References

Alexander Jordan, Fabian Krüger, Sebastian Lerch, Evaluating Probabilistic Forecasts with scoringRules, https://www.jstatsoft.org/article/view/v090i12

Examples

```
observed <- rpois(30, lambda = 1:30)
predicted <- replicate(200, rpois(n = 30, lambda = 1:30))
crps_sample(observed, predicted)
```

`dss_sample` *Dawid-Sebastiani score*

Description

Wrapper around the `dss_sample()` function from the **scoringRules** package.

Usage

```
dss_sample(observed, predicted, ...)
```

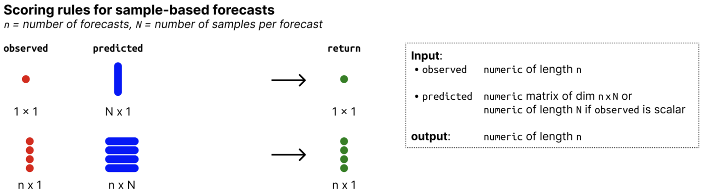
Arguments

`observed`	A vector with observed values of size n
`predicted`	nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of Monte Carlo samples. Alternatively, `predicted` can just be a vector of size n.
`...`	Additional arguments passed to dss_sample() from the scoringRules package.

Value

Vector with scores.

Input format


Scoring rules for sample-based forecasts
n = number of forecasts, N = number of samples per forecast
observed
predicted
return
1 × 1
N x 1
1 × 1
n x 1
n x N
n x 1

Input:
- `observed` `numeric` of length `n`
- `predicted` `numeric` matrix of dim `n` x `N` or `numeric` of length `N` if `observed` is scalar

output: `numeric` of length `n`

References

Alexander Jordan, Fabian Krüger, Sebastian Lerch, Evaluating Probabilistic Forecasts with scoringRules, https://www.jstatsoft.org/article/view/v090i12

Examples

```
observed <- rpois(30, lambda = 1:30)
predicted <- replicate(200, rpois(n = 30, lambda = 1:30))
dss_sample(observed, predicted)
```

`example_binary` *Binary forecast example data*

Description

A data set with binary predictions for COVID-19 cases and deaths constructed from data submitted to the European Forecast Hub.

Usage

```
example_binary
```

Format

An object of class `forecast_binary` (see `as_forecast_binary()`) with the following columns:

location the country for which a prediction was made

location_name name of the country for which a prediction was made

target_end_date the date for which a prediction was made

target_type the target to be predicted (cases or deaths)

observed A factor with observed values

forecast_date the date on which a prediction was made

model name of the model that generated the forecasts

horizon forecast horizon in weeks

predicted predicted value

Details

Predictions in the data set were constructed based on the continuous example data by looking at the number of samples below the mean prediction. The outcome was constructed as whether or not the actually observed value was below or above that mean prediction. This should not be understood as sound statistical practice, but rather as a practical way to create an example data set.

The data was created using the script create-example-data.R in the inst/ folder (or the top level folder in a compiled package).

Source

https://github.com/european-modelling-hubs/covid19-forecast-hub-europe_archive/commit/a42867b1ea152c57e25b04f9faa26cfd4bfd8fa6/

`example_nominal` *Nominal example data*

Description

A data set with predictions for COVID-19 cases and deaths submitted to the European Forecast Hub.

Usage

```
example_nominal
```

Format

An object of class `forecast_nominal` (see `as_forecast_nominal()`) with the following columns:

location the country for which a prediction was made

target_end_date the date for which a prediction was made

target_type the target to be predicted (cases or deaths)

observed Numeric: observed values

location_name name of the country for which a prediction was made

forecast_date the date on which a prediction was made

predicted_label outcome that a probabilty corresponds to

predicted predicted value

model name of the model that generated the forecasts

horizon forecast horizon in weeks

Details

The data was created using the script create-example-data.R in the inst/ folder (or the top level folder in a compiled package).

Source

https://github.com/european-modelling-hubs/covid19-forecast-hub-europe_archive/commit/a42867b1ea152c57e25b04f9faa26cfd4bfd8fa6/

`example_point` *Point forecast example data*

Description

A data set with predictions for COVID-19 cases and deaths submitted to the European Forecast Hub. This data set is like the quantile example data, only that the median has been replaced by a point forecast.

Usage

```
example_point
```

Format

An object of class `forecast_point` (see `as_forecast_point()`) with the following columns:

location the country for which a prediction was made

target_end_date the date for which a prediction was made

target_type the target to be predicted (cases or deaths)

observed observed values

location_name name of the country for which a prediction was made

forecast_date the date on which a prediction was made

predicted predicted value

model name of the model that generated the forecasts

horizon forecast horizon in weeks

Details

The data was created using the script create-example-data.R in the inst/ folder (or the top level folder in a compiled package).

Source

https://github.com/european-modelling-hubs/covid19-forecast-hub-europe_archive/commit/a42867b1ea152c57e25b04f9faa26cfd4bfd8fa6/

`example_quantile` *Quantile example data*

Description

A data set with predictions for COVID-19 cases and deaths submitted to the European Forecast Hub.

Usage

```
example_quantile
```

Format

An object of class `forecast_quantile` (see `as_forecast_quantile()`) with the following columns:

location the country for which a prediction was made

target_end_date the date for which a prediction was made

target_type the target to be predicted (cases or deaths)

observed Numeric: observed values

location_name name of the country for which a prediction was made

forecast_date the date on which a prediction was made

quantile_level quantile level of the corresponding prediction

predicted predicted value

model name of the model that generated the forecasts

horizon forecast horizon in weeks

Details

The data was created using the script create-example-data.R in the inst/ folder (or the top level folder in a compiled package).

Source

https://github.com/european-modelling-hubs/covid19-forecast-hub-europe_archive/commit/a42867b1ea152c57e25b04f9faa26cfd4bfd8fa6/

`example_sample_continuous`
Continuous forecast example data

Description

A data set with continuous predictions for COVID-19 cases and deaths constructed from data submitted to the European Forecast Hub.

Usage

```
example_sample_continuous
```

Format

An object of class `forecast_sample` (see `as_forecast_sample()`) with the following columns:

location the country for which a prediction was made

target_end_date the date for which a prediction was made

target_type the target to be predicted (cases or deaths)

observed observed values

location_name name of the country for which a prediction was made

forecast_date the date on which a prediction was made

model name of the model that generated the forecasts

horizon forecast horizon in weeks

predicted predicted value

sample_id id for the corresponding sample

Details

The data was created using the script create-example-data.R in the inst/ folder (or the top level folder in a compiled package).

Source

https://github.com/european-modelling-hubs/covid19-forecast-hub-europe_archive/commit/a42867b1ea152c57e25b04f9faa26cfd4bfd8fa6/

`example_sample_discrete`

Discrete forecast example data

Description

A data set with integer predictions for COVID-19 cases and deaths constructed from data submitted to the European Forecast Hub.

Usage

```
example_sample_discrete
```

Format

An object of class `forecast_sample` (see `as_forecast_sample()`) with the following columns:

location the country for which a prediction was made

target_end_date the date for which a prediction was made

target_type the target to be predicted (cases or deaths)

observed observed values

location_name name of the country for which a prediction was made

forecast_date the date on which a prediction was made

model name of the model that generated the forecasts

horizon forecast horizon in weeks

predicted predicted value

sample_id id for the corresponding sample

Details

The data was created using the script create-example-data.R in the inst/ folder (or the top level folder in a compiled package).

Source

`https://github.com/european-modelling-hubs/covid19-forecast-hub-europe_archive/commit/a42867b1ea152c57e25b04f9faa26cfd4bfd8fa6/`

`get_correlations` *Calculate correlation between metrics*

Description

Calculate the correlation between different metrics for a data.frame of scores as produced by `score()`.

Usage

```
get_correlations(scores, metrics = get_metrics.scores(scores), ...)
```

Arguments

`scores` An object of class `scores` (a data.table with scores and an additional attribute `metrics` as produced by `score()`).

`metrics` A character vector with the metrics to show. If set to `NULL` (default), all metrics present in `scores` will be shown.

`...` Additional arguments to pass down to `cor()`.

Value

An object of class `scores` (a data.table with an additional attribute `metrics` holding the names of the scores) with correlations between different metrics

Examples

```
library(magrittr) # pipe operator

scores <- example_quantile %>%
 as_forecast_quantile() %>%
 score()

get_correlations(scores)
```

`get_coverage` *Get quantile and interval coverage values for quantile-based forecasts*

Description

For a validated forecast object in a quantile-based format (see `as_forecast_quantile()` for more information), this function computes:

- interval coverage of central prediction intervals
- quantile coverage for predictive quantiles
- the deviation between desired and actual coverage (both for interval and quantile coverage)

Coverage values are computed for a specific level of grouping, as specified in the `by` argument. By default, coverage values are computed per model.

Interval coverage

Interval coverage for a given interval range is defined as the proportion of observations that fall within the corresponding central prediction intervals. Central prediction intervals are symmetric around the median and formed by two quantiles that denote the lower and upper bound. For example, the 50% central prediction interval is the interval between the 0.25 and 0.75 quantiles of the predictive distribution.

Quantile coverage

Quantile coverage for a given quantile level is defined as the proportion of observed values that are smaller than the corresponding predictive quantile. For example, the 0.5 quantile coverage is the proportion of observed values that are smaller than the 0.5 quantile of the predictive distribution. Just as above, for a single observation and the quantile of a single predictive distribution, the value will either be `TRUE` or `FALSE`.

Coverage deviation

The coverage deviation is the difference between the desired coverage (can be either interval or quantile coverage) and the actual coverage. For example, if the desired coverage is 90% and the actual coverage is 80%, the coverage deviation is -0.1.

Usage

```
get_coverage(forecast, by = "model")
```

Arguments

`forecast`	A forecast object (a validated data.table with predicted and observed values).
`by`	character vector that denotes the level of grouping for which the coverage values should be computed. By default (`"model"`), one coverage value per model will be returned.

Value

A data.table with columns as specified in `by` and additional columns for the coverage values described above

a data.table with columns "interval_coverage", "interval_coverage_deviation", "quantile_coverage", "quantile_coverage_deviation" and the columns specified in `by`.

Examples

```
library(magrittr) # pipe operator
example_quantile %>%
  as_forecast_quantile() %>%
  get_coverage(by = "model")
```

get_duplicate_forecasts *Find duplicate forecasts*

Description

Internal helper function to identify duplicate forecasts, i.e. instances where there is more than one forecast for the same prediction target.

Usage

```
get_duplicate_forecasts(data, forecast_unit = NULL, counts = FALSE)
```

Arguments

data	A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.
forecast_unit	(optional) Name of the columns in data (after any renaming of columns) that denote the unit of a single forecast. See get_forecast_unit() for details. If NULL (the default), all columns that are not required columns are assumed to form the unit of a single forecast. If specified, all columns that are not part of the forecast unit (or required columns) will be removed.
counts	Should the output show the number of duplicates per forecast unit instead of the individual duplicated rows? Default is FALSE.

Value

A data.frame with all rows for which a duplicate forecast was found

Examples

```
example <- rbind(example_quantile, example_quantile[1000:1010])
get_duplicate_forecasts(example)
```

get_forecast_counts *Count number of available forecasts*

Description

Given a data set with forecasts, this function counts the number of available forecasts. The level of grouping can be specified using the by argument (e.g. to count the number of forecasts per model, or the number of forecasts per model and location). This is useful to determine whether there are any missing forecasts.

Usage

```
get_forecast_counts(
  forecast,
  by = get_forecast_unit(forecast),
  collapse = c("quantile_level", "sample_id")
)
```

Arguments

`forecast` A forecast object (a validated data.table with predicted and observed values).

`by` character vector or `NULL` (the default) that denotes the categories over which the number of forecasts should be counted. By default this will be the unit of a single forecast (i.e. all available columns (apart from a few "protected" columns such as 'predicted' and 'observed') plus "quantile_level" or "sample_id" where present).

`collapse` character vector (default: `c("quantile_level", "sample_id")`) with names of categories for which the number of rows should be collapsed to one when counting. For example, a single forecast is usually represented by a set of several quantiles or samples and collapsing these to one makes sure that a single forecast only gets counted once. Setting `collapse = c()` would mean that all quantiles / samples would be counted as individual forecasts.

Value

A data.table with columns as specified in `by` and an additional column "count" with the number of forecasts.

Examples

```
library(magrittr) # pipe operator
example_quantile %>%
  as_forecast_quantile() %>%
  get_forecast_counts(by = c("model", "target_type"))
```

`get_forecast_type` *Get forecast type from forecast object*

Description

Get forecast type from forecast object

Usage

```
get_forecast_type(forecast)
```

Arguments

`forecast`	A forecast object (a validated data.table with predicted and observed values).

Value

Character vector of length one with the forecast type.

`get_forecast_unit` *Get unit of a single forecast*

Description

Helper function to get the unit of a single forecast, i.e. the column names that define where a single forecast was made for. This just takes all columns that are available in the data and subtracts the columns that are protected, i.e. those returned by `get_protected_columns()` as well as the names of the metrics that were specified during scoring, if any.

Usage

```
get_forecast_unit(data)
```

Arguments

`data`	A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.

Value

A character vector with the column names that define the unit of a single forecast

Forecast unit

In order to score forecasts, `scoringutils` needs to know which of the rows of the data belong together and jointly form a single forecasts. This is easy e.g. for point forecast, where there is one row per forecast. For quantile or sample-based forecasts, however, there are multiple rows that belong to a single forecast.

The *forecast unit* or *unit of a single forecast* is then described by the combination of columns that uniquely identify a single forecast. For example, we could have forecasts made by different models in various locations at different time points, each for several weeks into the future. The forecast unit could then be described as `forecast_unit = c("model", "location", "forecast_date", "forecast_horizon")`. `scoringutils` automatically tries to determine the unit of a single forecast. It uses all existing columns for this, which means that no columns must be present that are unrelated to the forecast unit. As a very simplistic example, if you had an additional row, "even", that is one if the row number is even and zero otherwise, then this would mess up scoring as `scoringutils` then thinks that this column was relevant in defining the forecast unit.

In order to avoid issues, we recommend setting the forecast unit explicitly, using the `forecast_unit` argument. This will simply drop unneeded columns, while making sure that all necessary, 'protected columns' like "predicted" or "observed" are retained.

get_metrics *Get metrics*

Description

Generic function to to obtain default metrics available for scoring or metrics that were used for scoring.

- If called on a `forecast` object it returns a list of functions that can be used for scoring.
- If called on a `scores` object (see `score()`), it returns a character vector with the names of the metrics that were used for scoring.

See the documentation for the actual methods in the `See Also` section below for more details. Alternatively call `?get_metrics.<forecast_type>` or `?get_metrics.scores`.

Usage

```
get_metrics(x, ...)
```

Arguments

`x`	A `forecast` or `scores` object.
`...`	Additional arguments passed to the method.

See Also

Other get_metrics functions: `get_metrics.forecast_binary()`, `get_metrics.forecast_nominal()`, `get_metrics.forecast_point()`, `get_metrics.forecast_quantile()`, `get_metrics.forecast_sample()`, `get_metrics.scores()`

get_metrics.forecast_binary *Get default metrics for binary forecasts*

Description

For binary forecasts, the default scoring rules are:

- "brier_score" = `brier_score()`
- "log_score" = `logs_binary()`

Usage

```
## S3 method for class 'forecast_binary'
get_metrics(x, select = NULL, exclude = NULL, ...)
```

Arguments

`x` A forecast object (a validated data.table with predicted and observed values, see `as_forecast_binary()`).

`select` A character vector of scoring rules to select from the list. If `select` is `NULL` (the default), all possible scoring rules are returned.

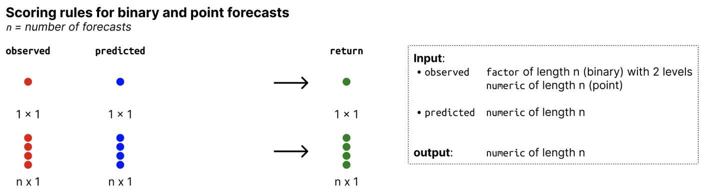
`exclude` A character vector of scoring rules to exclude from the list. If `select` is not `NULL`, this argument is ignored.

`...` unused

Value

A list of scoring functions.

Input format


Scoring rules for binary and point forecasts
n = number of forecasts
observed
predicted
return
1 × 1
1 × 1
1 × 1
n x 1
n x 1
n x 1
Input:
• observed factor of length n (binary) with 2 levels
numeric of length n (point)
• predicted numeric of length n
output: numeric of length n

See Also

Other get_metrics functions: `get_metrics()`, `get_metrics.forecast_nominal()`, `get_metrics.forecast_point()`, `get_metrics.forecast_quantile()`, `get_metrics.forecast_sample()`, `get_metrics.scores()`

Examples

```
get_metrics(example_binary)
get_metrics(example_binary, select = "brier_score")
get_metrics(example_binary, exclude = "log_score")
```

`get_metrics.forecast_nominal`

Get default metrics for nominal forecasts

Description

For nominal forecasts, the default scoring rule is:

- "log_score" = `logs_nominal()`

Usage

```
## S3 method for class 'forecast_nominal'
get_metrics(x, select = NULL, exclude = NULL, ...)
```

Arguments

`x`	A forecast object (a validated data.table with predicted and observed values, see `as_forecast_binary()`).
`select`	A character vector of scoring rules to select from the list. If `select` is `NULL` (the default), all possible scoring rules are returned.
`exclude`	A character vector of scoring rules to exclude from the list. If `select` is not `NULL`, this argument is ignored.
`...`	unused

See Also

Other get_metrics functions: `get_metrics()`, `get_metrics.forecast_binary()`, `get_metrics.forecast_point()`, `get_metrics.forecast_quantile()`, `get_metrics.forecast_sample()`, `get_metrics.scores()`

Examples

```
get_metrics(example_nominal)
```

---

get_metrics.forecast_point

Get default metrics for point forecasts

Description

For point forecasts, the default scoring rules are:

- "ae_point" = ae()
- "se_point" = se()
- "ape" = ape()

A note of caution: Every scoring rule for a point forecast is implicitly minimised by a specific aspect of the predictive distribution (see Gneiting, 2011).

The mean squared error, for example, is only a meaningful scoring rule if the forecaster actually reported the mean of their predictive distribution as a point forecast. If the forecaster reported the median, then the mean absolute error would be the appropriate scoring rule. If the scoring rule and the predictive task do not align, the results will be misleading.

Failure to respect this correspondence can lead to grossly misleading results! Consider the example in the section below.

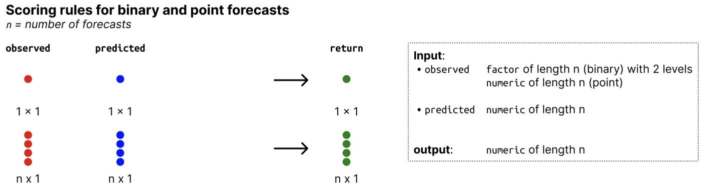
Usage

```
## S3 method for class 'forecast_point'
get_metrics(x, select = NULL, exclude = NULL, ...)
```

Arguments

`x`	A forecast object (a validated data.table with predicted and observed values, see `as_forecast_binary()`).
`select`	A character vector of scoring rules to select from the list. If `select` is `NULL` (the default), all possible scoring rules are returned.
`exclude`	A character vector of scoring rules to exclude from the list. If `select` is not `NULL`, this argument is ignored.
`...`	unused

Input format


Scoring rules for binary and point forecasts
n = number of forecasts
observed
predicted
return
1 × 1
1 × 1
1 × 1
n x 1
n x 1
n x 1
Input:
• observed factor of length n (binary) with 2 levels
numeric of length n (point)
• predicted numeric of length n
output: numeric of length n

References

Making and Evaluating Point Forecasts, Gneiting, Tilmann, 2011, Journal of the American Statistical Association.

See Also

Other get_metrics functions: `get_metrics()`, `get_metrics.forecast_binary()`, `get_metrics.forecast_nominal()`, `get_metrics.forecast_quantile()`, `get_metrics.forecast_sample()`, `get_metrics.scores()`

Examples

```
get_metrics(example_point, select = "ape")

library(magrittr)
set.seed(123)
n <- 500
observed <- rnorm(n, 5, 4)^2

predicted_mu <- mean(observed)
predicted_not_mu <- predicted_mu - rnorm(n, 10, 2)

df <- data.frame(
  model = rep(c("perfect", "bad"), each = n),
  predicted = c(rep(predicted_mu, n), predicted_not_mu),
  observed = rep(observed, 2),
  id = rep(1:n, 2)
) %>%
  as_forecast_point()
score(df) %>%
  summarise_scores()
```

get_metrics.forecast_quantile

Get default metrics for quantile-based forecasts

Description

For quantile-based forecasts, the default scoring rules are:

- "wis" = `wis()`
- "overprediction" = `overprediction_quantile()`
- "underprediction" = `underprediction_quantile()`
- "dispersion" = `dispersion_quantile()`
- "bias" = `bias_quantile()`
- "interval_coverage_50" = `interval_coverage()`
- "interval_coverage_90" = purrr::partial(interval_coverage, interval_range = 90)
- "ae_median" = `ae_median_quantile()`

Note: The `interval_coverage_90` scoring rule is created by modifying `interval_coverage()`, making use of the function `purrr::partial()`. This construct allows the function to deal with arbitrary arguments in `...`, while making sure that only those that `interval_coverage()` can accept get passed on to it. `interval_range = 90` is set in the function definition, as passing an argument `interval_range = 90` to `score()` would mean it would also get passed to `interval_coverage_50`.

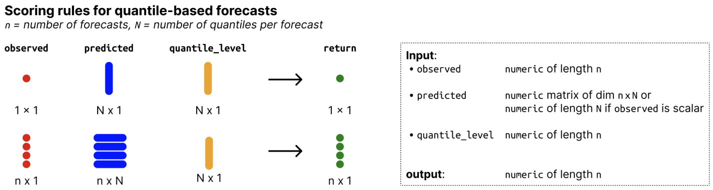
Usage

```
## S3 method for class 'forecast_quantile'
get_metrics(x, select = NULL, exclude = NULL, ...)
```

Arguments

`x`	A forecast object (a validated data.table with predicted and observed values, see `as_forecast_binary()`).
`select`	A character vector of scoring rules to select from the list. If `select` is `NULL` (the default), all possible scoring rules are returned.
`exclude`	A character vector of scoring rules to exclude from the list. If `select` is not `NULL`, this argument is ignored.
`...`	unused

Input format



See Also

Other get_metrics functions: get_metrics(), get_metrics.forecast_binary(), get_metrics.forecast_nominal(), get_metrics.forecast_point(), get_metrics.forecast_sample(), get_metrics.scores()

Examples

```
get_metrics(example_quantile, select = "wis")
```

---

get_metrics.forecast_sample

Get default metrics for sample-based forecasts

Description

For sample-based forecasts, the default scoring rules are:

- "crps" = crps_sample()
- "overprediction" = overprediction_sample()
- "underprediction" = underprediction_sample()
- "dispersion" = dispersion_sample()
- "log_score" = logs_sample()
- "dss" = dss_sample()
- "mad" = mad_sample()
- "bias" = bias_sample()
- "ae_median" = ae_median_sample()
- "se_mean" = se_mean_sample()

Usage

```
## S3 method for class 'forecast_sample'
get_metrics(x, select = NULL, exclude = NULL, ...)
```

Arguments

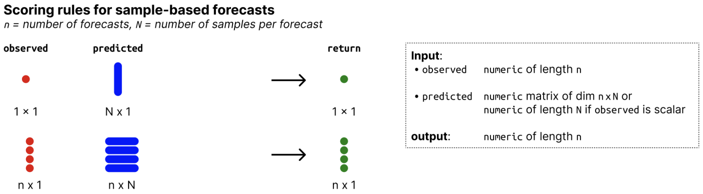
`x` A forecast object (a validated data.table with predicted and observed values, see `as_forecast_binary()`).

`select` A character vector of scoring rules to select from the list. If `select` is `NULL` (the default), all possible scoring rules are returned.

`exclude` A character vector of scoring rules to exclude from the list. If `select` is not `NULL`, this argument is ignored.

`...` unused

Input format


Scoring rules for sample-based forecasts
n = number of forecasts, N = number of samples per forecast
observed
predicted
return
1 × 1
N x 1
1 × 1
n x 1
n x N
n x 1
Input:
• observed numeric of length n
• predicted numeric matrix of dim n x N or
numeric of length N if observed is scalar
output: numeric of length n

See Also

Other get_metrics functions: `get_metrics()`, `get_metrics.forecast_binary()`, `get_metrics.forecast_nominal()`, `get_metrics.forecast_point()`, `get_metrics.forecast_quantile()`, `get_metrics.scores()`

Examples

```
get_metrics(example_sample_continuous, exclude = "mad")
```

`get_metrics.scores` *Get names of the metrics that were used for scoring*

Description

When applying a scoring rule via `score()`, the names of the scoring rules become column names of the resulting data.table. In addition, an attribute `metrics` will be added to the output, holding the names of the scores as a vector.

This is done so that functions like `get_forecast_unit()` or `summarise_scores()` can still identify which columns are part of the forecast unit and which hold a score.

`get_metrics()` accesses and returns the `metrics` attribute. If there is no attribute, the function will return `NULL` (or, if `error = TRUE` will produce an error instead). In addition, it checks the column names of the input for consistency with the data stored in the `metrics` attribute.

Handling a missing or inconsistent `metrics` attribute:

If the metrics attribute is missing or is not consistent with the column names of the data.table, you can either

- run score() again, specifying names for the scoring rules manually, or
- add/update the attribute manually using attr(scores, "metrics") <- c("names", "of", "your", "scores") (the order does not matter).

Usage

```
## S3 method for class 'scores'
get_metrics(x, error = FALSE, ...)
```

Arguments

x	A scores object, (a data.table with an attribute metrics as produced by score()).
error	Throw an error if there is no attribute called metrics? Default is FALSE.
...	unused

Value

Character vector with the names of the scoring rules that were used for scoring.

See Also

Other get_metrics functions: get_metrics(), get_metrics.forecast_binary(), get_metrics.forecast_nominal(), get_metrics.forecast_point(), get_metrics.forecast_quantile(), get_metrics.forecast_sample()

---

get_pairwise_comparisons

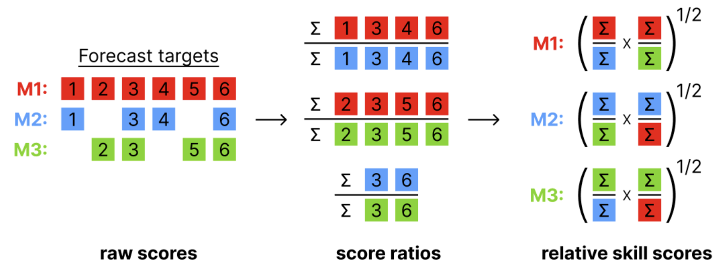
Obtain pairwise comparisons between models

Description

Compare scores obtained by different models in a pairwise tournament. All combinations of two models are compared against each other based on the overlapping set of available forecasts common to both models.

The input should be a scores object as produced by score(). Note that adding additional unrelated columns can unpredictably change results, as all present columns are taken into account when determining the set of overlapping forecasts between two models.

The output of the pairwise comparisons is a set of mean score ratios, relative skill scores and p-values.



Mean score ratios

For every pair of two models, a mean score ratio is computed. This is simply the mean score of the first model divided by the mean score of the second. Mean score ratios are computed based on the set of overlapping forecasts between the two models. That means that only scores for those targets are taken into account for which both models have submitted a forecast.

(Scaled) Relative skill scores

The relative score of a model is the geometric mean of all mean score ratios which involve that model. If a baseline is provided, scaled relative skill scores will be calculated as well. Scaled relative skill scores are simply the relative skill score of a model divided by the relative skill score of the baseline model.

p-values

In addition, the function computes p-values for the comparison between two models (again based on the set of overlapping forecasts). P-values can be computed in two ways: based on a nonparametric Wilcoxon signed-rank test (internally using `wilcox.test()` with `paired` = `TRUE`) or based on a permutation test. The permutation test is based on the difference in mean scores between two models. The default null hypothesis is that the mean score difference is zero (see `permutation_test()`). Adjusted p-values are computed by calling `p.adjust()` on the raw p-values.

The code for the pairwise comparisons is inspired by an implementation by Johannes Bracher. The implementation of the permutation test follows the function `permutationTest` from the `surveillance` package by Michael Höhle, Andrea Riebler and Michaela Paul.

Usage

```
get_pairwise_comparisons(
  scores,
  compare = "model",
  by = NULL,
  metric = intersect(c("wis", "crps", "brier_score"), names(scores)),
  baseline = NULL,
  ...
)
```

Arguments

`scores` An object of class `scores` (a data.table with scores and an additional attribute `metrics` as produced by `score()`).

`compare` Character vector with a single colum name that defines the elements for the pairwise comparison. For example, if this is set to "model" (the default), then elements of the "model" column will be compared.

`by` Character vector with column names that define further grouping levels for the pairwise comparisons. By default this is `NULL` and there will be one relative skill score per distinct entry of the column selected in `compare`. If further columns are given here, for example, `by = "location"` with `compare = "model"`, then one separate relative skill score is calculated for every model in every location.

`metric` A string with the name of the metric for which a relative skill shall be computed. By default this is either "crps", "wis" or "brier_score" if any of these are available.

`baseline` A string with the name of a model. If a baseline is given, then a scaled relative skill with respect to the baseline will be returned. By default (`NULL`), relative skill will not be scaled with respect to a baseline model.

`...` Additional arguments for the comparison between two models. See `compare_forecasts()` for more information.

Value

A data.table with the results of pairwise comparisons containing the mean score ratios (`mean_scores_ratio`), unadjusted (`pval`) and adjusted (`adj_pval`) p-values, and relative skill values of each model (`..._relative_skill`). If a baseline model is given then the scaled relative skill is reported as well (`..._scaled_relative_skill`).

Author(s)

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Examples

```
library(magrittr) # pipe operator

scores <- example_quantile %>%
 as_forecast_quantile() %>%
 score()

pairwise <- get_pairwise_comparisons(scores, by = "target_type")
pairwise2 <- get_pairwise_comparisons(
  scores, by = "target_type", baseline = "EuroCOVIDhub-baseline"
)

library(ggplot2)
plot_pairwise_comparisons(pairwise, type = "mean_scores_ratio") +
  facet_wrap(~target_type)
```

get_pit_histogram.forecast_quantile

Probability integral transformation histogram

Description

Generate a Probability Integral Transformation (PIT) histogram for validated forecast objects.

See the examples for how to plot the result of this function.

Usage

```
## S3 method for class 'forecast_quantile'
get_pit_histogram(forecast, num_bins = NULL, breaks = NULL, by, ...)

## S3 method for class 'forecast_sample'
get_pit_histogram(
  forecast,
  num_bins = 10,
  breaks = NULL,
  by,
  integers = c("nonrandom", "random", "ignore"),
  n_replicates = NULL,
  ...
)

get_pit_histogram(forecast, num_bins, breaks, by, ...)

## Default S3 method:
get_pit_histogram(forecast, num_bins, breaks, by, ...)
```

Arguments

`forecast`	A forecast object (a validated data.table with predicted and observed values).
`num_bins`	The number of bins in the PIT histogram. For sample-based forecasts, the default is 10 bins. For quantile-based forecasts, the default is one bin for each available quantile. You can control the number of bins by supplying a number. This is fine for sample-based pit histograms, but may fail for quantile-based formats. In this case it is preferred to supply explicit breaks points using the `breaks` argument.
`breaks`	Numeric vector with the break points for the bins in the PIT histogram. This is preferred when creating a PIT histogram based on quantile-based data. Default is `NULL` and breaks will be determined by `num_bins`. If `breaks` is used, `num_bins` will be ignored. 0 and 1 will always be added as left and right bounds, respectively.

`by` Character vector with the columns according to which the PIT values shall be grouped. If you e.g. have the columns 'model' and 'location' in the input data and want to have a PIT histogram for every model and location, specify `by = c("model", "location")`.

`...` Currently unused. You *cannot* pass additional arguments to scoring functions via `...`. See the *Customising metrics* section below for details on how to use `purrr::partial()` to pass arguments to individual metrics.

`integers` How to handle integer forecasts (count data). This is based on methods described Czado et al. (2007). If "nonrandom" (default) the function will use the non-randomised PIT method. If "random", will use the randomised PIT method. If "ignore", will treat integer forecasts as if they were continuous.

`n_replicates` The number of draws for the randomised PIT for discrete predictions. Will be ignored if forecasts are continuous or `integers` is not set to `random`.

Value

A data.table with density values for each bin in the PIT histogram.

References

Sebastian Funk, Anton Camacho, Adam J. Kucharski, Rachel Lowe, Rosalind M. Eggo, W. John Edmunds (2019) Assessing the performance of real-time epidemic forecasts: A case study of Ebola in the Western Area region of Sierra Leone, 2014-15, doi:10.1371/journal.pcbi.1006785

See Also

`pit_histogram_sample()`

Examples

```
library("ggplot2")

example <- as_forecast_sample(example_sample_continuous)
result <- get_pit_histogram(example, by = "model")
ggplot(result,  aes(x = mid, y = density)) +
  geom_col() +
  facet_wrap(. ~ model) +
  labs(x = "Quantile", "Density")

# example with quantile data
example <- as_forecast_quantile(example_quantile)
result <- get_pit_histogram(example, by = "model")
ggplot(result,  aes(x = mid, y = density)) +
  geom_col() +
  facet_wrap(. ~ model) +
  labs(x = "Quantile", "Density")
```

`get_type` *Get type of a vector or matrix of observed values or predictions*

Description

Internal helper function to get the type of a vector (usually of observed or predicted values). The function checks whether the input is a factor, or else whether it is integer (or can be coerced to integer) or whether it's continuous.

Usage

```
get_type(x)
```

Arguments

`x`	Input the type should be determined for.

Value

Character vector of length one with either "classification", "integer", or "continuous".

`interval_coverage` *Interval coverage (for quantile-based forecasts)*

Description

Check whether the observed value is within a given central prediction interval. The prediction interval is defined by a lower and an upper bound formed by a pair of predictive quantiles. For example, a 50% prediction interval is formed by the 0.25 and 0.75 quantiles of the predictive distribution.

Usage

```
interval_coverage(observed, predicted, quantile_level, interval_range = 50)
```

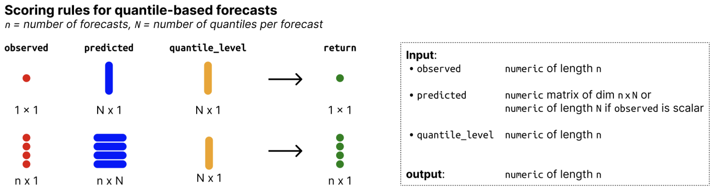
Arguments

`observed`	Numeric vector of size n with the observed values.
`predicted`	Numeric nxN matrix of predictive quantiles, n (number of rows) being the number of forecasts (corresponding to the number of observed values) and N (number of columns) the number of quantiles per forecast. If `observed` is just a single number, then predicted can just be a vector of size N.
`quantile_level`	Vector of of size N with the quantile levels for which predictions were made.
`interval_range`	A single number with the range of the prediction interval in percent (e.g. 50 for a 50% prediction interval) for which you want to compute interval coverage.

Value

A vector of length n with elements either TRUE, if the observed value is within the corresponding prediction interval, and FALSE otherwise.

Input format



Examples

```
observed <- c(1, -15, 22)
predicted <- rbind(
  c(-1, 0, 1, 2, 3),
  c(-2, 1, 2, 2, 4),
   c(-2, 0, 3, 3, 4)
)
quantile_level <- c(0.1, 0.25, 0.5, 0.75, 0.9)
interval_coverage(observed, predicted, quantile_level)
```

`interval_score` *Interval score*

Description

Proper Scoring Rule to score quantile predictions, following Gneiting and Raftery (2007). Smaller values are better.

The score is computed as

$$\text{score} = (\text{upper} - \text{lower}) + \frac{2}{\alpha}(\text{lower} - \text{observed}) * \mathbf{1}(\text{observed} < \text{lower}) + \frac{2}{\alpha}(\text{observed} - \text{upper}) * \mathbf{1}(\text{observed} > \text{upper})$$

where $\mathbf{1}()$ is the indicator function and indicates how much is outside the prediction interval. α is the decimal value that indicates how much is outside the prediction interval.

To improve usability, the user is asked to provide an interval range in percentage terms, i.e. interval_range = 90 (percent) for a 90 percent prediction interval. Correspondingly, the user would have to provide the 5% and 95% quantiles (the corresponding alpha would then be 0.1). No specific distribution is assumed, but the interval has to be symmetric around the median (i.e you can't use the 0.1 quantile as the lower bound and the 0.7 quantile as the upper bound). Non-symmetric quantiles can be scored using the function `quantile_score()`.

Usage

```
interval_score(
  observed,
  lower,
  upper,
  interval_range,
  weigh = TRUE,
  separate_results = FALSE
)
```

Arguments

`observed` A vector with observed values of size n

`lower` Vector of size n with the prediction for the lower quantile of the given interval range.

`upper` Vector of size n with the prediction for the upper quantile of the given interval range.

`interval_range` Numeric vector (either a single number or a vector of size n) with the range of the prediction intervals. For example, if you're forecasting the 0.05 and 0.95 quantile, the interval range would be 90. The interval range corresponds to $(100-\alpha)/100$, where α is the decimal value that indicates how much is outside the prediction interval (see e.g. Gneiting and Raftery (2007)).

`weigh` Logical. If `TRUE` (the default), weigh the score by $\alpha/2$, so it can be averaged into an interval score that, in the limit (for an increasing number of equally spaced quantiles/prediction intervals), corresponds to the CRPS. α is the value that corresponds to the $(\alpha/2)$ or $(1-\alpha/2)$, i.e. it is the decimal value that represents how much is outside a central prediction interval (E.g. for a 90 percent central prediction interval, alpha is 0.1).

`separate_results`

Logical. If `TRUE` (default is `FALSE`), then the separate parts of the interval score (dispersion penalty, penalties for over- and under-prediction get returned as separate elements of a list). If you want a `data.frame` instead, simply call `as.data.frame()` on the output.

Value

Vector with the scoring values, or a list with separate entries if `separate_results` is `TRUE`.

References

Strictly Proper Scoring Rules, Prediction,and Estimation, Tilmann Gneiting and Adrian E. Raftery, 2007, Journal of the American Statistical Association, Volume 102, 2007 - Issue 477

Evaluating epidemic forecasts in an interval format, Johannes Bracher, Evan L. Ray, Tilmann Gneiting and Nicholas G. Reich, `https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1008618` # nolint

Examples

```
observed <- rnorm(30, mean = 1:30)
interval_range <- rep(90, 30)
alpha <- (100 - interval_range) / 100
lower <- qnorm(alpha / 2, rnorm(30, mean = 1:30))
upper <- qnorm((1 - alpha / 2), rnorm(30, mean = 11:40))

scoringutils:::interval_score(
  observed = observed,
  lower = lower,
  upper = upper,
  interval_range = interval_range
)

# gives a warning, as the interval_range should likely be 50 instead of 0.5
scoringutils:::interval_score(
  observed = 4, upper = 8, lower = 2, interval_range = 0.5
)

# example with missing values and separate results
scoringutils:::interval_score(
  observed = c(observed, NA),
  lower = c(lower, NA),
  upper = c(NA, upper),
  separate_results = TRUE,
  interval_range = 90
)
```

is_forecast_binary *Test whether an object is a forecast object*

Description

Test whether an object is a forecast object.

You can test for a specific `forecast_<type>` class using the appropriate `is_forecast_<type>` function.

Usage

```
is_forecast_binary(x)

is_forecast_nominal(x)

is_forecast_point(x)

is_forecast_quantile(x)

is_forecast_sample(x)

is_forecast(x)
```

Arguments

`x` An R object.

Value

`is_forecast`: `TRUE` if the object is of class `forecast`, `FALSE` otherwise.

`is_forecast_<type>*`: `TRUE` if the object is of class `forecast_*` in addition to class `forecast`, `FALSE` otherwise.

Examples

```
forecast_binary <- as_forecast_binary(example_binary)
is_forecast(forecast_binary)
```

`logs_nominal` *Log score for nominal outcomes*

Description

Log score for nominal outcomes

The Log Score is the negative logarithm of the probability assigned to the observed value. It is a proper scoring rule. Small values are better (best is zero, worst is infinity).

Usage

```
logs_nominal(observed, predicted, predicted_label)
```

Arguments

`observed` A factor of length n with N levels holding the observed values.

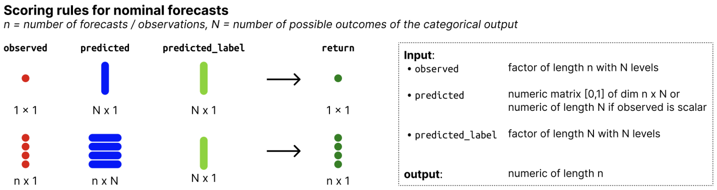
`predicted` nxN matrix of predictive probabilities, n (number of rows) being the number of observations and N (number of columns) the number of possible outcomes.

`predicted_label` A factor of length N, denoting the outcome that the probabilities in `predicted` correspond to.

Value

A numeric vector of size n with log scores

Input format


Scoring rules for nominal forecasts
n = number of forecasts / observations, N = number of possible outcomes of the categorical output
observed
predicted
predicted_label
return
1 × 1
N x 1
N x 1
1 × 1
n x 1
n x N
N x 1
n x 1
Input:
• observed
factor of length n with N levels
• predicted
numeric matrix [0,1] of dim n x N or
numeric of length N if observed is scalar
• predicted_label
factor of length N with N levels
output:
numeric of length n

See Also

Other log score functions: `logs_sample`(), `scoring-functions-binary`

Examples

```
factor_levels <- c("one", "two", "three")
predicted_label <- factor(c("one", "two", "three"), levels = factor_levels)
observed <- factor(c("one", "three", "two"), levels = factor_levels)
predicted <- matrix(c(0.8, 0.1, 0.4,
                      0.1, 0.2, 0.4,
                      0.1, 0.7, 0.2),
                    nrow = 3)
logs_nominal(observed, predicted, predicted_label)
```

`logs_sample` *Logarithmic score (sample-based version)*

Description

This function is a wrapper around the `logs_sample()` function from the **scoringRules** package.

The log score is the negative logarithm of the predictive density evaluated at the observed value.

The function should be used to score continuous predictions only. While the Log Score is in theory also applicable to discrete forecasts, the problem lies in the implementation: The function uses a kernel density estimation, which is not well defined with integer-valued Monte Carlo Samples. See the scoringRules package for more details and alternatives, e.g. calculating scores for specific discrete probability distributions.

Usage

```
logs_sample(observed, predicted, ...)
```

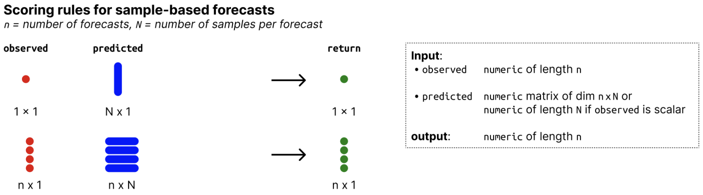
Arguments

`observed`	A vector with observed values of size n
`predicted`	nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of Monte Carlo samples. Alternatively, `predicted` can just be a vector of size n.
`...`	Additional arguments passed to logs_sample() from the scoringRules package.

Value

Vector with scores.

Input format


Scoring rules for sample-based forecasts
n = number of forecasts, N = number of samples per forecast
observed
predicted
return
1 × 1
N x 1
1 × 1
n x 1
n x N
n x 1
Input:
• observed numeric of length n
• predicted numeric matrix of dim n x N or numeric of length N if observed is scalar
output: numeric of length n

References

Alexander Jordan, Fabian Krüger, Sebastian Lerch, Evaluating Probabilistic Forecasts with scoringRules, https://www.jstatsoft.org/article/view/v090i12

See Also

Other log score functions: logs_nominal(), scoring-functions-binary

Examples

```
observed <- rpois(30, lambda = 1:30)
predicted <- replicate(200, rpois(n = 30, lambda = 1:30))
logs_sample(observed, predicted)
```

---

log_shift *Log transformation with an additive shift*

Description

Function that shifts a value by some offset and then applies the natural logarithm to it.

Usage

```
log_shift(x, offset = 0, base = exp(1))
```

Arguments

x	vector of input values to be transformed
offset	Number to add to the input value before taking the natural logarithm.
base	A positive number: the base with respect to which logarithms are computed. Defaults to e = exp(1).

Details

The output is computed as log(x + offset)

Value

A numeric vector with transformed values

References

Transformation of forecasts for evaluating predictive performance in an epidemiological context Nikos I. Bosse, Sam Abbott, Anne Cori, Edwin van Leeuwen, Johannes Bracher, Sebastian Funk medRxiv 2023.01.23.23284722 doi:10.1101/2023.01.23.23284722 `https://www.medrxiv.org/content/10.1101/2023.01.23.23284722v1` # nolint

Examples

```
library(magrittr) # pipe operator
log_shift(1:10)
log_shift(0:9, offset = 1)

example_quantile[observed > 0, ] %>%
  as_forecast_quantile() %>%
  transform_forecasts(fun = log_shift, offset = 1)
```

`mad_sample` *Determine dispersion of a probabilistic forecast*

Description

Sharpness is the ability of the model to generate predictions within a narrow range and dispersion is the lack thereof. It is a data-independent measure, and is purely a feature of the forecasts themselves.

Dispersion of predictive samples corresponding to one single observed value is measured as the normalised median of the absolute deviation from the median of the predictive samples. For details, see mad() and the explanations given in Funk et al. (2019)

Usage

```
mad_sample(observed = NULL, predicted, ...)
```

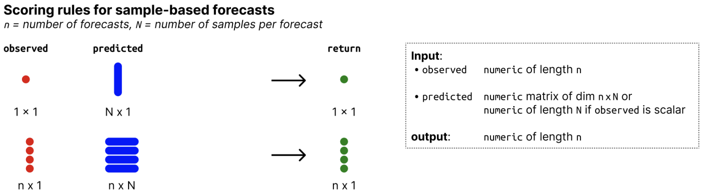
Arguments

`observed`	Place holder, argument will be ignored and exists only for consistency with other scoring functions. The output does not depend on any observed values.
`predicted`	nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of Monte Carlo samples. Alternatively, `predicted` can just be a vector of size n.
`...`	Additional arguments passed to mad().

Value

Vector with dispersion values.

Input format



Scoring rules for sample-based forecasts

n = number of forecasts, N = number of samples per forecast

Input:
- `observed` `numeric` of length `n`
- `predicted` `numeric` matrix of dim `n x N` or `numeric` of length `N` if `observed` is scalar

output: `numeric` of length `n`

References

Funk S, Camacho A, Kucharski AJ, Lowe R, Eggo RM, Edmunds WJ (2019) Assessing the performance of real-time epidemic forecasts: A case study of Ebola in the Western Area region of Sierra Leone, 2014-15. PLoS Comput Biol 15(2): e1006785. doi:10.1371/journal.pcbi.1006785

Examples

```
predicted <- replicate(200, rpois(n = 30, lambda = 1:30))
mad_sample(predicted = predicted)
```

`pit_histogram_sample` *Probability integral transformation for counts*

Description

Uses a Probability integral transformation (PIT) (or a randomised PIT for integer forecasts) to assess the calibration of predictive Monte Carlo samples.

Usage

```
pit_histogram_sample(
  observed,
  predicted,
  quantiles,
  integers = c("nonrandom", "random", "ignore"),
  n_replicates = NULL
)
```

Arguments

`observed` A vector with observed values of size n

`predicted` nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of Monte Carlo samples. Alternatively, `predicted` can just be a vector of size n.

`quantiles` A vector of quantiles between which to calculate the PIT.

`integers` How to handle integer forecasts (count data). This is based on methods described Czado et al. (2007). If "nonrandom" (default) the function will use the non-randomised PIT method. If "random", will use the randomised PIT method. If "ignore", will treat integer forecasts as if they were continuous.

`n_replicates` The number of draws for the randomised PIT for discrete predictions. Will be ignored if forecasts are continuous or `integers` is not set to `random`.

Details

Calibration or reliability of forecasts is the ability of a model to correctly identify its own uncertainty in making predictions. In a model with perfect calibration, the observed data at each time point look as if they came from the predictive probability distribution at that time.

Equivalently, one can inspect the probability integral transform of the predictive distribution at time t,

$$u_t = F_t(x_t)$$

where x_t is the observed data point at time t in $t_1, \ldots, t_n$, n being the number of forecasts, and F_t is the (continuous) predictive cumulative probability distribution at time t. If the true probability distribution of outcomes at time t is G_t then the forecasts F_t are said to be ideal if $F_t = G_t$ at all times t. In that case, the probabilities u_t are distributed uniformly.

In the case of discrete nonnegative outcomes such as incidence counts, the PIT is no longer uniform even when forecasts are ideal. In that case two methods are available ase described by Czado et al. (2007).

By default, a nonrandomised PIT is calculated using the conditional cumulative distribution function

$$F(u) = \begin{cases} 0 & \text{if } v < P_t(k_t - 1) \\ (v - P_t(k_t - 1))/(P_t(k_t) - P_t(k_t - 1)) & \text{if } P_t(k_t - 1) \leq v < P_t(k_t) \\ 1 & \text{if } v \geq P_t(k_t) \end{cases}$$

where k_t is the observed count, $P_t(x)$ is the predictive cumulative probability of observing incidence k at time t and $P_t(-1) = 0$ by definition. Values of the PIT histogram are then created by averaging over the n predictions,

$$\bar{F}(u) = \frac{i = 1}{n} \sum_{i=1}^{n} F^{(i)}(u)$$

And calculating the value at each bin between quantile q_i and quantile q_{i+1} as

$$\bar{F}(q_i) - \bar{F}(q_{i+1})$$

Alternatively, a randomised PIT can be used instead. In this case, the PIT is

$$u_t = P_t(k_t) + v * (P_t(k_t) - P_t(k_t - 1))$$

where v is standard uniform and independent of k. The values of the PIT histogram are then calculated by binning the u_t values as above.

Value

A vector with PIT histogram densities for the bins corresponding to the given quantiles.

References

Claudia Czado, Tilmann Gneiting Leonhard Held (2009) Predictive model assessment for count data. Biometrika, 96(4), 633-648. Sebastian Funk, Anton Camacho, Adam J. Kucharski, Rachel Lowe, Rosalind M. Eggo, W. John Edmunds (2019) Assessing the performance of real-time epidemic forecasts: A case study of Ebola in the Western Area region of Sierra Leone, 2014-15, doi:10.1371/journal.pcbi.1006785

See Also

`get_pit_histogram()`

Examples

```
## continuous predictions
observed <- rnorm(20, mean = 1:20)
predicted <- replicate(100, rnorm(n = 20, mean = 1:20))
pit <- pit_histogram_sample(observed, predicted, quantiles = seq(0, 1, 0.1))

## integer predictions
observed <- rpois(20, lambda = 1:20)
predicted <- replicate(100, rpois(n = 20, lambda = 1:20))
pit <- pit_histogram_sample(observed, predicted, quantiles = seq(0, 1, 0.1))

## integer predictions, randomised PIT
observed <- rpois(20, lambda = 1:20)
predicted <- replicate(100, rpois(n = 20, lambda = 1:20))
pit <- pit_histogram_sample(
  observed, predicted, quantiles = seq(0, 1, 0.1),
  integers = "random", n_replicates = 30
)
```

plot_correlations *Plot correlation between metrics*

Description

Plots a heatmap of correlations between different metrics.

Usage

```
plot_correlations(correlations, digits = NULL)
```

Arguments

`correlations`	A data.table of correlations between scores as produced by `get_correlations()`.
`digits`	A number indicating how many decimal places the correlations should be rounded to. By default (`digits = NULL`) no rounding takes place.

Value

A ggplot object showing a coloured matrix of correlations between metrics.

A ggplot object with a visualisation of correlations between metrics

Examples

```
library(magrittr) # pipe operator
scores <- example_quantile %>%
  as_forecast_quantile %>%
  score()
correlations <- scores %>%
  summarise_scores() %>%
  get_correlations()
plot_correlations(correlations, digits = 2)
```

plot_forecast_counts *Visualise the number of available forecasts*

Description

Visualise Where Forecasts Are Available.

Usage

```
plot_forecast_counts(
  forecast_counts,
  x,
  y = "model",
  x_as_factor = TRUE,
  show_counts = TRUE
)
```

Arguments

`forecast_counts`	A data.table (or similar) with a column `count` holding forecast counts, as produced by `get_forecast_counts()`.
`x`	Character vector of length one that denotes the name of the column to appear on the x-axis of the plot.
`y`	Character vector of length one that denotes the name of the column to appear on the y-axis of the plot. Default is "model".
`x_as_factor`	Logical (default is `TRUE`). Whether or not to convert the variable on the x-axis to a factor. This has an effect e.g. if dates are shown on the x-axis.
`show_counts`	Logical (default is `TRUE`) that indicates whether or not to show the actual count numbers on the plot.

Value

A ggplot object with a plot of forecast counts

Examples

```
library(ggplot2)
library(magrittr) # pipe operator
forecast_counts <- example_quantile %>%
  as_forecast_quantile %>%
  get_forecast_counts(by = c("model", "target_type", "target_end_date"))
plot_forecast_counts(
 forecast_counts, x = "target_end_date", show_counts = FALSE
) +
 facet_wrap("target_type")
```

`plot_heatmap` *Create a heatmap of a scoring metric*

Description

This function can be used to create a heatmap of one metric across different groups, e.g. the interval score obtained by several forecasting models in different locations.

Usage

```
plot_heatmap(scores, y = "model", x, metric)
```

Arguments

`scores`	A data.frame of scores based on quantile forecasts as produced by `score()`.
`y`	The variable from the scores you want to show on the y-Axis. The default for this is "model"
`x`	The variable from the scores you want to show on the x-Axis. This could be something like "horizon", or "location"
`metric`	String, the metric that determines the value and colour shown in the tiles of the heatmap.

Value

A ggplot object showing a heatmap of the desired metric

Examples

```
library(magrittr) # pipe operator
scores <- example_quantile %>%
  as_forecast_quantile %>%
  score()
scores <- summarise_scores(scores, by = c("model", "target_type"))
scores <- summarise_scores(
  scores, by = c("model", "target_type"),
  fun = signif, digits = 2
)

plot_heatmap(scores, x = "target_type", metric = "bias")
```

`plot_interval_coverage` *Plot interval coverage*

Description

Plot interval coverage values (see `get_coverage()` for more information).

Usage

```
plot_interval_coverage(coverage, colour = "model")
```

Arguments

`coverage`	A data frame of coverage values as produced by `get_coverage()`.
`colour`	According to which variable shall the graphs be coloured? Default is "model".

Value

ggplot object with a plot of interval coverage

Examples

```
example <- as_forecast_quantile(example_quantile)
coverage <- get_coverage(example, by = "model")
plot_interval_coverage(coverage)
```

---

plot_pairwise_comparisons

Plot heatmap of pairwise comparisons

Description

Creates a heatmap of the ratios or pvalues from a pairwise comparison between models.

Usage

```
plot_pairwise_comparisons(
  comparison_result,
  type = c("mean_scores_ratio", "pval")
)
```

Arguments

comparison_result
A data.frame as produced by `get_pairwise_comparisons()`.

type
Character vector of length one that is either "mean_scores_ratio" or "pval". This denotes whether to visualise the ratio or the p-value of the pairwise comparison. Default is "mean_scores_ratio".

Value

A ggplot object with a heatmap of mean score ratios from pairwise comparisons.

Examples

```
library(ggplot2)
library(magrittr) # pipe operator
scores <- example_quantile %>%
  as_forecast_quantile %>%
  score()
pairwise <- get_pairwise_comparisons(scores, by = "target_type")
plot_pairwise_comparisons(pairwise, type = "mean_scores_ratio") +
  facet_wrap(~target_type)
```

plot_quantile_coverage *Plot quantile coverage*

Description

Plot quantile coverage values (see `get_coverage()` for more information).

Usage

```
plot_quantile_coverage(coverage, colour = "model")
```

Arguments

`coverage`	A data frame of coverage values as produced by `get_coverage()`.
`colour`	String, according to which variable shall the graphs be coloured? Default is "model".

Value

A ggplot object with a plot of interval coverage

Examples

```
example <- as_forecast_quantile(example_quantile)
coverage <- get_coverage(example, by = "model")
plot_quantile_coverage(coverage)
```

plot_wis *Plot contributions to the weighted interval score*

Description

Visualise the components of the weighted interval score: penalties for over-prediction, under-prediction and for high dispersion (lack of sharpness).

Usage

```
plot_wis(scores, x = "model", relative_contributions = FALSE, flip = FALSE)
```

Arguments

scores	A data.table of scores based on quantile forecasts as produced by score() and summarised using summarise_scores().
x	The variable from the scores you want to show on the x-Axis. Usually this will be "model".
relative_contributions	Logical. Show relative contributions instead of absolute contributions? Default is FALSE and this functionality is not available yet.
flip	Boolean (default is FALSE), whether or not to flip the axes.

Value

A ggplot object showing a contributions from the three components of the weighted interval score.

A ggplot object with a visualisation of the WIS decomposition

References

Bracher J, Ray E, Gneiting T, Reich, N (2020) Evaluating epidemic forecasts in an interval format. https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1008618

Examples

```
library(ggplot2)
library(magrittr) # pipe operator
scores <- example_quantile %>%
  as_forecast_quantile %>%
  score()
scores <- summarise_scores(scores, by = c("model", "target_type"))

plot_wis(scores,
  x = "model",
  relative_contributions = TRUE
) +
  facet_wrap(~target_type)
plot_wis(scores,
  x = "model",
  relative_contributions = FALSE
) +
  facet_wrap(~target_type, scales = "free_x")
```

print.forecast *Print information about a forecast object*

Description

This function prints information about a forecast object, including "Forecast type", "Score columns", "Forecast unit".

Usage

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

Arguments

`x`	A forecast object
`...`	Additional arguments for `print()`.

Value

Returns `x` invisibly.

Examples

```
dat <- as_forecast_quantile(example_quantile)
print(dat)
```

`quantile_score` *Quantile score*

Description

Proper Scoring Rule to score quantile predictions. Smaller values are better. The quantile score is closely related to the interval score (see `wis()`) and is the quantile equivalent that works with single quantiles instead of central prediction intervals.

The quantile score, also called pinball loss, for a single quantile level τ is defined as

$$\text{QS}_\tau(F, y) = 2 \cdot \{\mathbf{1}(y \leq q_\tau) - \tau\} \cdot (q_\tau - y) = \begin{cases} 2 \cdot (1 - \tau) * q_\tau - y, & \text{if } y \leq q_\tau \\ 2 \cdot \tau * |q_\tau - y|, & \text{if } y > q_\tau, \end{cases}$$

with q_τ being the τ-quantile of the predictive distribution F, and $\mathbf{1}(\cdot)$ the indicator function.

The weighted interval score for a single prediction interval can be obtained as the average of the quantile scores for the lower and upper quantile of that prediction interval:

$$\text{WIS}_\alpha(F, y) = \frac{\text{QS}_{\alpha/2}(F, y) + \text{QS}_{1-\alpha/2}(F, y)}{2}.$$

See the SI of Bracher et al. (2021) for more details.

`quantile_score()` returns the average quantile score across the quantile levels provided. For a set of quantile levels that form pairwise central prediction intervals, the quantile score is equivalent to the interval score.

Usage

```
quantile_score(observed, predicted, quantile_level, weigh = TRUE)
```

Arguments

`observed` Numeric vector of size n with the observed values.

`predicted` Numeric nxN matrix of predictive quantiles, n (number of rows) being the number of forecasts (corresponding to the number of observed values) and N (number of columns) the number of quantiles per forecast. If `observed` is just a single number, then predicted can just be a vector of size N.

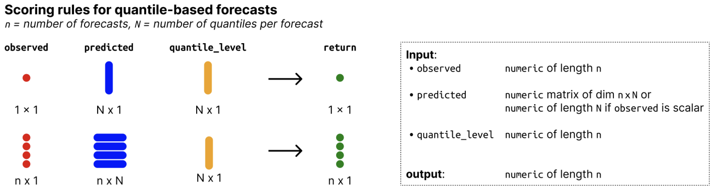
`quantile_level` Vector of of size N with the quantile levels for which predictions were made.

`weigh` Logical. If `TRUE` (the default), weigh the score by $\alpha/2$, so it can be averaged into an interval score that, in the limit (for an increasing number of equally spaced quantiles/prediction intervals), corresponds to the CRPS. α is the value that corresponds to the $(\alpha/2)$ or $(1-\alpha/2)$, i.e. it is the decimal value that represents how much is outside a central prediction interval (E.g. for a 90 percent central prediction interval, alpha is 0.1).

Value

Numeric vector of length n with the quantile score. The scores are averaged across quantile levels if multiple quantile levels are provided (the result of calling `rowMeans()` on the matrix of quantile scores that is computed based on the observed and predicted values).

Input format



Scoring rules for quantile-based forecasts

n = number of forecasts, N = number of quantiles per forecast

Input:
- `observed` `numeric` of length `n`
- `predicted` `numeric` matrix of dim `n x N` or `numeric` of length `N` if `observed` is scalar
- `quantile_level` `numeric` of length `n`

output: `numeric` of length `n`

References

Strictly Proper Scoring Rules, Prediction,and Estimation, Tilmann Gneiting and Adrian E. Raftery, 2007, Journal of the American Statistical Association, Volume 102, 2007 - Issue 477

Evaluating epidemic forecasts in an interval format, Johannes Bracher, Evan L. Ray, Tilmann Gneiting and Nicholas G. Reich, 2021, https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1008618

Examples

```
observed <- rnorm(10, mean = 1:10)
alpha <- 0.5

lower <- qnorm(alpha / 2, observed)
upper <- qnorm((1 - alpha / 2), observed)

qs_lower <- quantile_score(observed,
  predicted = matrix(lower),
  quantile_level = alpha / 2
)
qs_upper <- quantile_score(observed,
  predicted = matrix(upper),
  quantile_level = 1 - alpha / 2
)
interval_score <- (qs_lower + qs_upper) / 2
interval_score2 <- quantile_score(
  observed,
  predicted = cbind(lower, upper),
  quantile_level = c(alpha / 2, 1 - alpha / 2)
)

# this is the same as the following
wis(
  observed,
  predicted = cbind(lower, upper),
  quantile_level = c(alpha / 2, 1 - alpha / 2)
)
```

score.forecast_binary *Evaluate forecasts*

Description

score() applies a selection of scoring metrics to a forecast object. score() is a generic that dispatches to different methods depending on the class of the input data.

See as_forecast_binary(), as_forecast_quantile() etc. for information on how to create a forecast object.

See get_forecast_unit() for more information on the concept of a forecast unit.

For additional help and examples, check out the paper Evaluating Forecasts with scoringutils in R.

Usage

```
## S3 method for class 'forecast_binary'
score(forecast, metrics = get_metrics(forecast), ...)

## S3 method for class 'forecast_nominal'
score(forecast, metrics = get_metrics(forecast), ...)

## S3 method for class 'forecast_point'
score(forecast, metrics = get_metrics(forecast), ...)

## S3 method for class 'forecast_quantile'
score(forecast, metrics = get_metrics(forecast), ...)

## S3 method for class 'forecast_sample'
```

```
score(forecast, metrics = get_metrics(forecast), ...)

score(forecast, metrics, ...)
```

Arguments

`forecast` A forecast object (a validated data.table with predicted and observed values).

`metrics` A named list of scoring functions. Names will be used as column names in the output. See `get_metrics()` for more information on the default metrics used. See the *Customising metrics* section below for information on how to pass custom arguments to scoring functions.

`...` Currently unused. You *cannot* pass additional arguments to scoring functions via `...`. See the *Customising metrics* section below for details on how to use `purrr::partial()` to pass arguments to individual metrics.

Details

Customising metrics

If you want to pass arguments to a scoring function, you need change the scoring function itself via e.g. `purrr::partial()` and pass an updated list of functions with your custom metric to the `metrics` argument in `score()`. For example, to use `interval_coverage()` with `interval_range = 90`, you would define a new function, e.g. `interval_coverage_90 <- purrr::partial(interval_coverage, interval_range = 90)` and pass this new function to `metrics` in `score()`.

Note that if you want to pass a variable as an argument, you can unquote it with `!!` to make sure the value is evaluated only once when the function is created. Consider the following example:

```
custom_arg <- "foo"
print1 <- purrr::partial(print, x = custom_arg)
print2 <- purrr::partial(print, x = !!custom_arg)

custom_arg <- "bar"
print1() # prints 'bar'
print2() # prints 'foo'
```

Value

An object of class `scores`. This object is a data.table with unsummarised scores (one score per forecast) and has an additional attribute `metrics` with the names of the metrics used for scoring. See `summarise_scores()`) for information on how to summarise scores.

Author(s)

Nikos Bosse <`nikosbosse@gmail.com`>

References

Bosse NI, Gruson H, Cori A, van Leeuwen E, Funk S, Abbott S (2022) Evaluating Forecasts with scoringutils in R. doi:10.48550/arXiv.2205.07090

Examples

```
library(magrittr) # pipe operator


validated <- as_forecast_quantile(example_quantile)
score(validated) %>%
  summarise_scores(by = c("model", "target_type"))

# set forecast unit manually (to avoid issues with scoringutils trying to
# determine the forecast unit automatically)
example_quantile %>%
  as_forecast_quantile(
    forecast_unit = c(
      "location", "target_end_date", "target_type", "horizon", "model"
    )
  ) %>%
  score()

# forecast formats with different metrics
## Not run:
score(as_forecast_binary(example_binary))
score(as_forecast_quantile(example_quantile))
score(as_forecast_point(example_point))
score(as_forecast_sample(example_sample_discrete))
score(as_forecast_sample(example_sample_continuous))

## End(Not run)
```

---

scoring-functions-binary

Metrics for binary outcomes

Description

Brier score

The Brier Score is the mean squared error between the probabilistic prediction and the observed outcome. The Brier score is a proper scoring rule. Small values are better (best is 0, the worst is 1).

$$\text{Brier\_Score} = (\text{prediction} - \text{outcome})^2,$$

where outcome $\in \{0, 1\}$, and prediction $\in [0, 1]$ represents the probability that the outcome is equal to 1.

Log score for binary outcomes

The Log Score is the negative logarithm of the probability assigned to the observed value. It is a proper scoring rule. Small values are better (best is zero, worst is infinity).

Usage

```
brier_score(observed, predicted)

logs_binary(observed, predicted)
```

Arguments

`observed`	A factor of length n with exactly two levels, holding the observed values. The highest factor level is assumed to be the reference level. This means that `predicted` represents the probability that the observed value is equal to the highest factor level.
`predicted`	A numeric vector of length n, holding probabilities. Values represent the probability that the corresponding outcome is equal to the highest level of the factor `observed`.

Details

The functions require users to provide observed values as a factor in order to distinguish its input from the input format required for scoring point forecasts. Internally, however, factors will be converted to numeric values. A factor `observed = factor(c(0, 1, 1, 0, 1)` with two levels (`0` and `1`) would internally be coerced to a numeric vector (in this case this would result in the numeric vector `c(1, 2, 2, 1, 1)`). After subtracting 1, the resulting vector (`c(0, 1, 1, 0)` in this case) is used for internal calculations. All predictions are assumed represent the probability that the outcome is equal of the last/highest factor level (in this case that the outcome is equal to 1).

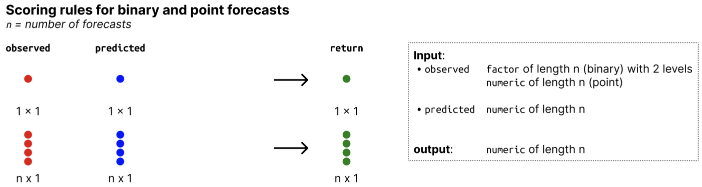
You could alternatively also provide a vector like `observed = factor(c("a", "b", "b", "a"))` (with two levels, `a` and `b`), which would result in exactly the same internal representation. Probabilities then represent the probability that the outcome is equal to "b". If you want your predictions to be probabilities that the outcome is "a", then you could of course make `observed` a factor with levels swapped, i.e. `observed = factor(c("a", "b", "b", "a"), levels = c("b", "a"))`

Value

A numeric vector of size n with the Brier scores

A numeric vector of size n with log scores

Input format



See Also

Other log score functions: `logs_nominal()`, `logs_sample()`

Examples

```
observed <- factor(sample(c(0, 1), size = 30, replace = TRUE))
predicted <- runif(n = 30, min = 0, max = 1)

brier_score(observed, predicted)
logs_binary(observed, predicted)
```

`select_metrics` *Select metrics from a list of functions*

Description

Helper function to return only the scoring rules selected by the user from a list of possible functions.

Usage

```
select_metrics(metrics, select = NULL, exclude = NULL)
```

Arguments

`metrics`	A list of scoring functions.
`select`	A character vector of scoring rules to select from the list. If `select` is `NULL` (the default), all possible scoring rules are returned.
`exclude`	A character vector of scoring rules to exclude from the list. If `select` is not `NULL`, this argument is ignored.

Value

A list of scoring functions.

Examples

```
select_metrics(
  metrics = get_metrics(example_binary),
  select = "brier_score"
)
select_metrics(
  metrics = get_metrics(example_binary),
  exclude = "log_score"
)
```

`set_forecast_unit` *Set unit of a single forecast manually*

Description

Helper function to set the unit of a single forecast (i.e. the combination of columns that uniquely define a single forecast) manually. This simple function keeps the columns specified in `forecast_unit` (plus additional protected columns, e.g. for observed values, predictions or quantile levels) and removes duplicate rows. `set_forecast_unit()` will mainly be called when constructing a `forecast` object via the `forecast_unit` argument in `as_forecast_<type>`.

If not done explicitly, `scoringutils` attempts to determine the unit of a single forecast automatically by simply assuming that all column names are relevant to determine the forecast unit. This may lead to unexpected behaviour, so setting the forecast unit explicitly can help make the code easier to debug and easier to read.

Usage

```
set_forecast_unit(data, forecast_unit)
```

Arguments

`data`	A data.frame (or similar) with predicted and observed values. See the details section of for additional information on the required input format.
`forecast_unit`	Character vector with the names of the columns that uniquely identify a single forecast.

Value

A data.table with only those columns kept that are relevant to scoring or denote the unit of a single forecast as specified by the user.

Examples

```
library(magrittr) # pipe operator
example_quantile %>%
  scoringutils:::set_forecast_unit(
    c("location", "target_end_date", "target_type", "horizon", "model")
  )
```

se_mean_sample *Squared error of the mean (sample-based version)*

Description

Squared error of the mean calculated as

$$\text{mean}(\text{observed} - \text{mean prediction})^2$$

The mean prediction is calculated as the mean of the predictive samples.

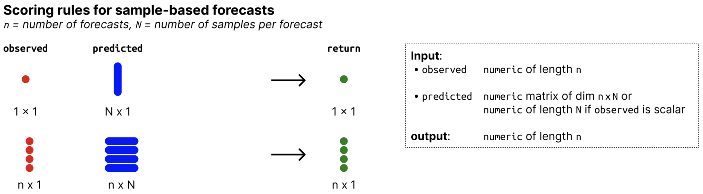
Usage

```
se_mean_sample(observed, predicted)
```

Arguments

`observed`	A vector with observed values of size n
`predicted`	nxN matrix of predictive samples, n (number of rows) being the number of data points and N (number of columns) the number of Monte Carlo samples. Alternatively, `predicted` can just be a vector of size n.

Input format



Scoring rules for sample-based forecasts

n = number of forecasts, N = number of samples per forecast

Input:
- `observed` `numeric` of length `n`
- `predicted` `numeric` matrix of dim `n` x `N` or `numeric` of length `N` if `observed` is scalar

output: `numeric` of length `n`

Examples

```
observed <- rnorm(30, mean = 1:30)
predicted_values <- matrix(rnorm(30, mean = 1:30))
se_mean_sample(observed, predicted_values)
```

`summarise_scores` *Summarise scores as produced by `score()`*

Description

Summarise scores as produced by `score()`.

`summarise_scores` relies on a way to identify the names of the scores and distinguish them from columns that denote the unit of a single forecast. Internally, this is done via a stored attribute, `metrics` that stores the names of the scores. This means, however, that you need to be careful with renaming scores after they have been produced by `score()`. If you do, you also have to manually update the attribute by calling `attr(scores, "metrics") <- new_names`.

Usage

```
summarise_scores(scores, by = "model", fun = mean, ...)

summarize_scores(scores, by = "model", fun = mean, ...)
```

Arguments

`scores`	An object of class `scores` (a data.table with scores and an additional attribute `metrics` as produced by `score()`).
`by`	Character vector with column names to summarise scores by. Default is "model", i.e. scores are summarised by the "model" column.
`fun`	A function used for summarising scores. Default is `mean()`.
`...`	Additional parameters that can be passed to the summary function provided to `fun`. For more information see the documentation of the respective function.

Value

A data.table with summarised scores. Scores are summarised according to the names of the columns of the original data specified in by using the `fun` passed to `summarise_scores()`.

Examples

```
library(magrittr) # pipe operator
scores <- example_sample_continuous %>%
 as_forecast_sample() %>%
 score()

# get scores by model
summarise_scores(scores, by = "model")

# get scores by model and target type
summarise_scores(scores, by = c("model", "target_type"))

# get standard deviation
```

```
summarise_scores(scores, by = "model", fun = sd)

# round digits
summarise_scores(scores, by = "model") %>%
  summarise_scores(fun = signif, digits = 2)
```

test_columns_not_present *Test whether column names are NOT present in a data.frame*

Description

The function checks whether all column names are NOT present. If none of the columns are present, the function returns TRUE. If one or more columns are present, the function returns FALSE.

Usage

```
test_columns_not_present(data, columns)
```

Arguments

data	A data.frame or similar to be checked
columns	A character vector of column names to check

Value

Returns TRUE if none of the columns are present and FALSE otherwise

test_columns_present *Test whether all column names are present in a data.frame*

Description

The function checks whether all column names are present. If one or more columns are missing, the function returns FALSE. If all columns are present, the function returns TRUE.

Usage

```
test_columns_present(data, columns)
```

Arguments

data	A data.frame or similar to be checked
columns	A character vector of column names to check

Value

Returns TRUE if all columns are present and FALSE otherwise

theme_scoringutils *Scoringutils ggplot2 theme*

Description

A theme for ggplot2 plots used in `scoringutils`.

Usage

```
theme_scoringutils()
```

Value

A ggplot2 theme

transform_forecasts *Transform forecasts and observed values*

Description

Function to transform forecasts and observed values before scoring.

Usage

```
transform_forecasts(
  forecast,
  fun = log_shift,
  append = TRUE,
  label = "log",
  ...
)
```

Arguments

`forecast` A forecast object (a validated data.table with predicted and observed values).

`fun` A function used to transform both observed values and predictions. The default function is `log_shift()`, a custom function that is essentially the same as `log()`, but has an additional arguments (`offset`) that allows you add an offset before applying the logarithm. This is often helpful as the natural log transformation is not defined at zero. A common, and pragmatic solution, is to add a small offset to the data before applying the log transformation. In our work we have often used an offset of 1 but the precise value will depend on your application.

append	Logical, defaults to TRUE. Whether or not to append a transformed version of the data to the currently existing data (TRUE). If selected, the data gets transformed and appended to the existing data, making it possible to use the outcome directly in score(). An additional column, 'scale', gets created that denotes which rows or untransformed ('scale' has the value "natural") and which have been transformed ('scale' has the value passed to the argument label).
label	A string for the newly created 'scale' column to denote the newly transformed values. Only relevant if append = TRUE.
...	Additional parameters to pass to the function you supplied. For the default option of log_shift() this could be the offset argument.

Details

There are a few reasons, depending on the circumstances, for why this might be desirable (check out the linked reference for more info). In epidemiology, for example, it may be useful to log-transform incidence counts before evaluating forecasts using scores such as the weighted interval score (WIS) or the continuous ranked probability score (CRPS). Log-transforming forecasts and observations changes the interpretation of the score from a measure of absolute distance between forecast and observation to a score that evaluates a forecast of the exponential growth rate. Another motivation can be to apply a variance-stabilising transformation or to standardise incidence counts by population.

Note that if you want to apply a transformation, it is important to transform the forecasts and observations and then apply the score. Applying a transformation after the score risks losing propriety of the proper scoring rule.

Value

A forecast object with either a transformed version of the data, or one with both the untransformed and the transformed data. includes the original data as well as a transformation of the original data. There will be one additional column, 'scale', present which will be set to "natural" for the untransformed forecasts.

Author(s)

Nikos Bosse <nikosbosse@gmail.com>

References

Transformation of forecasts for evaluating predictive performance in an epidemiological context Nikos I. Bosse, Sam Abbott, Anne Cori, Edwin van Leeuwen, Johannes Bracher, Sebastian Funk medRxiv 2023.01.23.23284722 doi:10.1101/2023.01.23.23284722 https://www.medrxiv.org/content/10.1101/2023.01.23.23284722v1

Examples

```
library(magrittr) # pipe operator

# transform forecasts using the natural logarithm
# negative values need to be handled (here by replacing them with 0)
```

```
example_quantile %>%
  .[, observed := ifelse(observed < 0, 0, observed)] %>%
  as_forecast_quantile() %>%
# Here we use the default function log_shift() which is essentially the same
# as log(), but has an additional arguments (offset) that allows you add an
# offset before applying the logarithm.
  transform_forecasts(append = FALSE) %>%
  head()

# alternatively, integrating the truncation in the transformation function:
example_quantile %>%
  as_forecast_quantile() %>%
 transform_forecasts(
   fun = function(x) {log_shift(pmax(0, x))}, append = FALSE
 ) %>%
 head()

# specifying an offset for the log transformation removes the
# warning caused by zeros in the data
example_quantile %>%
  as_forecast_quantile() %>%
  .[, observed := ifelse(observed < 0, 0, observed)] %>%
  transform_forecasts(offset = 1, append = FALSE) %>%
  head()

# adding square root transformed forecasts to the original ones
example_quantile %>%
  .[, observed := ifelse(observed < 0, 0, observed)] %>%
  as_forecast_quantile() %>%
  transform_forecasts(fun = sqrt, label = "sqrt") %>%
  score() %>%
  summarise_scores(by = c("model", "scale"))

# adding multiple transformations
example_quantile %>%
  as_forecast_quantile() %>%
  .[, observed := ifelse(observed < 0, 0, observed)] %>%
  transform_forecasts(fun = log_shift, offset = 1) %>%
  transform_forecasts(fun = sqrt, label = "sqrt") %>%
  head()
```

`validate_metrics` *Validate metrics*

Description

This function validates whether the list of metrics is a list of valid functions.

The function is used in `score()` to make sure that all metrics are valid functions.

Usage

```
validate_metrics(metrics)
```

Arguments

`metrics`	A named list with metrics. Every element should be a scoring function to be applied to the data.

Value

A named list of metrics, with those filtered out that are not valid functions

wis *Weighted interval score (WIS)*

Description

The WIS is a proper scoring rule used to evaluate forecasts in an interval- / quantile-based format. See Bracher et al. (2021). Smaller values are better.

As the name suggest the score assumes that a forecast comes in the form of one or multiple central prediction intervals. A prediction interval is characterised by a lower and an upper bound formed by a pair of predictive quantiles. For example, a 50% central prediction interval is formed by the 0.25 and 0.75 quantiles of the predictive distribution.

Interval score

The interval score (IS) is the sum of three components: overprediction, underprediction and dispersion. For a single prediction interval only one of the components is non-zero. If for a single prediction interval the observed value is below the lower bound, then the interval score is equal to the absolute difference between the lower bound and the observed value ("underprediction"). "Overprediction" is defined analogously. If the observed value falls within the bounds of the prediction interval, then the interval score is equal to the width of the prediction interval, i.e. the difference between the upper and lower bound. For a single interval, we therefore have:

$$\text{IS} = (\text{upper} - \text{lower}) + \frac{2}{\alpha}(\text{lower} - \text{observed}) * \mathbf{1}(\text{observed} < \text{lower}) + \frac{2}{\alpha}(\text{observed} - \text{upper}) * \mathbf{1}(\text{observed} > \text{upper})$$

where $\mathbf{1}()$ is the indicator function and indicates how much is outside the prediction interval. α is the decimal value that indicates how much is outside the prediction interval. For a 90% prediction interval, for example, α is equal to 0.1. No specific distribution is assumed, but the interval formed by the quantiles has to be symmetric around the median (i.e you can't use the 0.1 quantile as the lower bound and the 0.7 quantile as the upper bound). Non-symmetric quantiles can be scored using the function `quantile_score()`.

For a set of $k = 1, \ldots, K$ prediction intervals and the median m, we can compute a weighted interval score (WIS) as the sum of the interval scores for individual intervals:

$$\text{WIS}_{\alpha_{\{0:K\}}}(F, y) = \frac{1}{K + 1/2} \times \left(w_0 \times |y - m| + \sum_{k=1}^{K} \{ w_k \times \text{IS}_{\alpha_k}(F, y) \} \right)$$

The individual scores are usually weighted with $w_k = \frac{\alpha_k}{2}$. This weight ensures that for an increasing number of equally spaced quantiles, the WIS converges to the continuous ranked probability score (CRPS).

Quantile score

In addition to the interval score, there also exists a quantile score (QS) (see `quantile_score()`), which is equal to the so-called pinball loss. The quantile score can be computed for a single quantile (whereas the interval score requires two quantiles that form an interval). However, the intuitive decomposition into overprediction, underprediction and dispersion does not exist for the quantile score.

Two versions of the weighted interval score

There are two ways to conceptualise the weighted interval score across several quantiles / prediction intervals and the median.

In one view, you would treat the WIS as the average of quantile scores (and the median as 0.5-quantile) (this is the default for `wis()`). In another view, you would treat the WIS as the average of several interval scores + the difference between the observed value and median forecast. The effect of that is that in contrast to the first view, the median has twice as much weight (because it is weighted like a prediction interval, rather than like a single quantile). Both are valid ways to conceptualise the WIS and you can control the behaviour with the `count_median_twice`-argument.

WIS components: WIS components can be computed individually using the functions `overprediction`, `underprediction`, and `dispersion.`

Usage

```
wis(
  observed,
  predicted,
  quantile_level,
  separate_results = FALSE,
  weigh = TRUE,
  count_median_twice = FALSE,
  na.rm = FALSE
)

dispersion_quantile(observed, predicted, quantile_level, ...)

overprediction_quantile(observed, predicted, quantile_level, ...)

underprediction_quantile(observed, predicted, quantile_level, ...)
```

Arguments

`observed` Numeric vector of size n with the observed values.

`predicted` Numeric nxN matrix of predictive quantiles, n (number of rows) being the number of forecasts (corresponding to the number of observed values) and N (number of columns) the number of quantiles per forecast. If `observed` is just a single number, then predicted can just be a vector of size N.

`quantile_level` Vector of of size N with the quantile levels for which predictions were made.

`separate_results`
: Logical. If `TRUE` (default is `FALSE`), then the separate parts of the interval score (dispersion penalty, penalties for over- and under-prediction get returned as separate elements of a list). If you want a `data.frame` instead, simply call `as.data.frame()` on the output.

`weigh`
: Logical. If `TRUE` (the default), weigh the score by $\alpha/2$, so it can be averaged into an interval score that, in the limit (for an increasing number of equally spaced quantiles/prediction intervals), corresponds to the CRPS. α is the value that corresponds to the $(\alpha/2)$ or $(1 - \alpha/2)$, i.e. it is the decimal value that represents how much is outside a central prediction interval (E.g. for a 90 percent central prediction interval, alpha is 0.1).

`count_median_twice`
: If TRUE, count the median twice in the score.

`na.rm`
: If TRUE, ignore NA values when computing the score.

`...`
: Additional arguments passed on to `wis()` from functions `overprediction_quantile()`, `underprediction_quantile()` and `dispersion_quantile()`.

Value

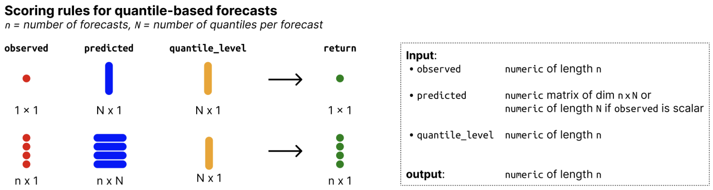
`wis()`: a numeric vector with WIS values of size n (one per observation), or a list with separate entries if `separate_results` is `TRUE`.

`dispersion_quantile()`: a numeric vector with dispersion values (one per observation).

`overprediction_quantile()`: a numeric vector with overprediction values (one per observation).

`underprediction_quantile()`: a numeric vector with underprediction values (one per observation)

Input format


Scoring rules for quantile-based forecasts
n = number of forecasts, N = number of quantiles per forecast
observed
predicted
quantile_level
return
1 × 1
N x 1
N x 1
1 × 1
n x 1
n x N
N x 1
n x 1

Input:
- `observed` — `numeric` of length `n`
- `predicted` — `numeric` matrix of dim `n` x `N` or `numeric` of length `N` if `observed` is scalar
- `quantile_level` — `numeric` of length `n`

output: `numeric` of length `n`

References

Evaluating epidemic forecasts in an interval format, Johannes Bracher, Evan L. Ray, Tilmann Gneiting and Nicholas G. Reich, 2021, https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1008618

Examples

```
observed <- c(1, -15, 22)
predicted <- rbind(
  c(-1, 0, 1, 2, 3),
  c(-2, 1, 2, 2, 4),
  c(-2, 0, 3, 3, 4)
)
quantile_level <- c(0.1, 0.25, 0.5, 0.75, 0.9)
wis(observed, predicted, quantile_level)
```

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