R package scoringRules: Getting started

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This vignette provides a two-page introduction to the *scoringRules* package. For a more detailed introduction, see the paper 'Evaluating probabilistic forecasts with scoringRules' (Jordan, Krüger, and Lerch, *Journal of Statistical Software* 90, 2019) which is available as a further vignette to *scoringRules*.

Background

Forecasting a continuous random variable, such as temperature (in degrees Celsius) or the inflation rate (in percent) is important in many situations. Since forecasts are usually surrounded by uncertainty, it makes sense to state forecast distributions, rather than point forecasts. The *scoringRules* package offers statistical tools to evaluate a forecast distribution, F, after an outcome y has realized. To this end, we use scoring rules which assign a penalty score $S(y, F)$ to the realization/forecast pair; a smaller score corresponds to a better forecast. See Gneiting and Katzfuss ('Probabilistic Forecasting', *Annual Review of Statistics and Its Application* 1, 2014) for an introduction to the relevant statistical literature.

scoringRules supports two types of forecast distributions, F: Distributions given by a parametric family (such as Normal or Gamma), and distributions given by a simulated sample. Furthermore, the package covers the two most popular scoring rules S: The logarithmic score (LogS), given by

$$\mathrm{LogS}(y, F) = -\log f(y),$$

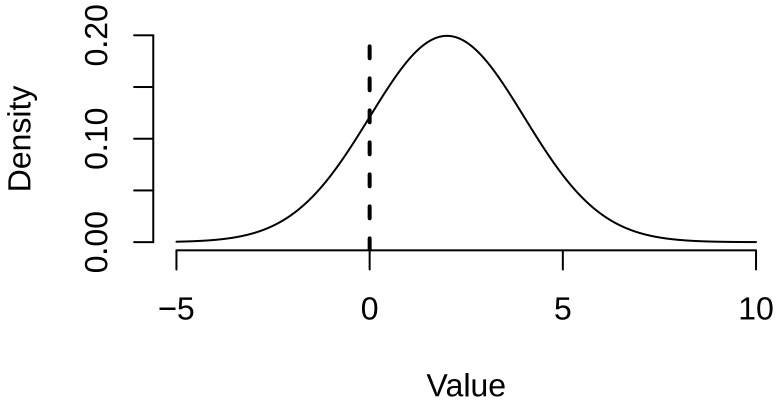
where f is the density conforming to F, and the continuous ranked probability score (CRPS), given by

$$\mathrm{CRPS}(y, F) = \int_{-\infty}^{\infty} (F(z) - \mathbf{1}(y \leq z))^2 dz,$$

where $\mathbf{1}(A)$ is the indicator function of the event A. The LogS is typically easy to compute, and we include it mainly for reference purposes. By contrast, the CRPS can be very tricky to compute analytically, and cumbersome to approximate numerically. To tackle this challenge, the *scoringRules* includes many previously unknown analytical expressions, and incorporates recent findings on how to best compute the CRPS of a simulated forecast distribution.

Example 1: Parametric forecast distribution

Suppose the forecast distribution is $\mathcal{N}(2, 4)$, and an outcome of zero realizes:



The following piece of code computes the CRPS for this situation:

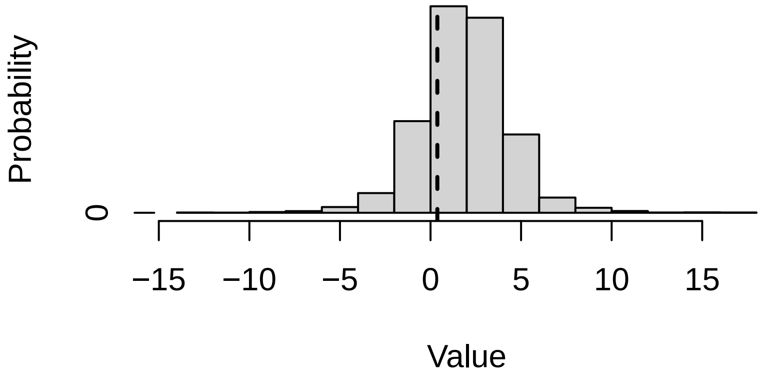
```
library(scoringRules)
# CRPS of a normal distribution with mean = standard deviation = 2, outcome is zero
crps(y = 0, family = "normal", mean = 2, sd = 2)
```

```
## [1] 1.204883
```

As documented under `?crps.numeric`, many additional parametric families have been implemented in *scoringRules*, covering both continuous and discrete random variables. Whenever possible, our syntax and parametrization closely follow base R. For distributions not supported by base R, we have created documentation pages with details; see for example `?f2pnorm`.

Example 2: Simulated forecast distribution

Via `data(gdp_mcmc)`, the user can load a sample data set with forecasts and realizations for the growth rate of US gross domestic product, a widely regarded economic indicator. The following plot shows the histogram of a simulated forecast distribution for the fourth quarter of 2012:



Let's now compute the CRPS for this simulated forecast distribution:

```
# Load data
data(gdp_mcmc)
# Get forecast distribution for 2012:Q4
dat <- gdp_mcmc$forecasts[, "X2012Q4"]
# Get realization for 2012:Q4
y <- gdp_mcmc$actuals[, "X2012Q4"]
# Compute CRPS of simulated sample
crps_sample(y = y, dat = dat)
```

```
## [1] 0.9058803
```