Evaluating forecasts from the ECDC Forecast Hub

```
library(dplyr)
library(here)
library(stringr)
library(data.table)
devtools::install_github("epiforecasts/scoringutils@major-update", force = FALSE)
library(scoringutils)
library(purrr)
library(tidyr)
library(ggplot2)
```

(Possible) Objectives

Data - Forecasts submitted to the European Forecast Hub

All forecasts are made in a quantile-based format, meaning that forecasters provide a predictive distribution in the form of 23 quantiles (11 prediction intervals plus the median prediction), specifying how likely they think the true observed value will fall in a given range.

These forecasts were submitted to the European Forecast Hub by different research institutions. The file contains forecasts as well as true observations.

The data has the following columns:

Column name	Column prediction
location_name	Name of the country
target_end_date	Date for which a forecast was made. This is always a Saturday
target_type	The target variable to be predicted, cases or deaths
true_value	The corresponding true observed value
population	population of the target country
forecast_date	Date on which a forecast was made. This is always a Monday
quantile	quantile-level of the predictive distribution
prediction	Predicted value corresponding to the quantile-level specified in 'quantile'
model	Name of the forecaster
target	Summary of the prediction target variable (redundant information)
horizon	Forecast horizon
expert	Whether or not a forecaster self-identified as an expert

Updating the data

To update the data, you must

1. either use git or subversion to downlaod the data. Git only allows to clone the entire Forecast Hub repository, svn makes it possible to only download one relevant folder

```
git clone https://github.com/epiforecasts/covid19-forecast-hub-europe/
```

or

```
svn checkout https://github.com/epiforecasts/covid19-forecast-hub-europe/trunk/data-processed
```

Then, run the script `R/update-data-from-server.R`

```
Rscript R/update-data-from-server.R
```

Loading the data

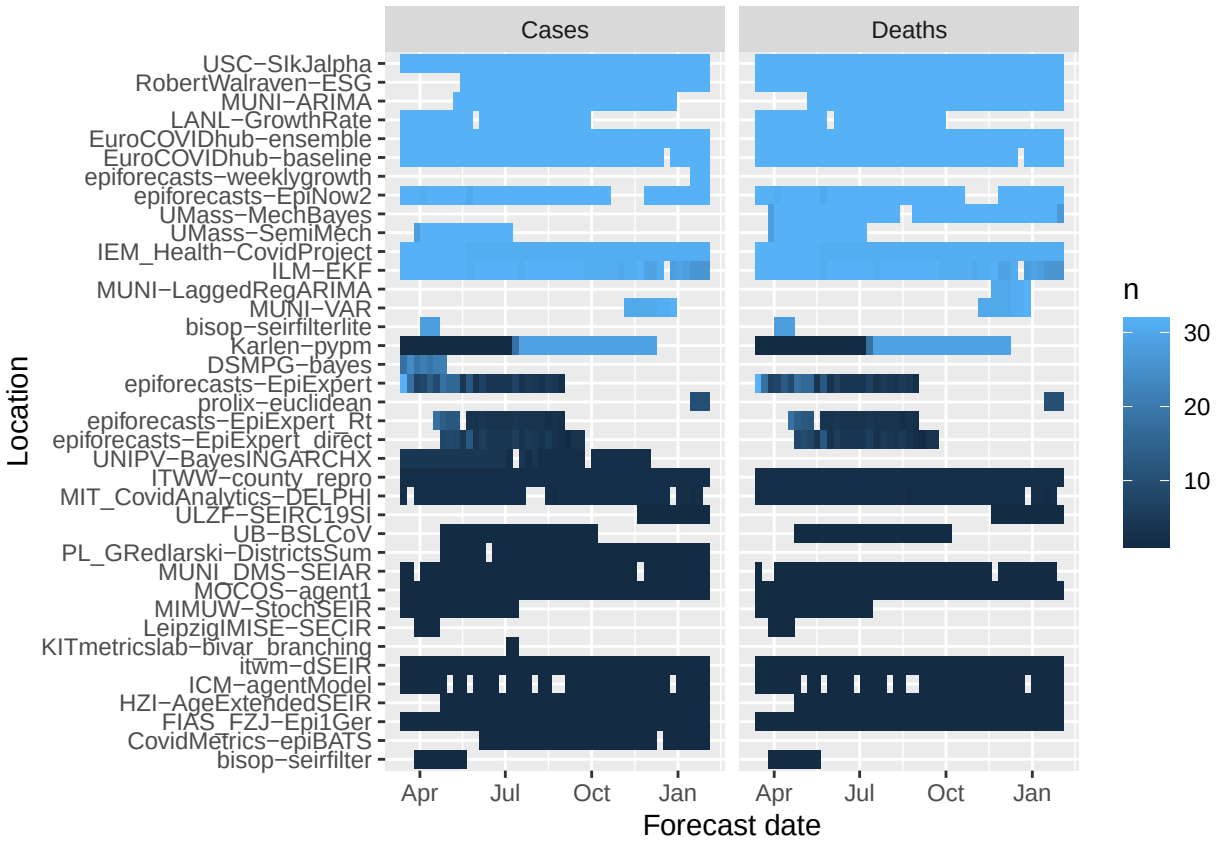
```
hub_data <- rbindlist(
  list(
    fread("data/full-data-european-forecast-hub-1.csv"),
    fread("data/full-data-european-forecast-hub-2.csv"),
    fread("data/full-data-european-forecast-hub-3.csv")
  )
)
```

Filtering data

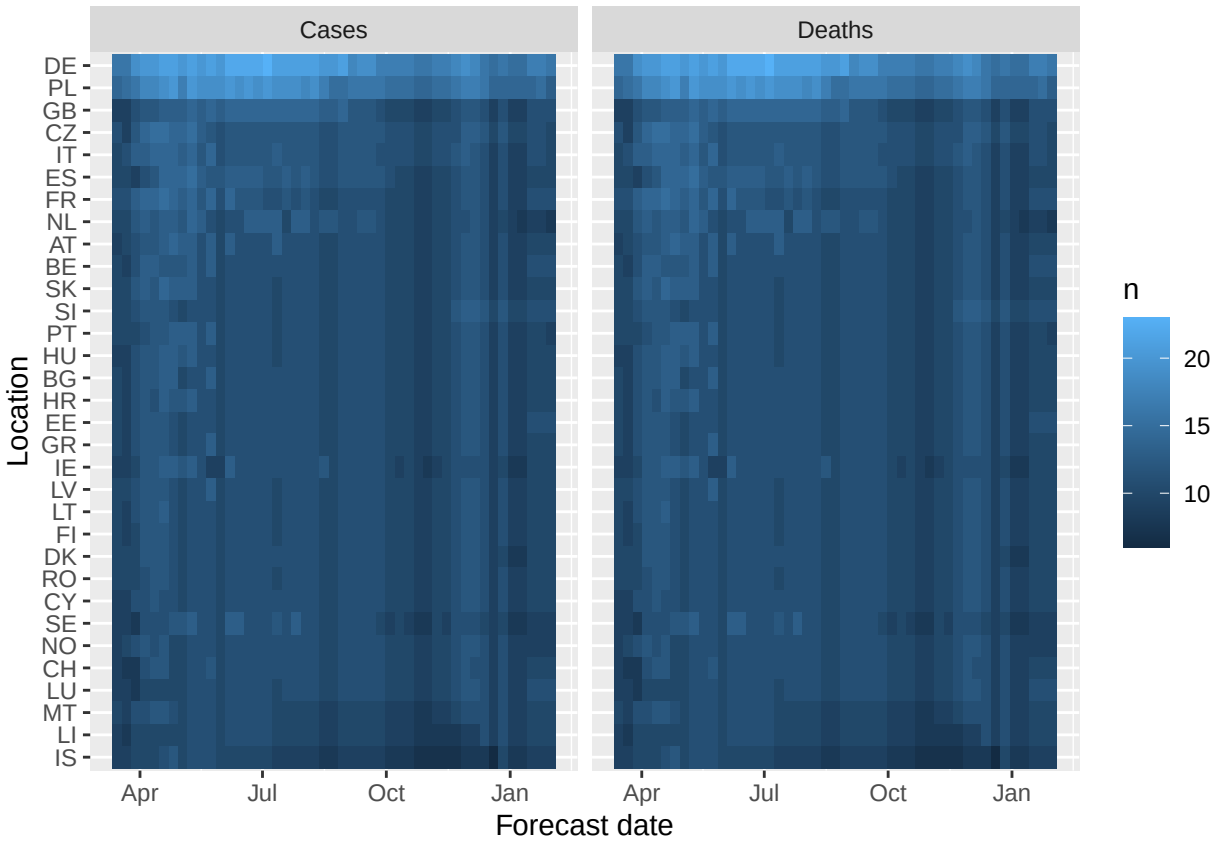
Optionally, the Hub data can be filtered to obtain a complete set of forecasts, as the current data set has missing forecasts:

```
# helper functions for visualisation
plot_models_per_loc <- function(data) {
data |>
  group_by(location, forecast_date) |>
  mutate(n = length(unique(model))) |>
  ggplot(aes(y = reorder(location, n), x = as.Date(forecast_date), fill = n)) +
  geom_tile() +
  facet_wrap(~ target_type) +
  labs(y = "Location", x = "Forecast date")
}

plot_locs_per_model <- function(data) {
data |>
  group_by(model, forecast_date) |>
  mutate(n = length(unique(location))) |>
  ggplot(aes(y = reorder(model, n), x = as.Date(forecast_date), fill = n)) +
  geom_tile() +
  facet_wrap(~ target_type) +
  labs(y = "Location", x = "Forecast date")
}
```

```
plot_locs_per_model(hub_data)
```

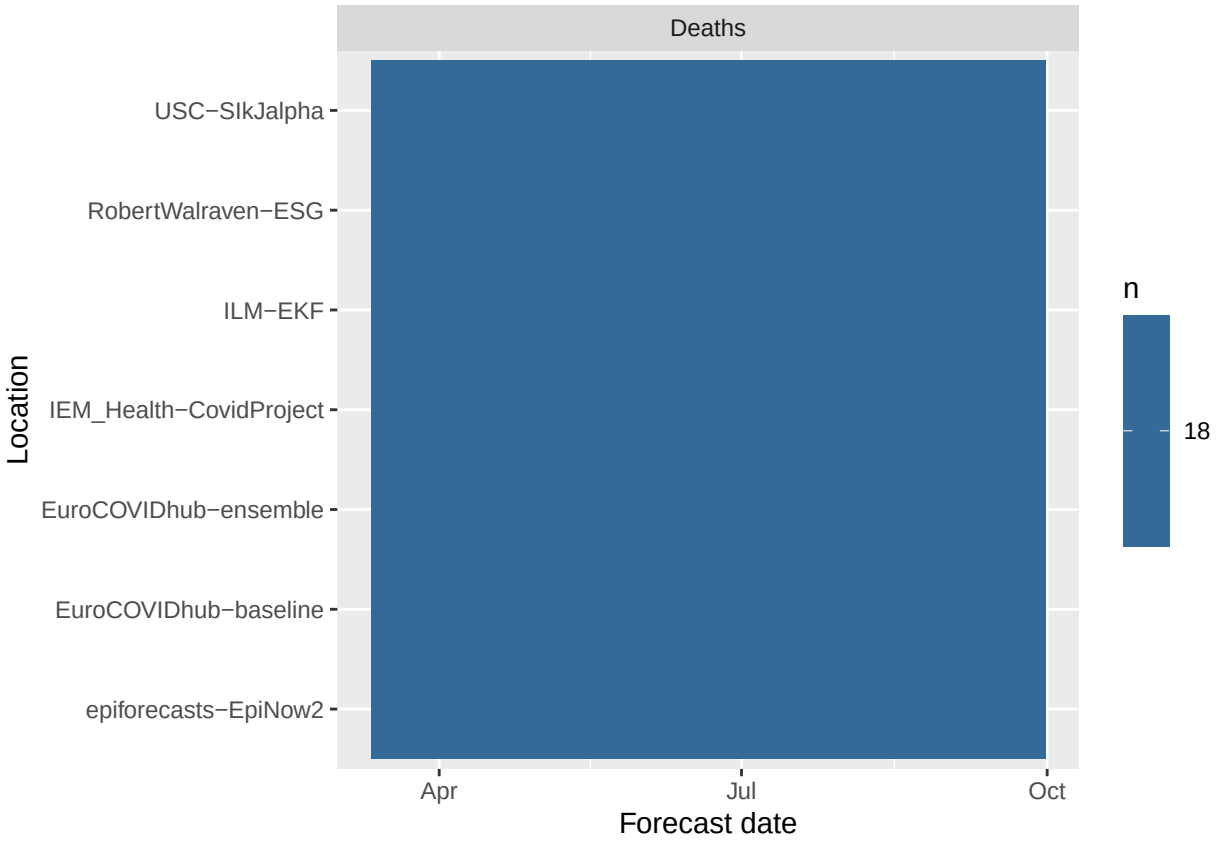



```
plot_models_per_loc(hub_data)
```

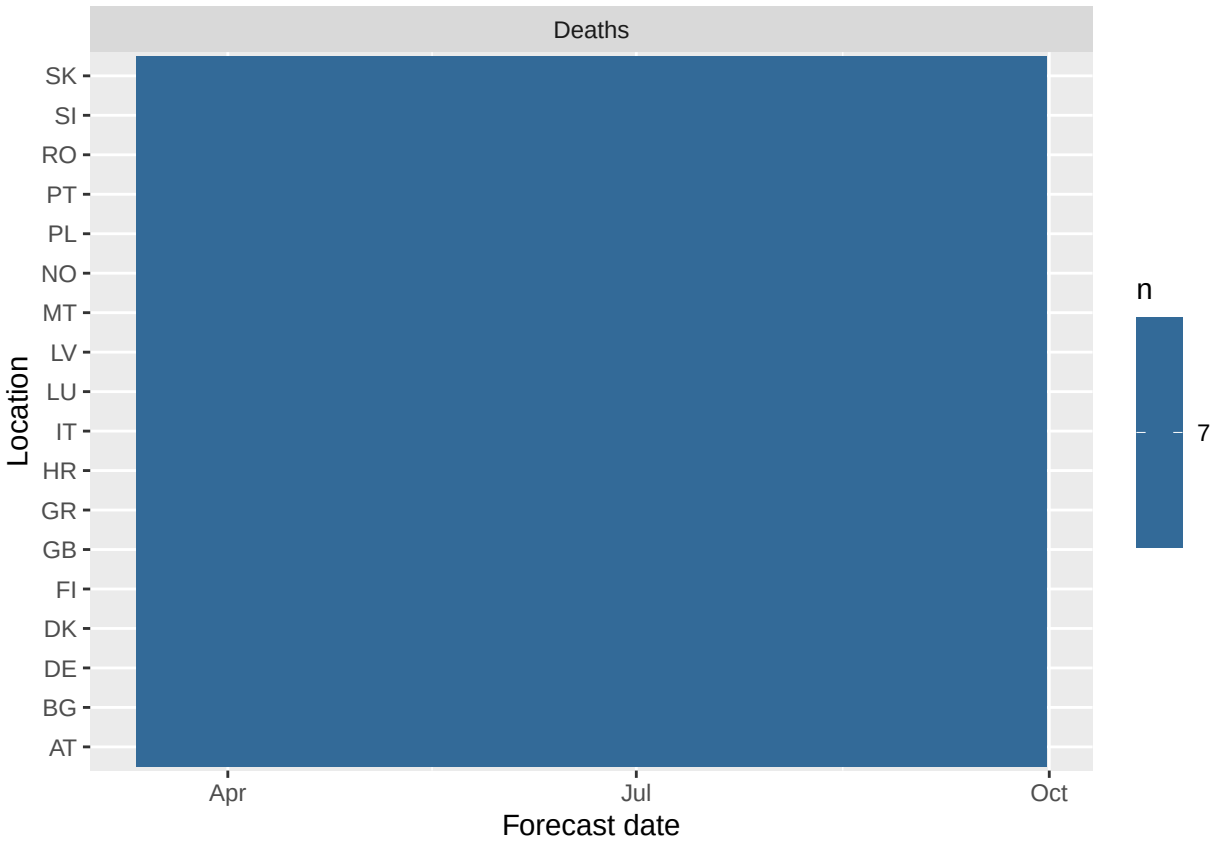



```r
# helper function to make a complete set. The data can be either complete
# per location (meaning that different locations will have different numbers of
# models) or it can be complete overall (removing models and locations)
make_complete_set <- function(hub_data,
                              forecast_dates = c("2021-03-15",
                                                 "2021-09-27"),
                              min_locations = 19,
                              per_location = FALSE) {

  # define the unit of a single forecast
  unit_observation <- c("location", "forecast_date", "horizon",
                        "model", "target_type")

  h <- hub_data |>
    # filter out models that don't have all forecast dates
    filter(forecast_date >= forecast_dates[1],
           forecast_date <= forecast_dates[2]) |>
    group_by_at(c(unit_observation)) |>
    ungroup(forecast_date) |>
    mutate(n = length(unique(forecast_date))) |>
    ungroup() |>
    filter(n == max(n))

  # per_location means a complete set per location, meaning that every location
  # has a complete set, but the numbers of models per location may be different
  # if this is not desired, we need to restrict the models and locations
```

```
  if (!per_location) {
    h <- h|>
      # filter out models that don't have at least min_locations
      group_by_at(unit_observation) |>
      ungroup(location) |>
      mutate(n = length(unique(location))) |>
      ungroup() |>
      filter(n >= min_locations) |>
      # filter out locations that don't have a full set of forecasts
      group_by(location, target_type) |>
      mutate(n = n()) |>
      ungroup() |>
      filter(n == max(n))
  }
  return(h)
}

hub_complete <- make_complete_set(hub_data)
print(plot_locs_per_model(hub_complete))
```

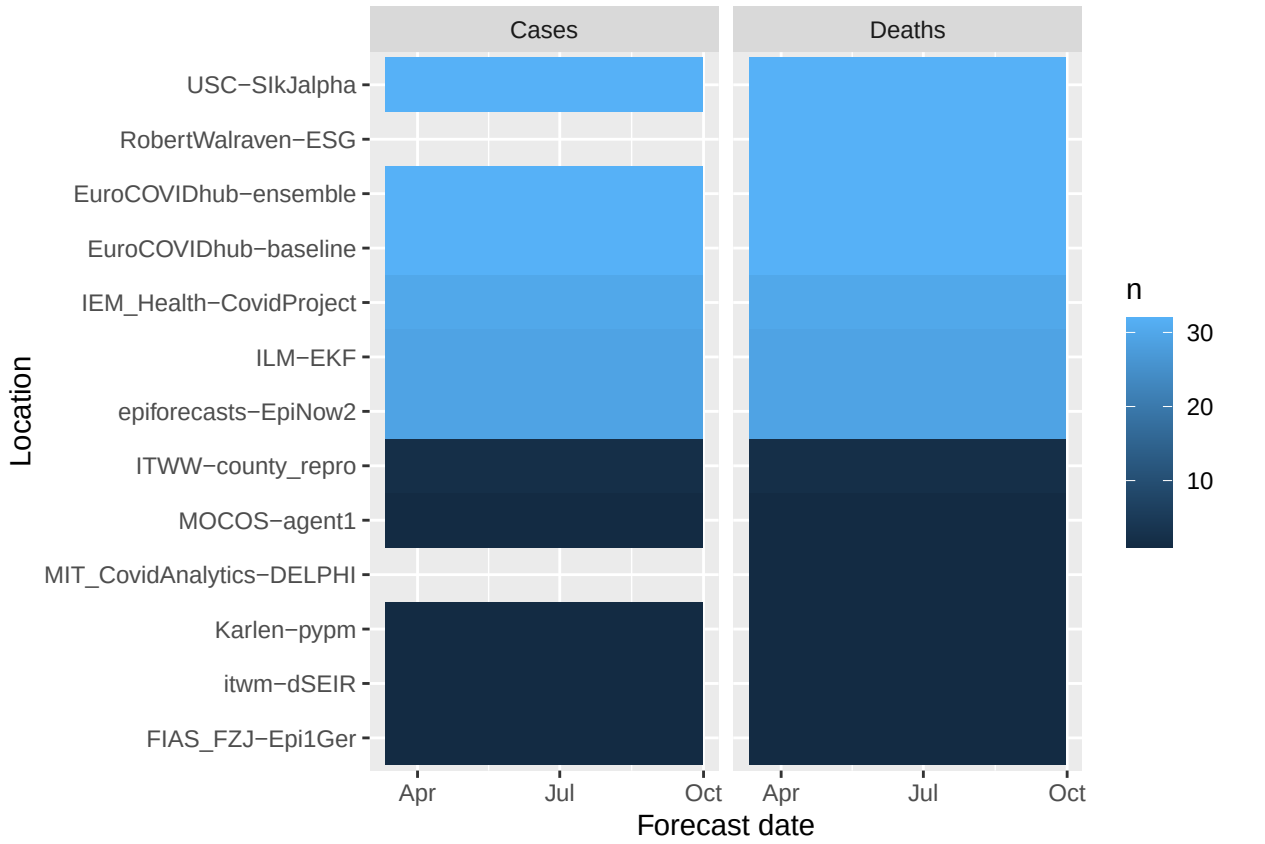



```
print(plot_models_per_loc(hub_complete))
```

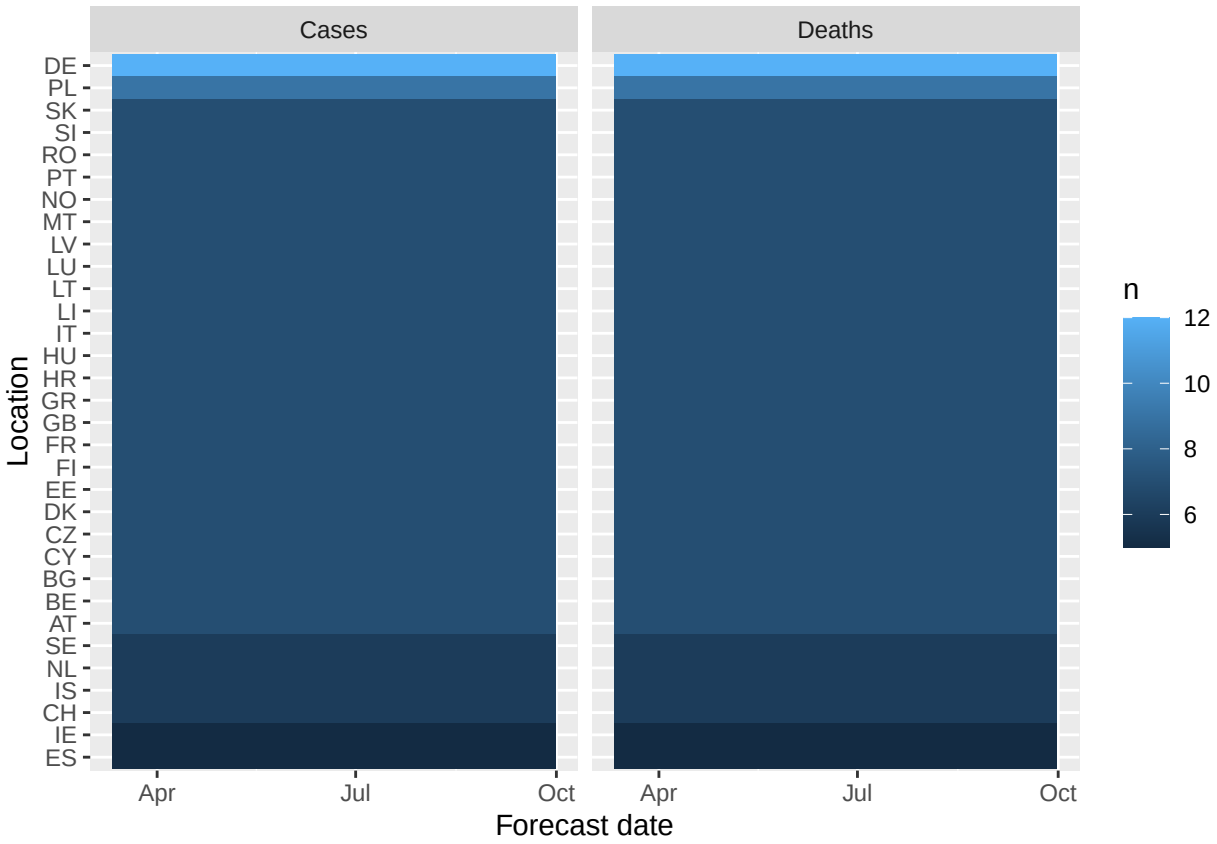


Or allowing different numbers of models per location:

```
hub_complete_loc <- make_complete_set(hub_data, per_location = TRUE)
print(plot_locs_per_model(hub_complete_loc))
```




```
plot_models_per_loc(hub_complete_loc)
```



Methods

Forecast evaluation

Proper scoring rules Forecasts in a quantile-based forecast can be evaluated using the weighted interval score (WIS, lower values are better), a proper scoring rule. Proper scoring rules incentivise the forecaster to state their true best belief and cannot be 'cheated'.

The WIS can be decomposed into three components: a penalty for dispersion (i.e. large forecast uncertainty) as well as penalties for over- and underprediction.

WIS = Dispersion + Over-prediction + Under-prediction

For a single prediction interval, the interval score is computed as

$$IS_\alpha(F, y) = (u - l) + \frac{2}{\alpha} \cdot (l - y) \cdot 1(y \leq l) + \frac{2}{\alpha} \cdot (y - u) \cdot 1(y \geq u),$$

where $1()$ is the indicator function, y is the true value, and l and u are the $\frac{\alpha}{2}$ and $1 - \frac{\alpha}{2}$ quantiles of the predictive distribution F, i.e. the lower and upper bound of a single prediction interval. For a set of K prediction intervals and the median m, the WIS is computed as a weighted sum,

$$WIS = \frac{1}{K + 0.5} \cdot (w_0 \cdot |y - m| + \sum_{k=1}^{K} w_k \cdot IS_\alpha(F, y)),$$

where w_k is a weight for every interval. Usually, $w_k = \frac{\alpha_k}{2}$ and $w_0 = 0.5$

The WIS is closely related to the absolute error. Over- and under-prediction should therefore also be understood as a form of absolute forecasting error.

Forecast calibration **Coverage** In addition to the WIS it makes sense to look at forecast calibration in terms of interval coverage. On average, all 50% or 90% prediction intervals should ideally cover 50% or 90% of the true observations. By comparing nominal and empirical coverage we can quickly determine whether a model is over- or underconfident.

Bias The over- and under-prediction penalties of the WIS capture absolute forecasting errors. In addition we can examine whether a forecast has relative tendency to over- or under-predict. This is less susceptible to large outlier predictions

PIT histograms

Probability integral transform (PIT) histograms are another way of examining forecast calibration

Evaluating forecasts in R Forecasts can be evaluated in R using the `scoringutils` package.

```
scores <- score(hub_data) |>
  summarise_scores(by = c("model", "target_type"))

scores
```