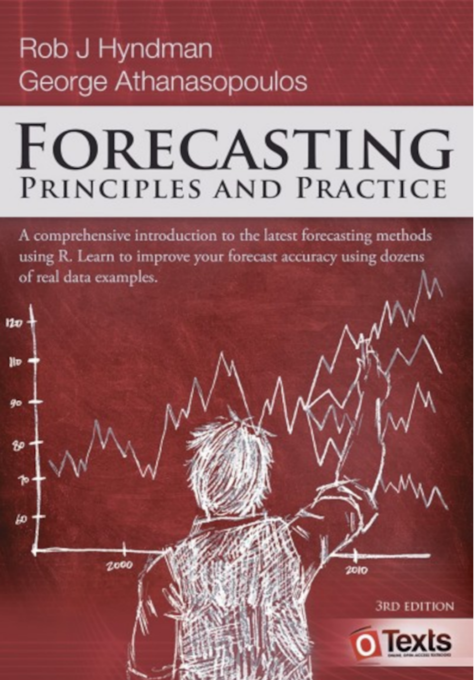

5. The forecaster’s toolbox

5.5 Distributional forecasts

OTexts.org/fpp3/

Forecast distributions

- A forecast $\hat{y}_{T+h|T}$ is (usually) the mean of the conditional distribution $y_{T+h} \mid y_1, \dots, y_T$.
- Most time series models produce normally distributed forecasts.
- The forecast distribution describes the probability of observing any future value.

Forecast distributions

Assuming residuals are normal, uncorrelated, sd = $\hat{\sigma}$:

Mean:	$y_{T+h\|T} \sim N(\bar{y}, (1 + 1/T)\hat{\sigma}^2)$
Naïve:	$y_{T+h\|T} \sim N(y_T, h\hat{\sigma}^2)$
Seasonal naïve:	$y_{T+h\|T} \sim N(y_{T+h-m(k+1)}, (k + 1)\hat{\sigma}^2)$
Drift:	$y_{T+h\|T} \sim N(y_T + \frac{h}{T-1}(y_T - y_1), h\frac{T+h}{T}\hat{\sigma}^2)$

where k is the integer part of $(h - 1)/m$.

Note that when $h = 1$ and T is large, these all give the same approximate forecast variance: $\hat{\sigma}^2$.

Prediction intervals

- A prediction interval gives a region within which we expect y_{T+h} to lie with a specified probability.
- Assuming forecast errors are normally distributed, then a 95% PI is

$$\hat{y}_{T+h|T} \pm 1.96\hat{\sigma}_h$$

  where $\hat{\sigma}_h$ is the st dev of the h-step distribution.
- When $h = 1$, $\hat{\sigma}_h$ can be estimated from the residuals.

Prediction intervals

```r
aus_production |>
  filter(!is.na(Bricks)) |>
  model(Seasonal_naive = SNAIVE(Bricks)) |>
  forecast(h = "5 years")
```

```
## # A fable: 20 x 4 [1Q]
## # Key:     .model [1]
##    .model          Quarter          Bricks .mean
##    <chr>             <qtr>          <dist> <dbl>
##  1 Seasonal_naive 2005 Q3  N(428, 2336)   428
##  2 Seasonal_naive 2005 Q4  N(397, 2336)   397
##  3 Seasonal_naive 2006 Q1  N(355, 2336)   355
##  4 Seasonal_naive 2006 Q2  N(435, 2336)   435
##  5 Seasonal_naive 2006 Q3  N(428, 4672)   428
##  6 Seasonal_naive 2006 Q4  N(397, 4672)   397
##  7 Seasonal_naive 2007 Q1  N(355, 4672)   355
```

Prediction intervals

```
aus_production |>
  filter(!is.na(Bricks)) |>
  model(Seasonal_naive = SNAIVE(Bricks)) |>
  forecast(h = "5 years") |>
  hilo(level = 95)
```

```
## # A tsibble: 20 x 5 [1Q]
## # Key:       .model [1]
##    .model         Quarter        Bricks .mean        `95%`
##    <chr>            <qtr>        <dist> <dbl>       <hilo>
##  1 Seasonal_naive 2005 Q3  N(428, 2336)   428 [333, 523]95
##  2 Seasonal_naive 2005 Q4  N(397, 2336)   397 [302, 492]95
##  3 Seasonal_naive 2006 Q1  N(355, 2336)   355 [260, 450]95
##  4 Seasonal_naive 2006 Q2  N(435, 2336)   435 [340, 530]95
##  5 Seasonal_naive 2006 Q3  N(428, 4672)   428 [294, 562]95
##  6 Seasonal_naive 2006 Q4  N(397, 4672)   397 [263, 531]95
```

Prediction intervals

```
aus_production |>
  filter(!is.na(Bricks)) |>
  model(Seasonal_naive = SNAIVE(Bricks)) |>
  forecast(h = "5 years") |>
  hilo(level = 95)  |>
  unpack_hilo("95%")
```

Prediction intervals

- Point forecasts are often useless without a measure of uncertainty (such as prediction intervals).
- Prediction intervals require a stochastic model (with random errors, etc).
- For most models, prediction intervals get wider as the forecast horizon increases.
- Use `level` argument to control coverage.
- Check residual assumptions before believing them.
- Prediction intervals are usually too narrow due to unaccounted uncertainty.