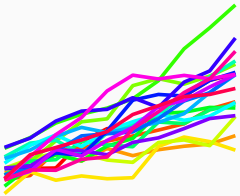
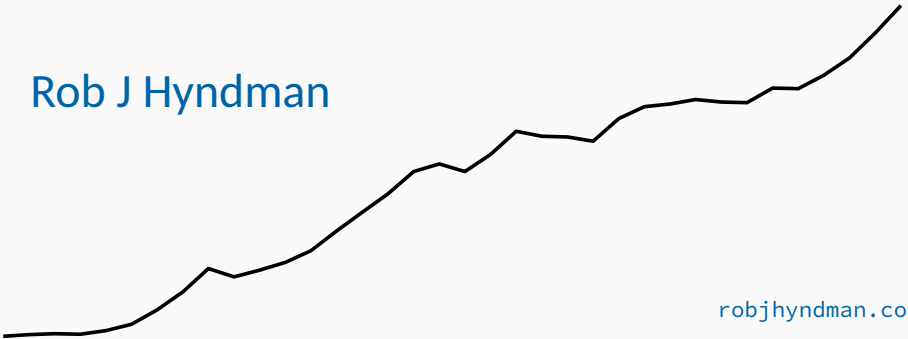
Uncertain futures: what can we forecast and when should we give up?



Rob J Hyndman



robjhyndman.com/uncertain_futures

MONASH University

Outline

1. What can we forecast?
2. Forecastability factors
3. Forecasting is difficult
4. PBS forecasting
5. COVID19 case forecasting

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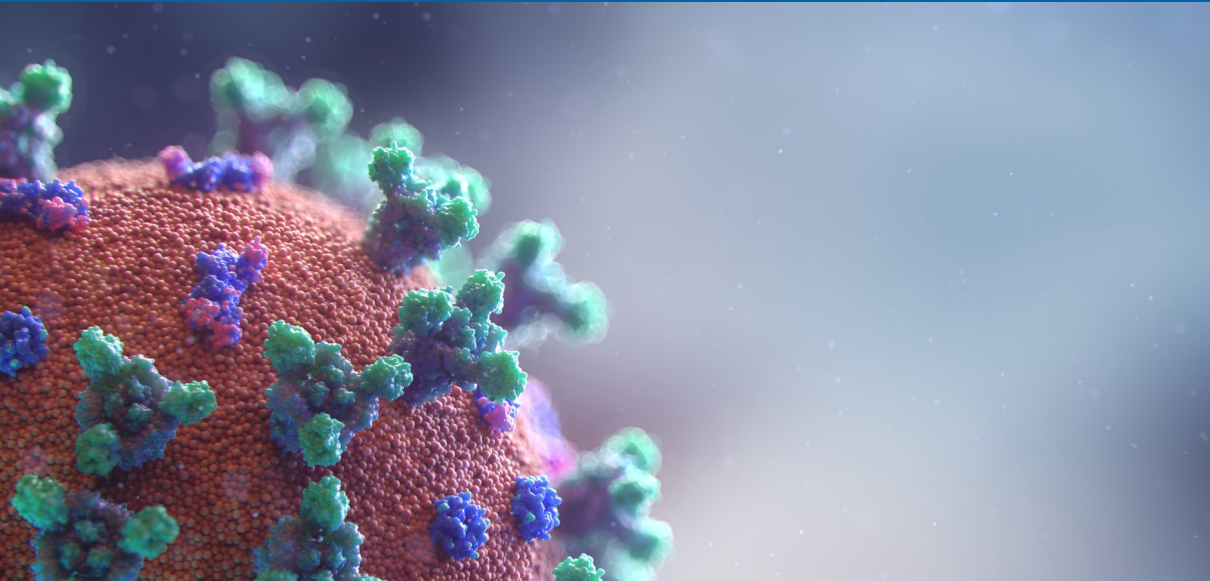

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Which is easiest to forecast?

- daily electricity demand in 3 days time
- timing of next Halley's comet appearance
- time of sunrise this day next year
- Google stock price tomorrow
- Google stock price in 6 months time
- maximum temperature tomorrow
- exchange rate of $US/AUS next week
- total sales of drugs in Australian pharmacies next month

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Forecastability factors

Something is easier to forecast if:

1. we have a good understanding of the factors that contribute to it
2. there is lots of data available;
3. the future is somewhat similar to the past
4. the forecasts cannot affect the thing we are trying to forecast.

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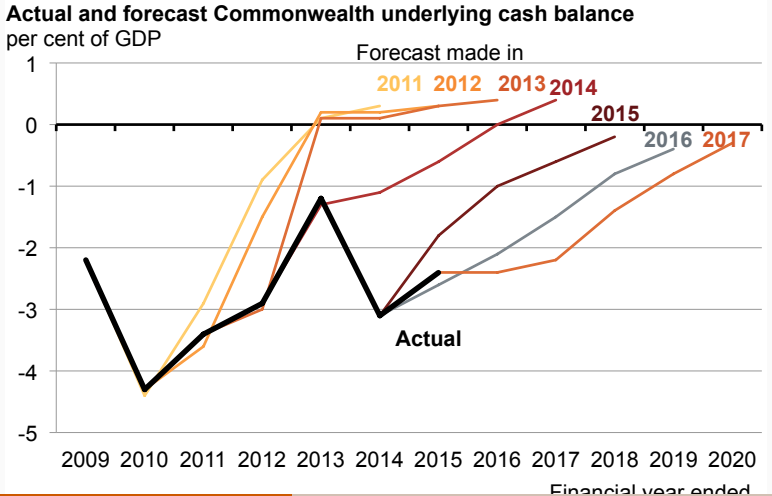
"We're going to be opening relatively soon . . . The virus . . . will go away in April." (Donald Trump, February 2020)

"We expect that Australians will be fully vaccinated by the end of October." (Scott Morrison, December 2020)

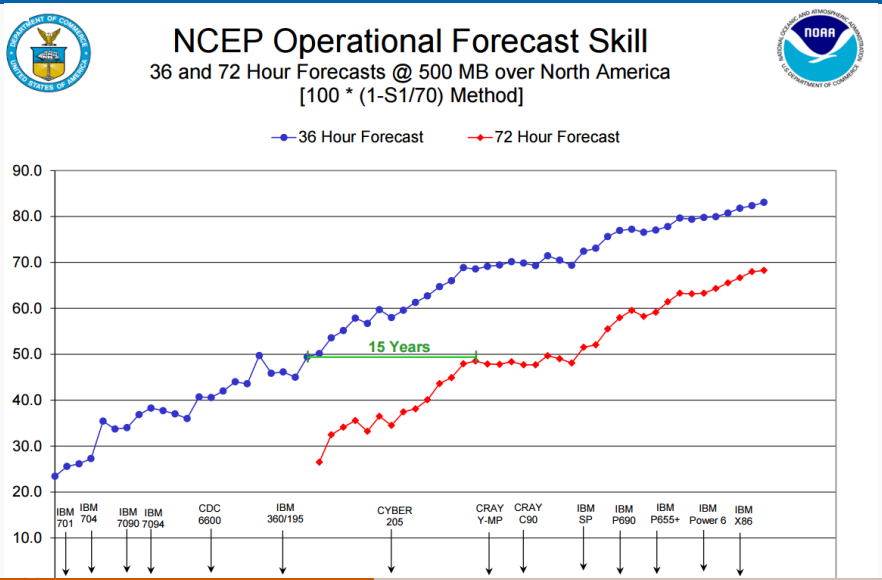
Forecasting is difficult

Commonwealth plans to drift back to surplus show the triumph of hope over experience

GRATTAN Institute



Improving forecasts



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PBS forecasting

The Pharmaceutical Benefits Scheme (PBS) is the Australian government drugs subsidy scheme.

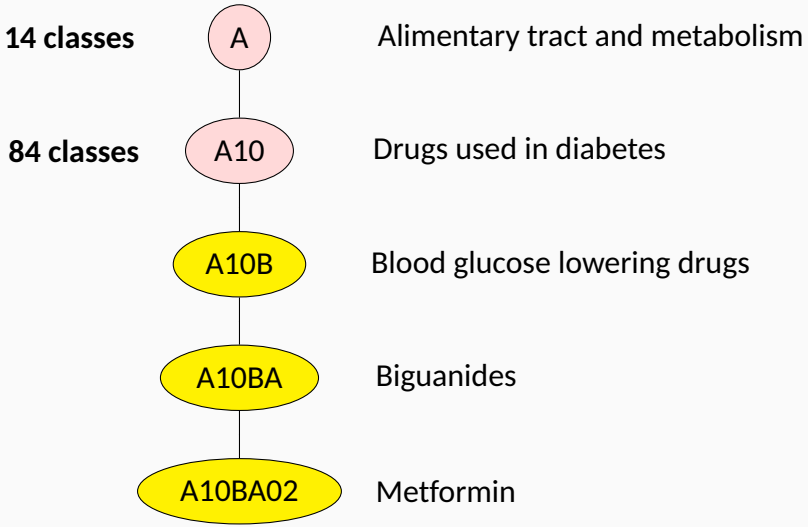
- Many drugs bought from pharmacies are subsidised to allow more equitable access to modern drugs.
- The cost to government is determined by the number and types of drugs purchased. Currently nearly 1% of GDP.
- The total cost is budgeted based on forecasts of drug usage.

PBS forecasting

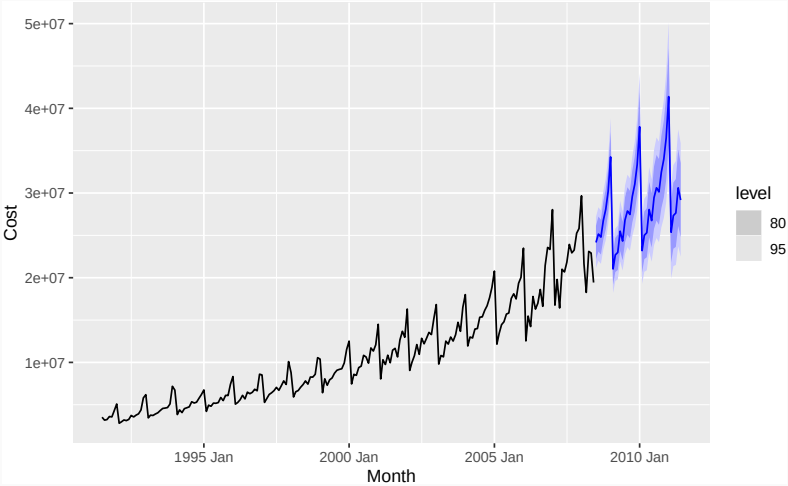
PBS forecasting

- In 2001: $4.5 billion budget, under-forecasted by $800 million.
- Thousands of products. Seasonal demand.
- Subject to covert marketing, volatile products, uncontrollable expenditure.
- Although monthly data available for 10 years, data are aggregated to annual values, and only the first three years are used in estimating the forecasts.
- All forecasts being done with the `FORECAST` function in MS-Excel!

ATC drug classification



ETS forecasts of PBS data



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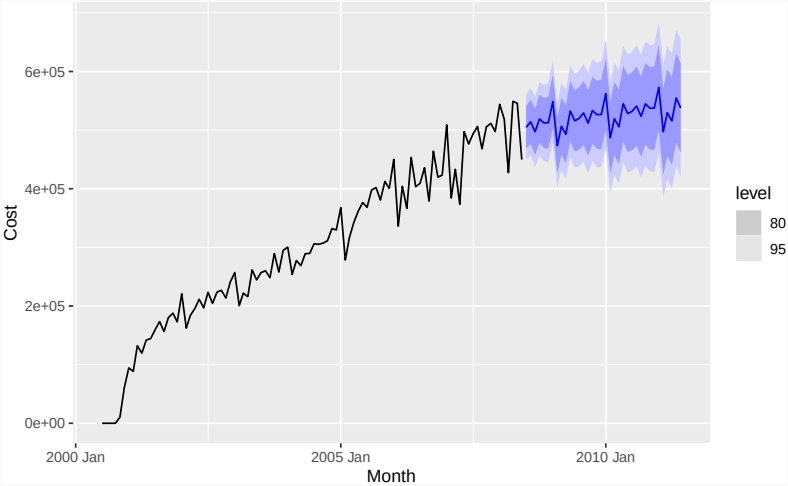

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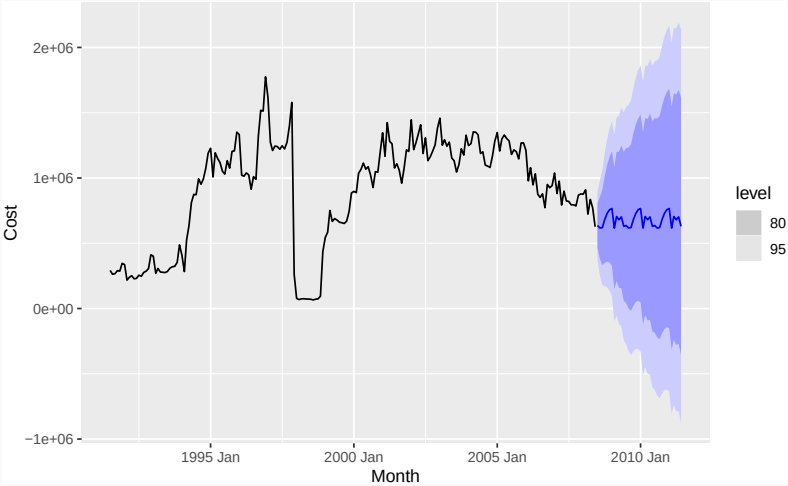

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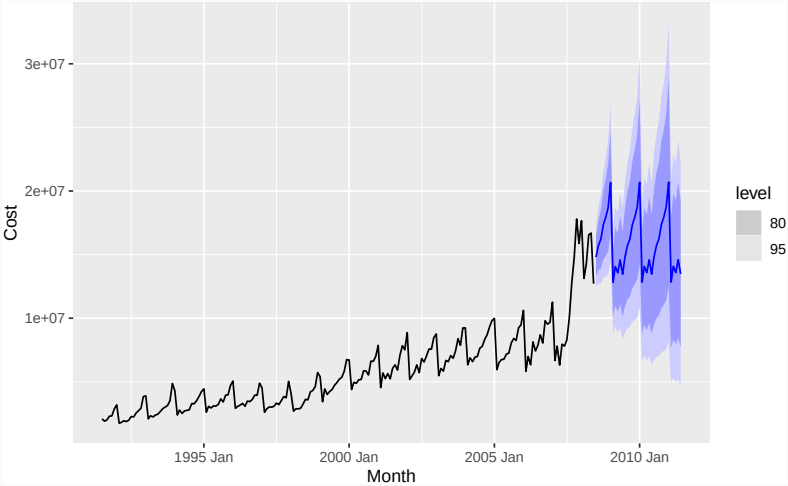

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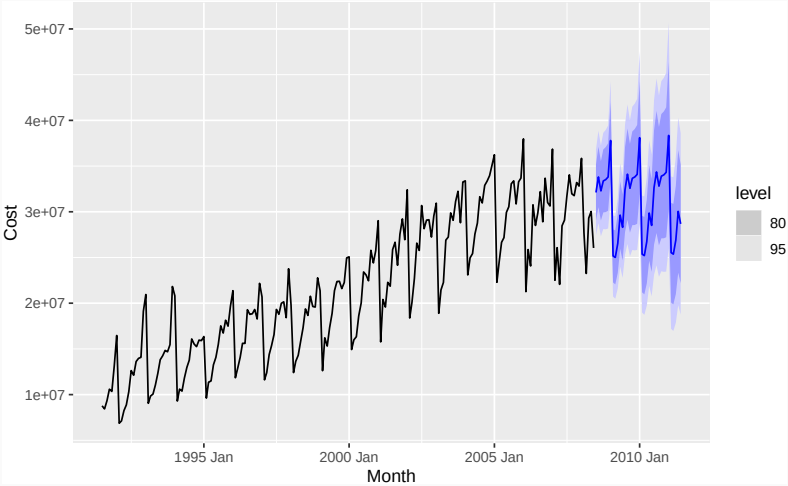

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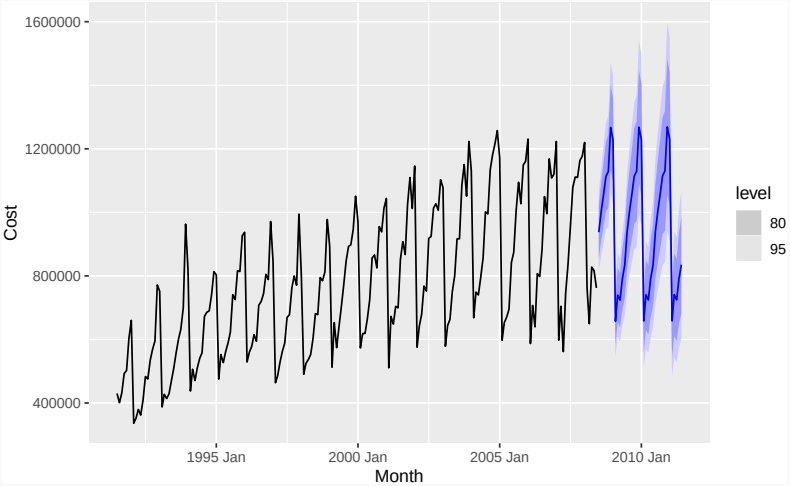

Forecasting the PBS

- As part of this project, we developed an automatic forecasting algorithm for exponential smoothing state space models based on the AIC.
- Exponential smoothing models allowed for time-changing trend and seasonal patterns.
- Forecast MAPE reduced from 15–20% to 0.6%.
- State space models provide prediction intervals which give a sense of uncertainty.
- Algorithm now implemented in R as `ets()` in forecast package and `ETS()` function in fable package.

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Data sources

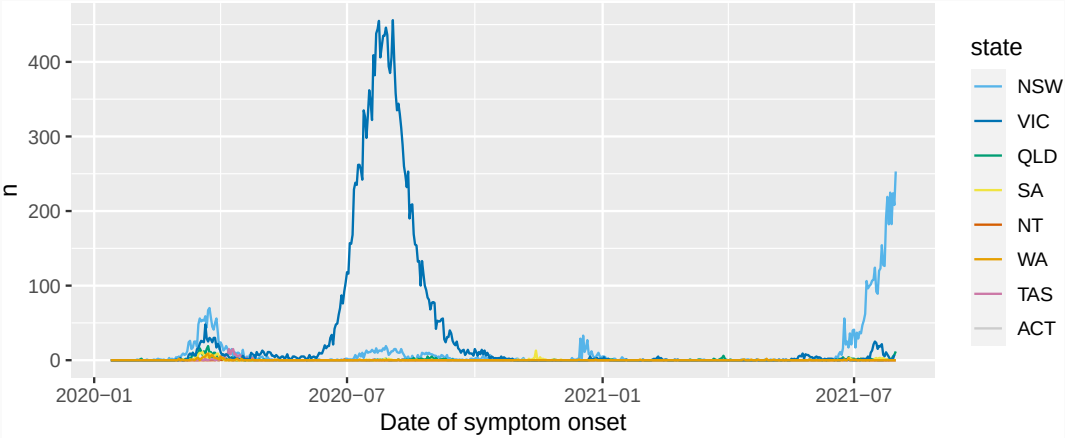
- Case-level data of all positive COVID-19 tests: onset and detection times.
- Daily population mobility data from Google, Apple & Facebook
- Weekly non-household contact surveys
- Weekly behavioural surveys
- Daily case numbers from many countries and regions via the Johns Hopkins COVID-19 repository

Case numbers

```
localcases %>% filter(state == "VIC", date >= "2020-07-01")
```

```
## # A tsibble: 395 x 3 [1D]
## # Key:       state [1]
##    date       state     n
##    <date>     <chr> <dbl>
##  1 2020-07-01 VIC     118
##  2 2020-07-02 VIC     116
##  3 2020-07-03 VIC     157
##  4 2020-07-04 VIC     156
##  5 2020-07-05 VIC     168
##  6 2020-07-06 VIC     229
##  7 2020-07-07 VIC     238
##  8 2020-07-08 VIC     235
##  9 2020-07-09 VIC     262
```

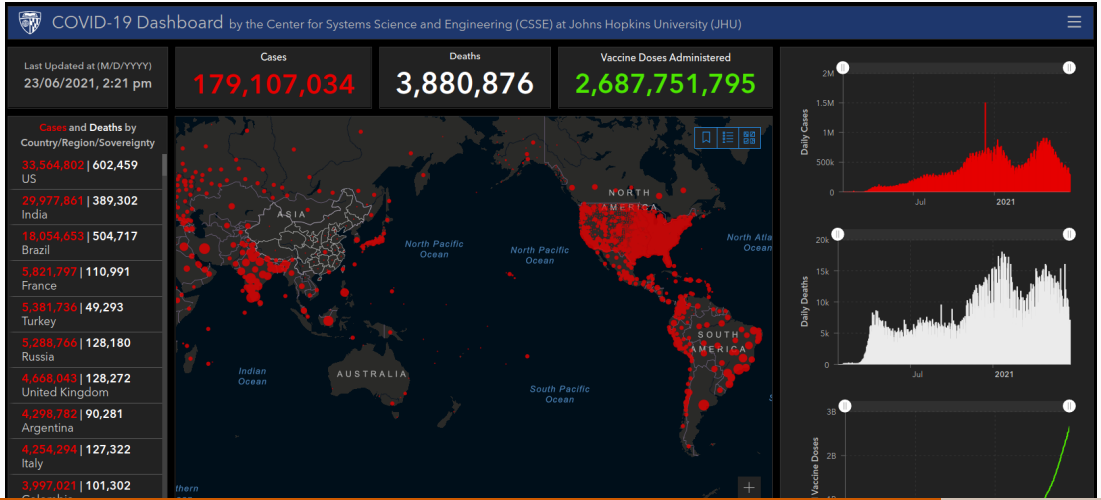
Case numbers



- Recent case numbers are uncertain and incomplete as date of onset is not known until symptoms show and a test is obtained.

Global daily cases by region from Johns Hopkins

https://github.com/CSSEGISandData/COVID-19



Model 3: Global AR model (Monash)

- Uses Johns Hopkins data from countries and regions with sufficient data.
- Series with obvious anomalies (negative cases and large step changes) removed.
- $n_{t,i}$ = daily cases on day t in country/region i (scaled so all data have same mean and variance).
- $y_{t,i} = \phi_1 y_{t-1,i} + \cdots + \phi_p y_{t-p,i} + \varepsilon_{t,i}$
  where $y_{t,i} = \log(n_{t,i} + 0.5)$ and $\varepsilon_{t,i} \sim N(0, \sigma_i^2)$.
- No stationarity constraints. Common coefficients.
- Current model has $p = 24$ (selected to minimize the 7-day-ahead MAE on recent Australian data).

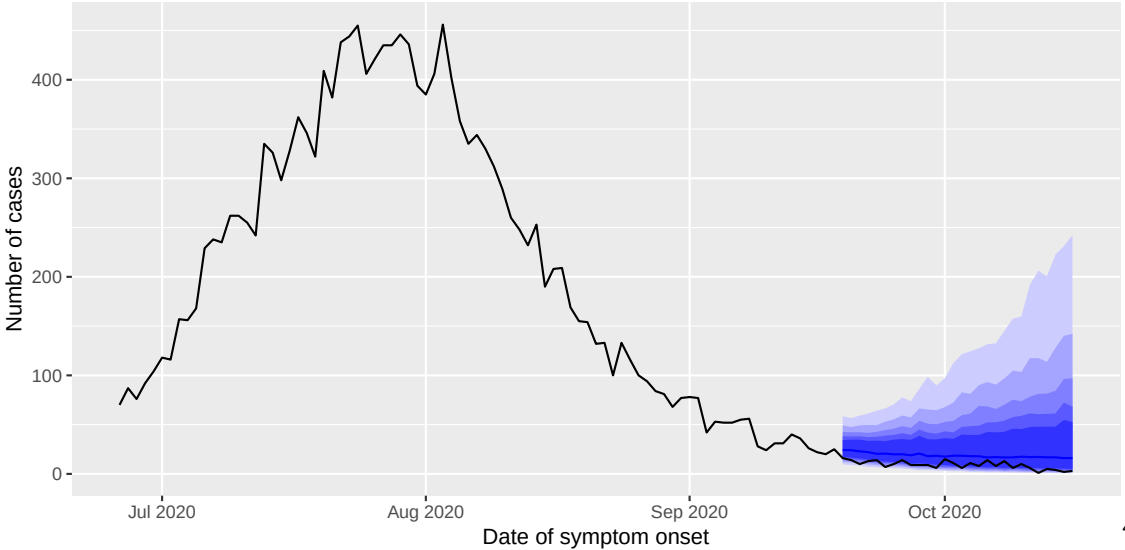
Forecasting ensemble

- Forecasts obtained from a mixture distribution of the component models.

$$\tilde{p}(y_{t+h}|I_t) = \sum_{k=1}^{3} w_{t+h|t,k} p_k(y_{t+h}|I_t)$$

  where $p_k(y_{t+h}|I_t)$ is the forecast distribution from model k, I_t denotes the data available at time t and the weights $w_{t+h|t,k} > 0$ sum to one.
- Also known as “linear pooling”
- Works best when individual models are over-confident and use different data sources.
- We have used equal weights $w_{t+h|t,k} = 1/3$.

Ensemble forecasts: Victoria



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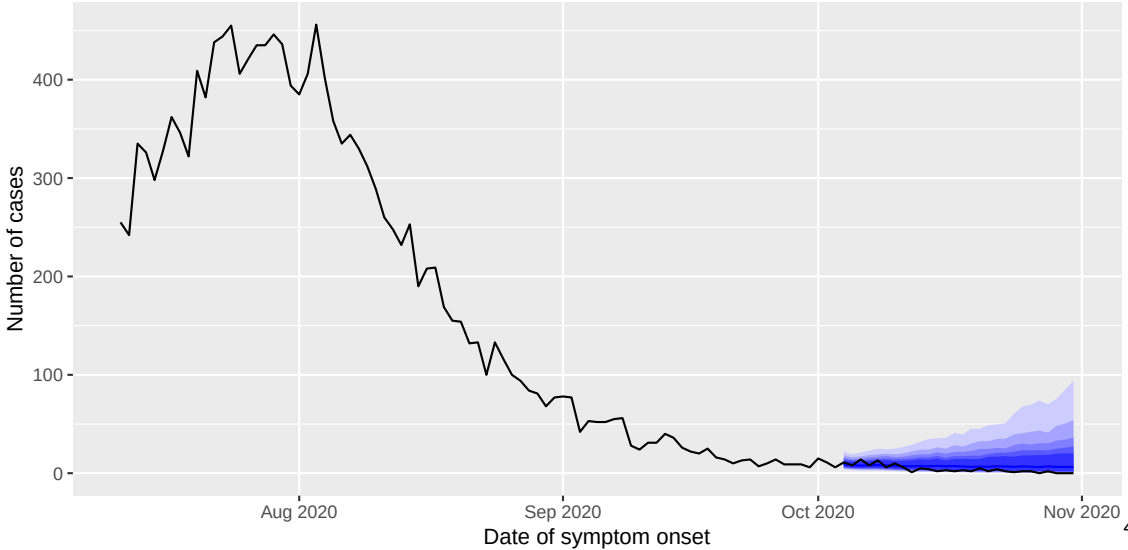

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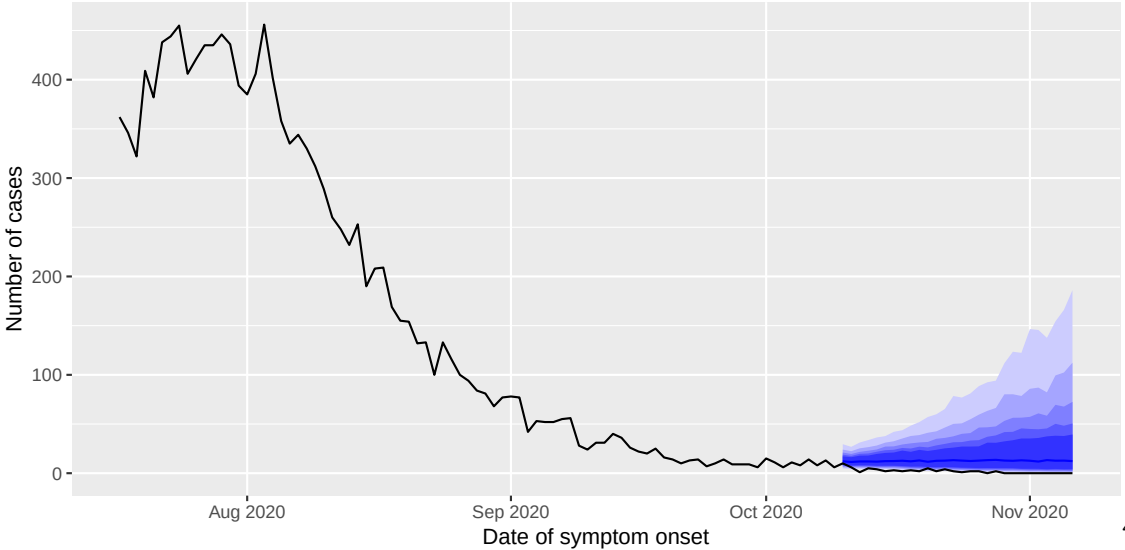

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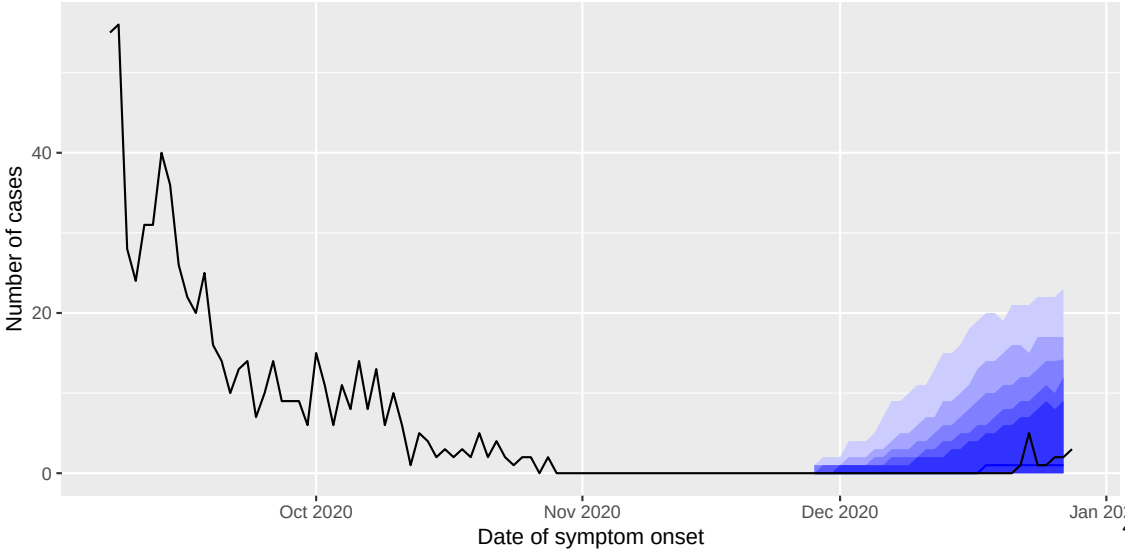

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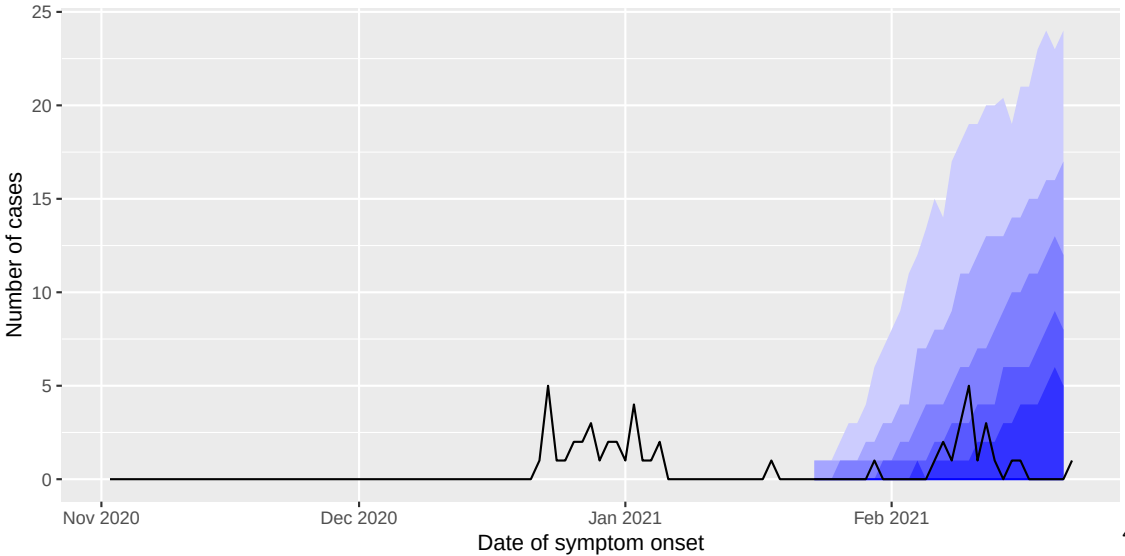

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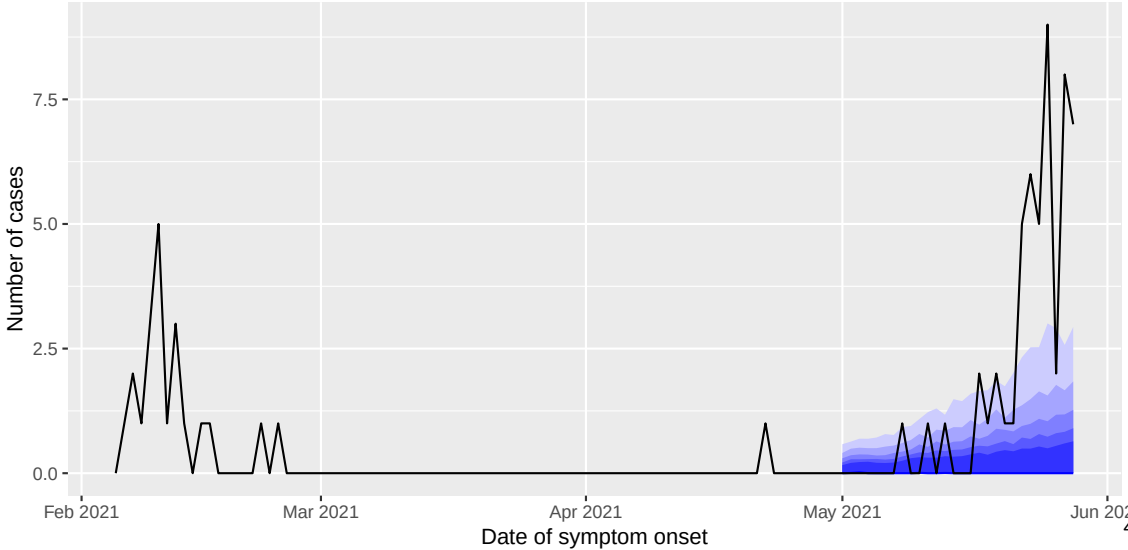

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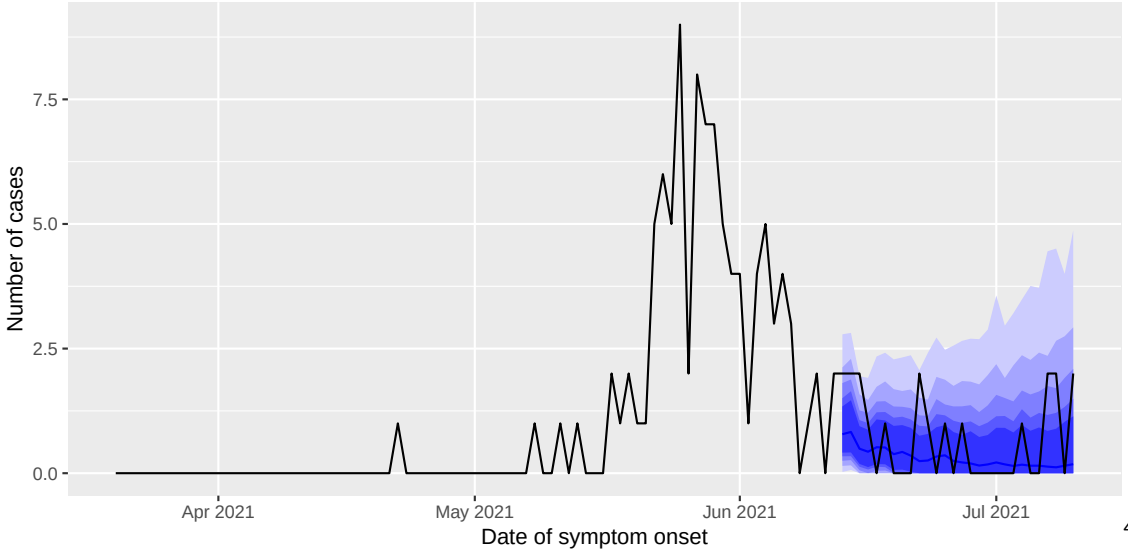

Evaluating probabilistic forecasts

$f_{p,t}$ = quantile forecast with prob. p at time t.

y_t = observation at time t

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Quantile score

$$Q_{p,t} = \begin{cases} 2(1-p)|y_t - f_{p,t}|, & \text{if } y_t < f_{p,t} \\ 2p|y_t - f_{p,t}|, & \text{if } y_t \geq f_{p,t} \end{cases}$$

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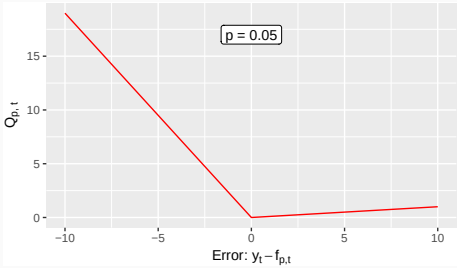

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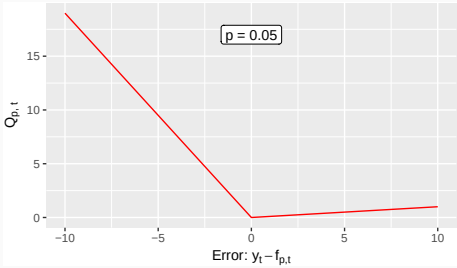


- Low $Q_{p,t}$ is good
- Multiplier of 2 often omitted, but useful for interpretation
- $Q_{p,t}$ like absolute error (weighted to account for likely exceedance)
- Average $Q_{p,t}$ over p = CRPS (Continuous Ranked Probability Score)

CRPS: Continuous Ranked Probability Score

y_t = observation at time t

$F_t(u) = \Pr(Y_t \leq u)$ = forecast distribution

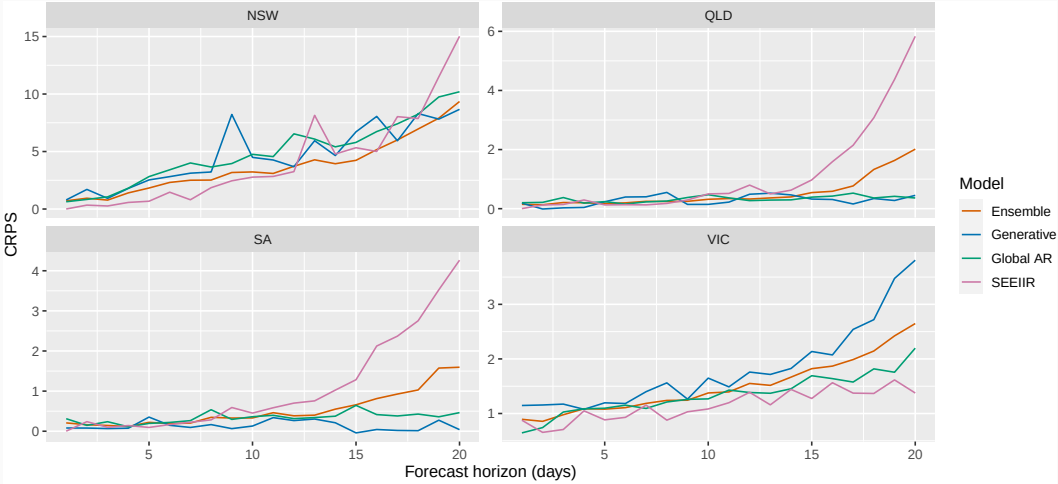
$f_{p,t} = F_t^{-1}(p)$ = quantile forecast with prob. p

$$Q_{p,t} = \begin{cases} 2(1-p)|y_t - f_{p,t}|, & \text{if } y_t < f_{p,t} \\ 2p|y_t - f_{p,t}|, & \text{if } y_t \geq f_{p,t} \end{cases}$$

Y_t and $Y_t^* \sim$ iid with distribution F_t.

$$\begin{aligned} \text{CRPS}_t &= \int_0^1 Q_{p,t}\, dp \\ &= \int_{-\infty}^{\infty} \left[F_t(u) - 1_{y_t \leq u}\right]^2 du \\ &= \text{E}|Y_t - y_t| - \tfrac{1}{2}\text{E}|Y_t - Y_t^*| \end{aligned}$$

CRPS: Continuous Ranked Probability Score



For weekly forecasts created from 17 September 2020 to 15 June 2021

What have we learned?

- Diverse models in an ensemble are better than one model, especially when they use different information.
- Understand the data, learn from the data custodians.
- Have a well-organized workflow for data processing, modelling and generation of forecasts, including version control and reproducible scripts.
- Communicating probabilistic forecasts is difficult, but consistent visual design is helpful.

More information

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