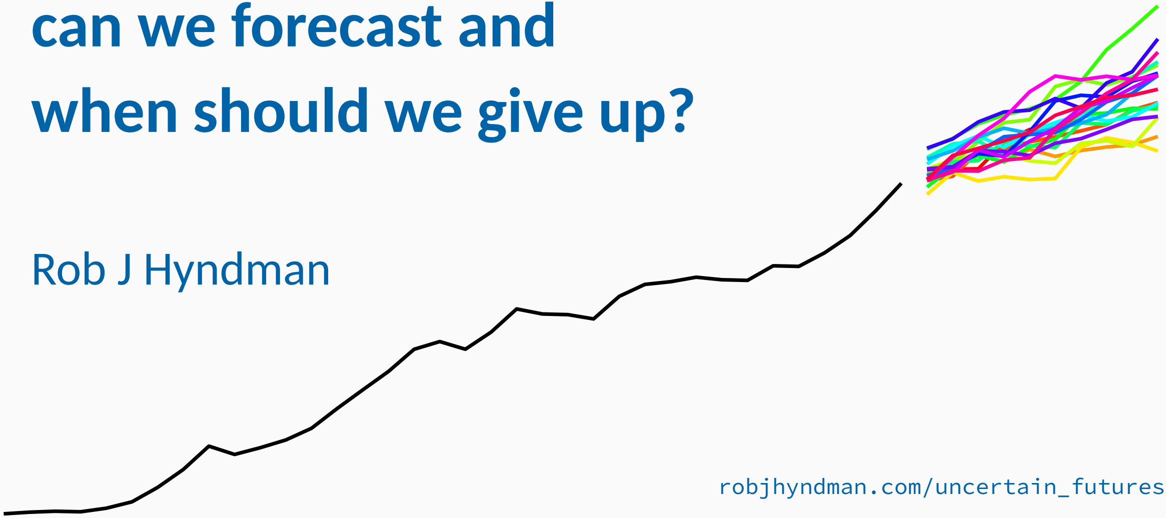
Uncertain futures: what can we forecast and when should we give up?

Rob J Hyndman



robjhyndman.com/uncertain_futures

MONASH University

Outline

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What can we forecast?

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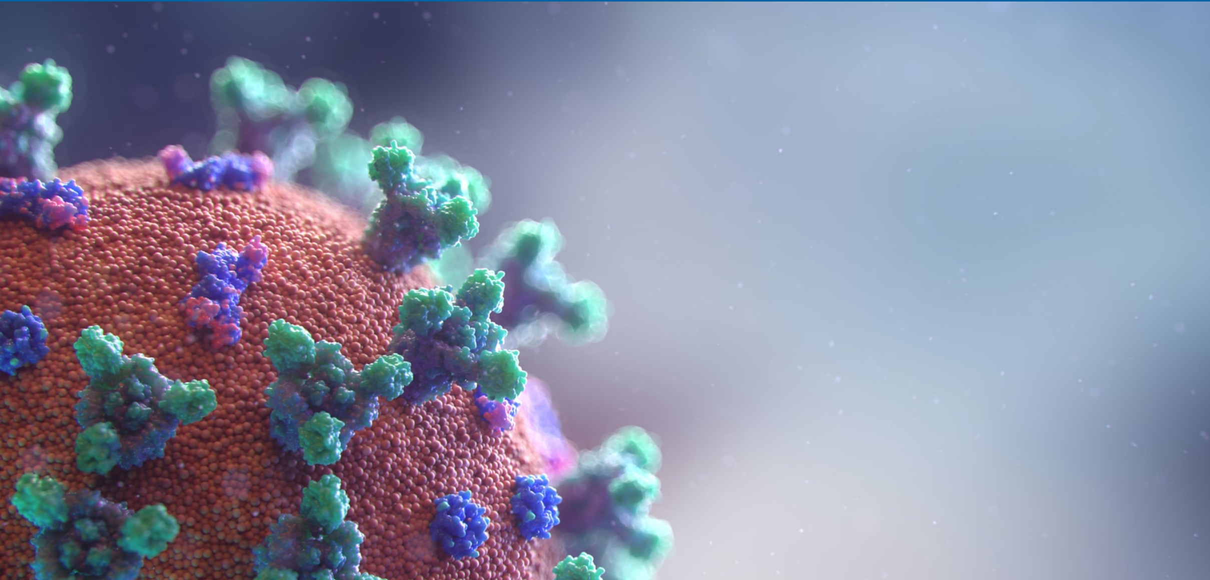

Outline

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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8. Google stock price in 6 months time

- how do we measure "easiest"?
- what makes something easy/difficult to forecast?

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.

Outline

Reputations can be made and lost

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"We're going to be opening relatively soon . . . The virus . . . will go away in April."

(Donald Trump, February 2020)

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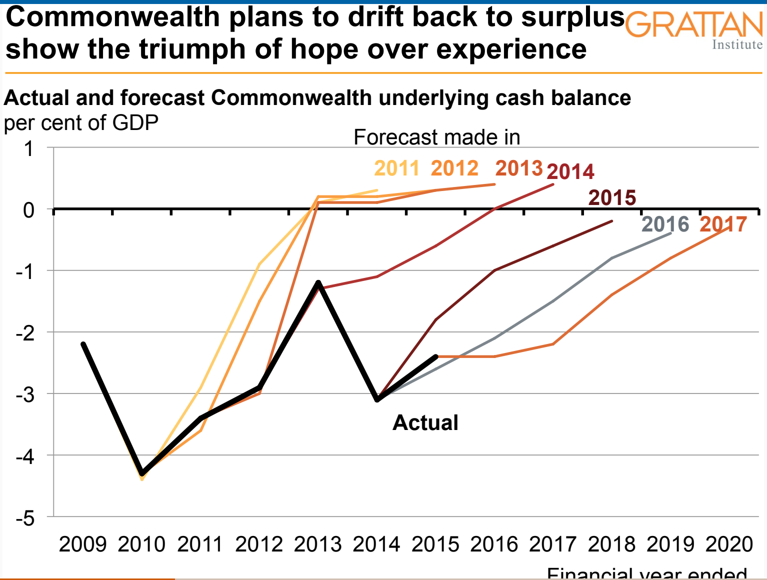
"We're going to be opening relatively soon . . . The virus . . . will go away in April."

(Donald Trump, February 2020)

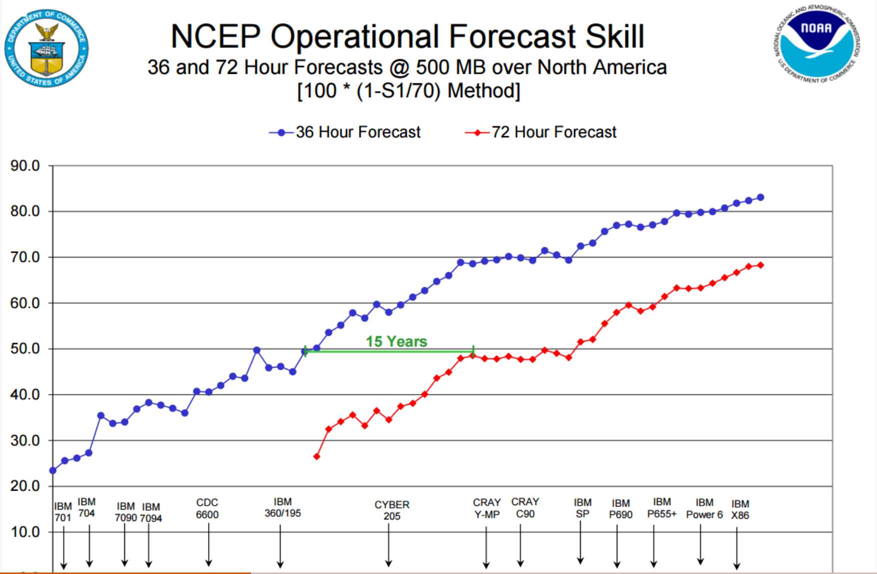
"We expect that Australians will be fully vaccinated by the end of October."

(Scott Morrison, December 2020)

Forecasting is difficult



Improving forecasts



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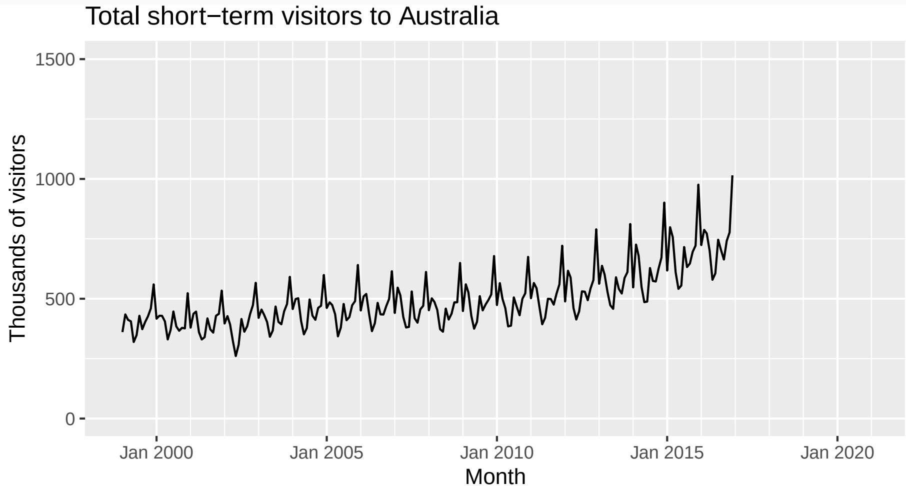

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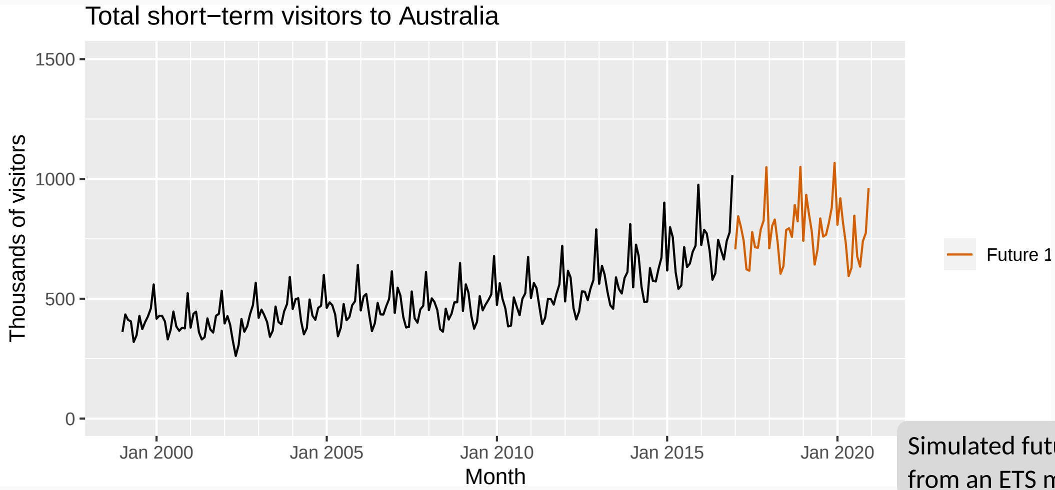

Simulated futures from an ETS model

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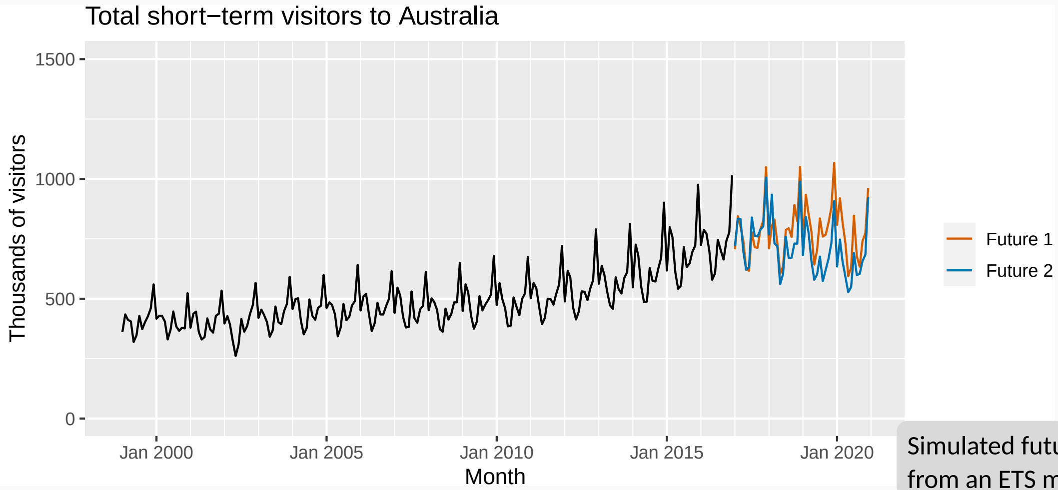

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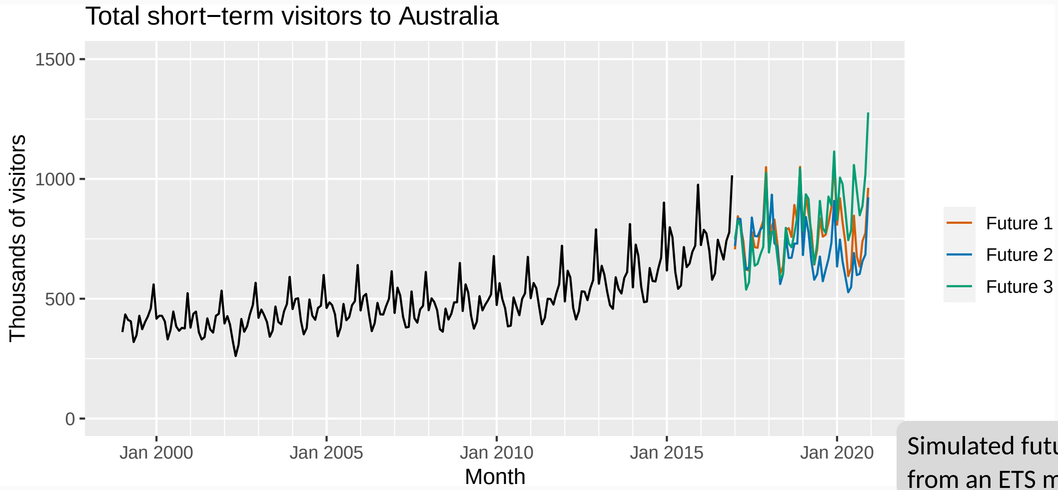

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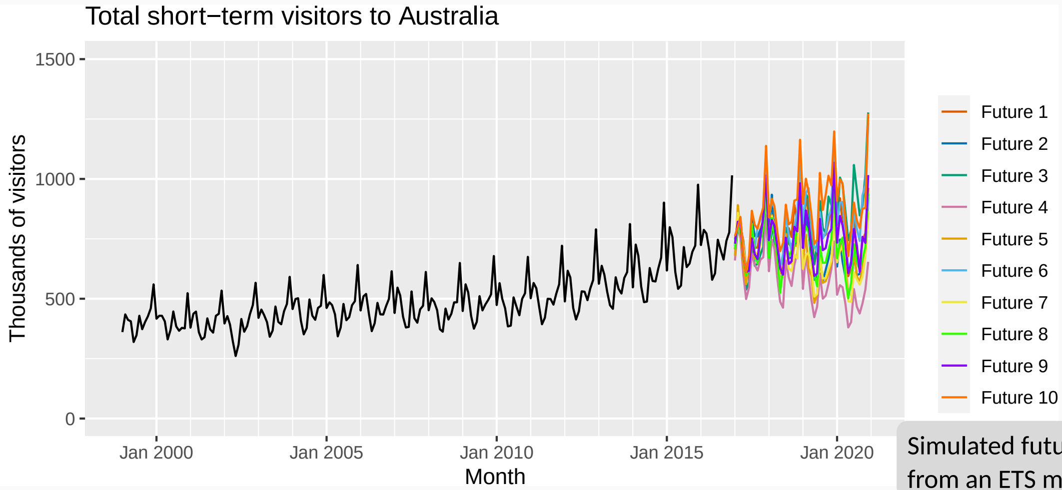

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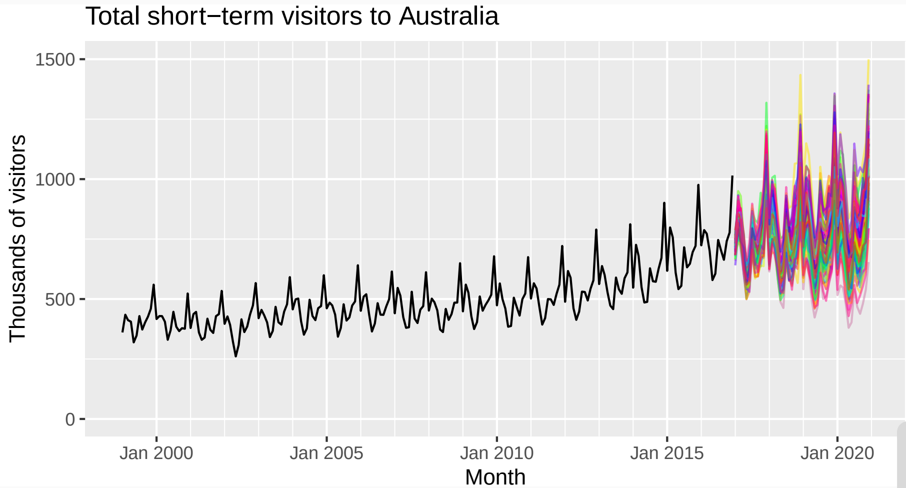

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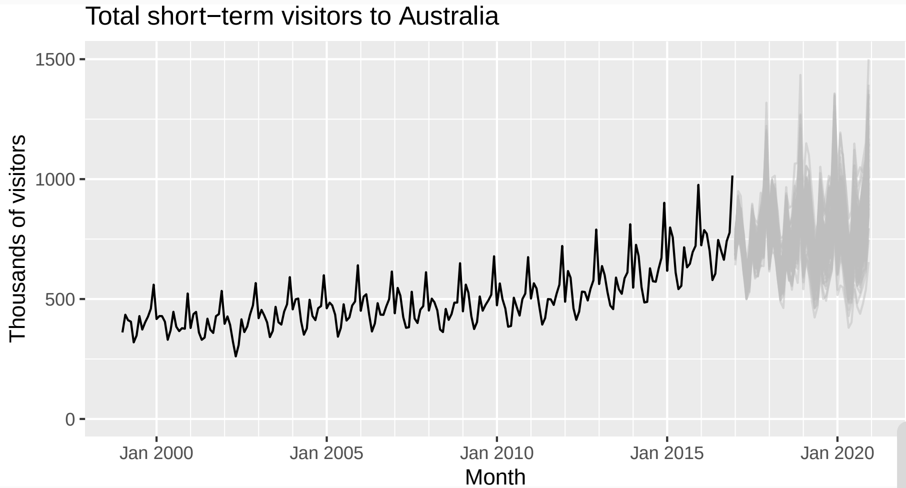

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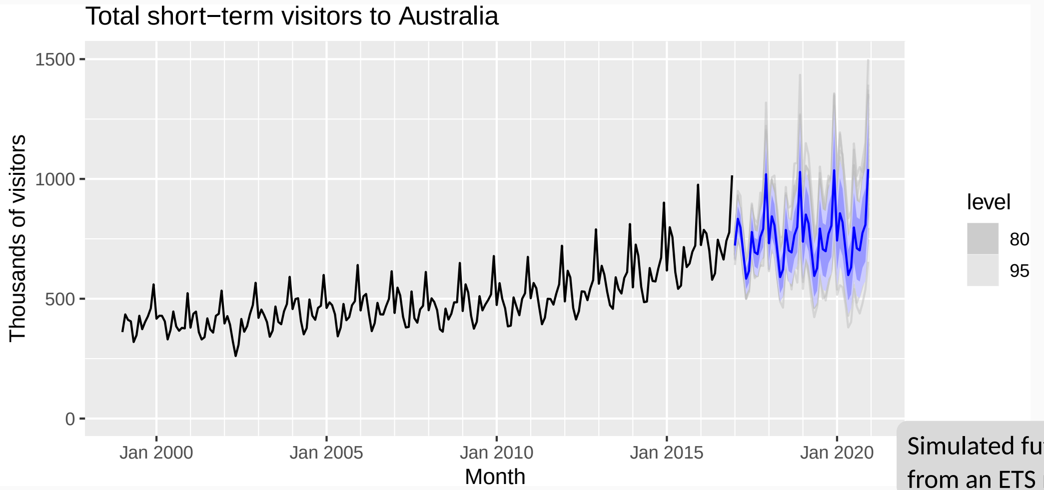

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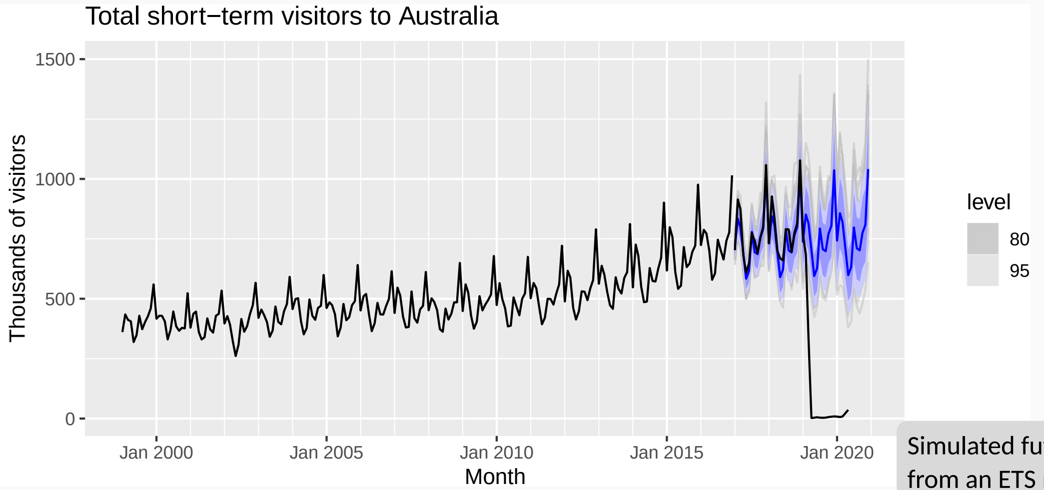

Simulated futures from an ETS model

Outline

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


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Opp demands drug price restriction after PBS budget blow-out

The Federal Opposition has called for tighter controls on drug prices after the Pharmaceutical Benefits Scheme (PBS) budget blew out by almost $800 million.

The money was spent on two new drugs including the controversial anti-smoking aid Zyban, which dropped in price from $220 to $22 after it was listed on the

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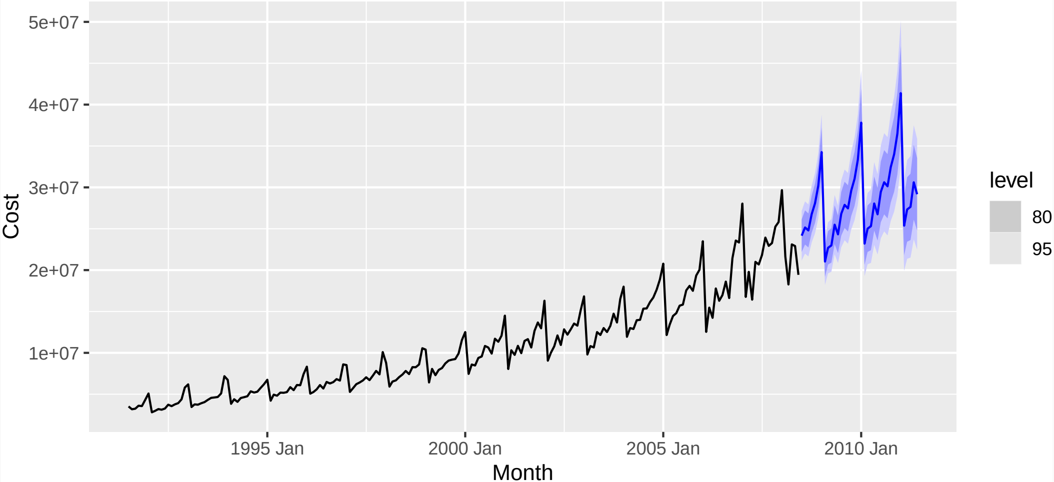
PBS forecasting

- 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

14 classes	A	Alimentary tract and metabolism
84 classes	A10	Drugs used in diabetes
	A10B	Blood glucose lowering drugs
	A10BA	Biguanides
	A10BA02	Metformin

ETS forecasts of PBS data



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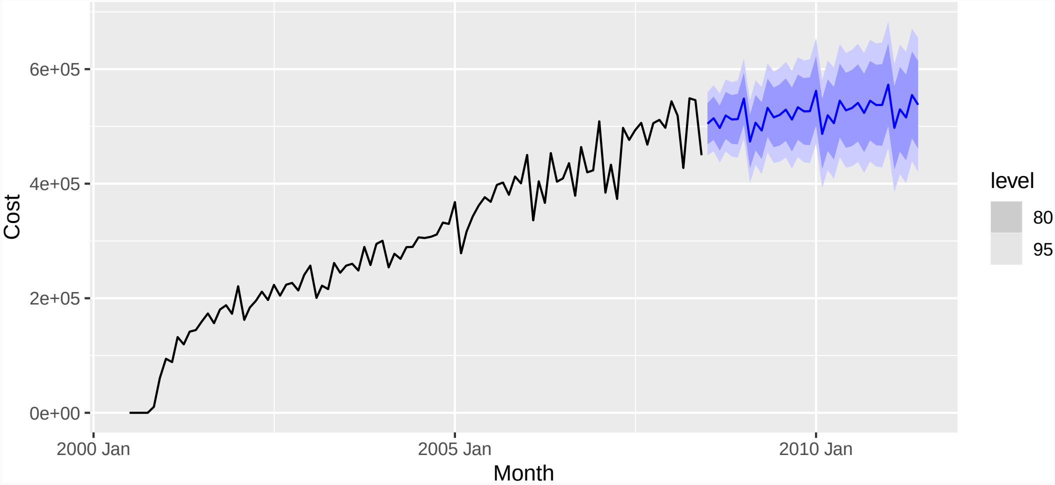

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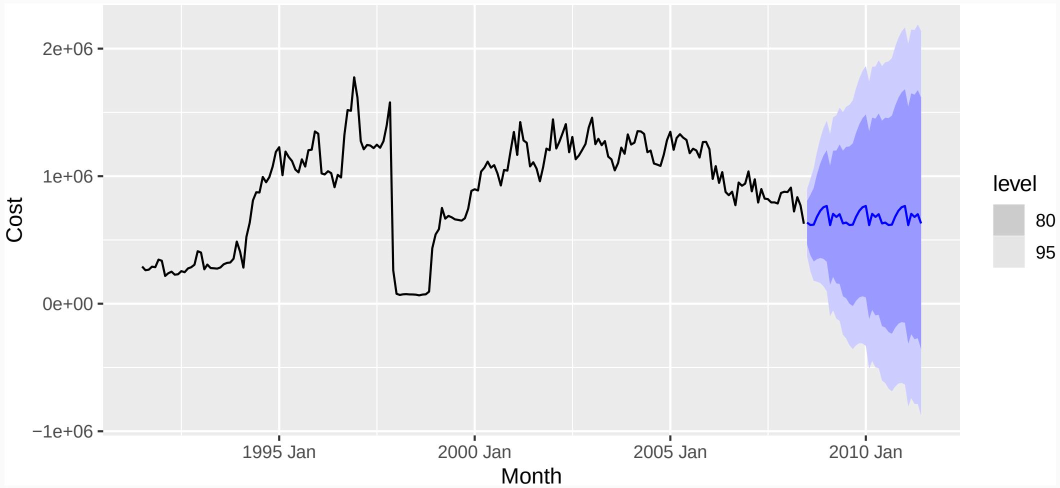

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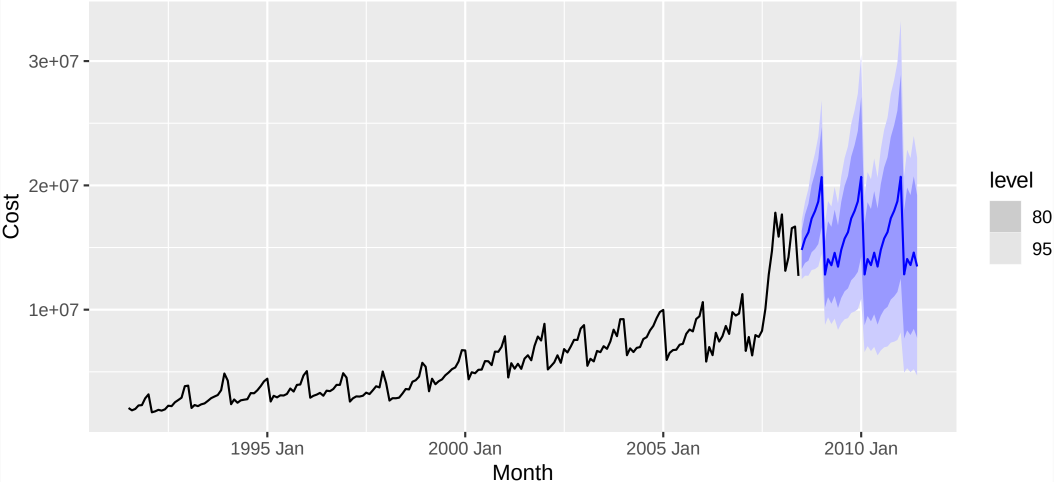

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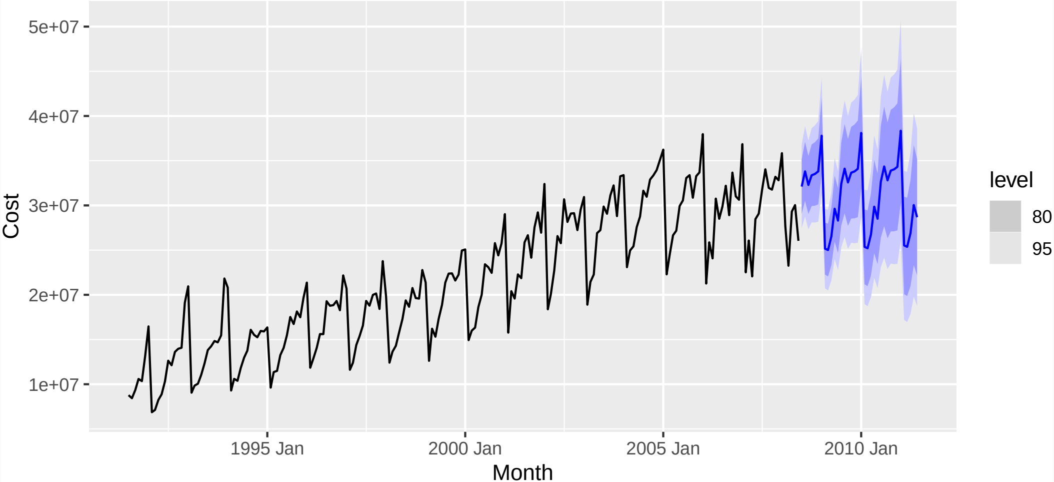

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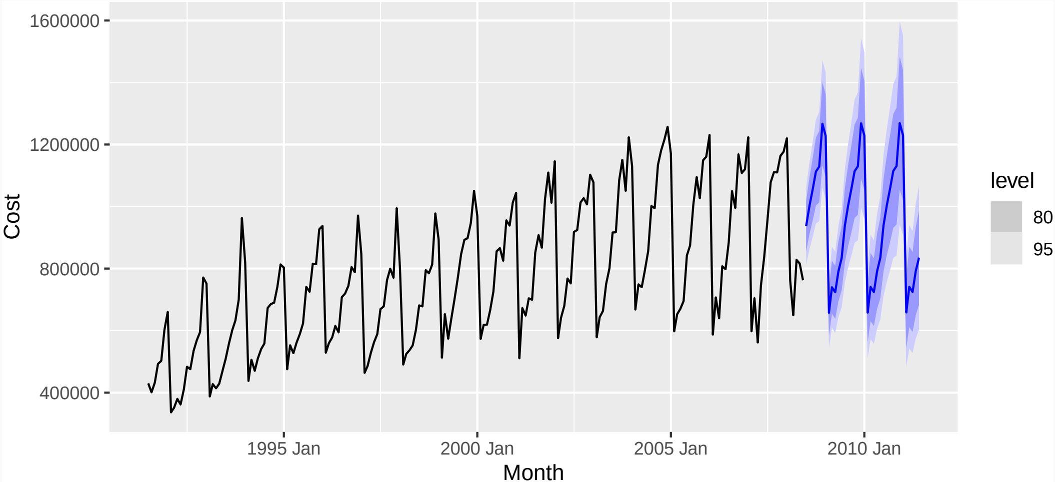


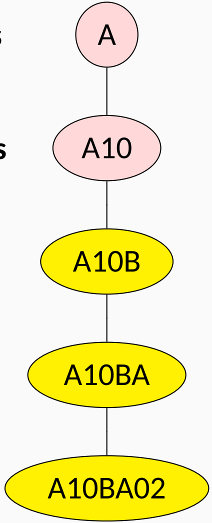
Forecasting the PBS

- 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.
- Theory and algorithm published as Hyndman et al (IJF, 2002).
- Now implemented in R as `ets()` in forecast package, as `ETS()` function in fable package, and in Tableau and elsewhere.
- NOT implemented in `FORECAST.ETS` function in MS-Excel.

Hierarchical forecasting

14 classes — Alimentary tract and metabolism

84 classes — Drugs used in diabetes



Blood glucose lowering drugs

Biguanides

Metformin

Hierarchical forecasting

- Nearly ten years later, Hyndman et al (CSDA, 2011) proposed forecast reconciliation to handle hierarchical time series.
- Now widely used in business and industry and implemented in the `hts` and `fable` packages.

Outline

Data sources

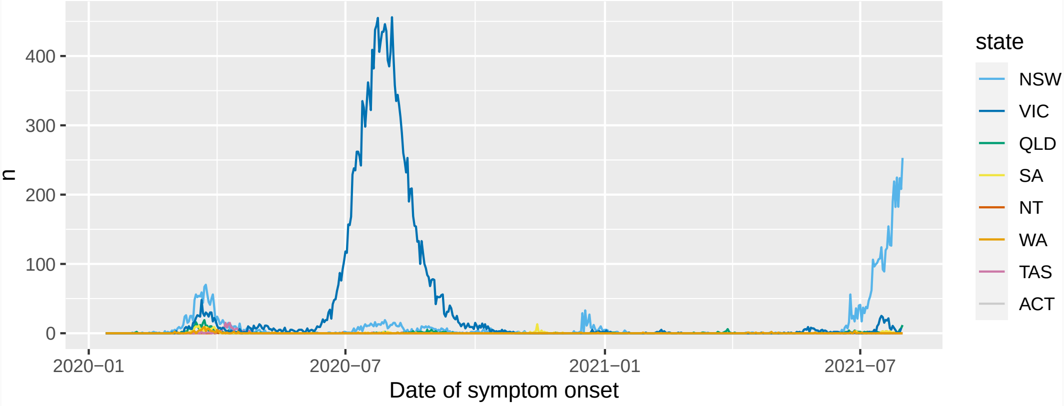
- Case-level data of all positive COVID-19 tests: onset and detection times.
- Daily population mobility data from Google, Apple & Facebook
- Weekly non-household contact surveys
- Weekly behavioural surveys
- Daily case numbers from many countries and regions via the Johns Hopkins COVID-19 repository

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
```

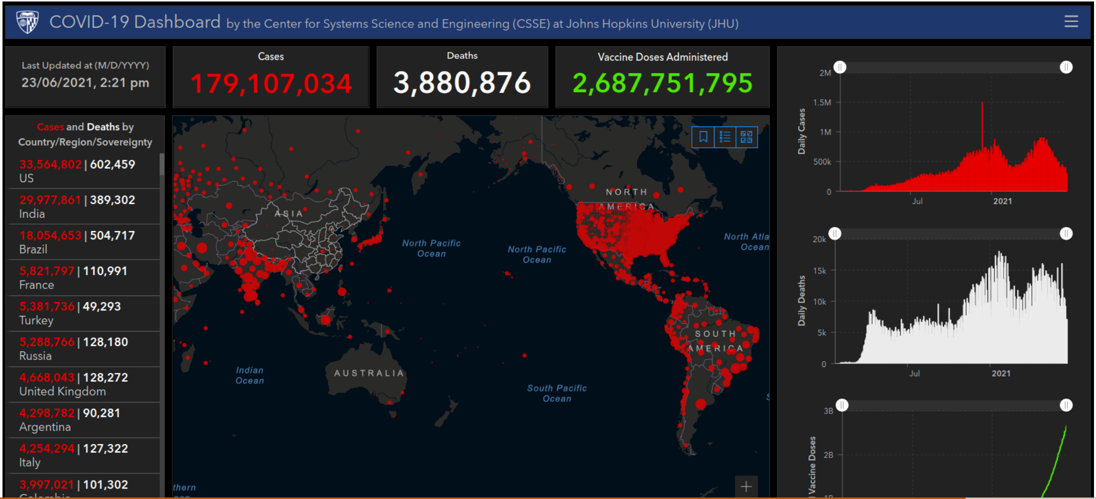
Case numbers



- 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).

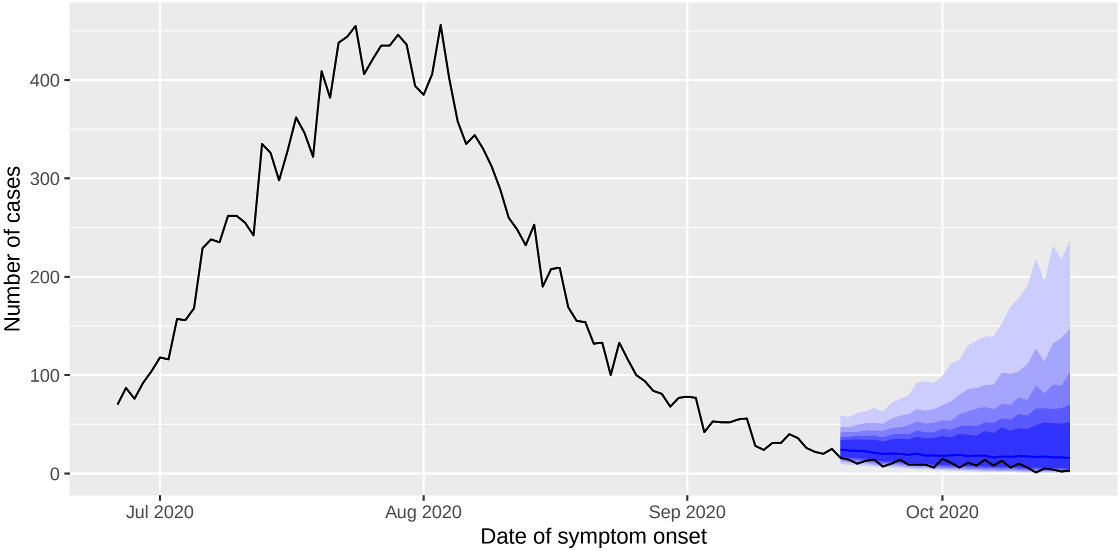
Forecasting ensemble

- 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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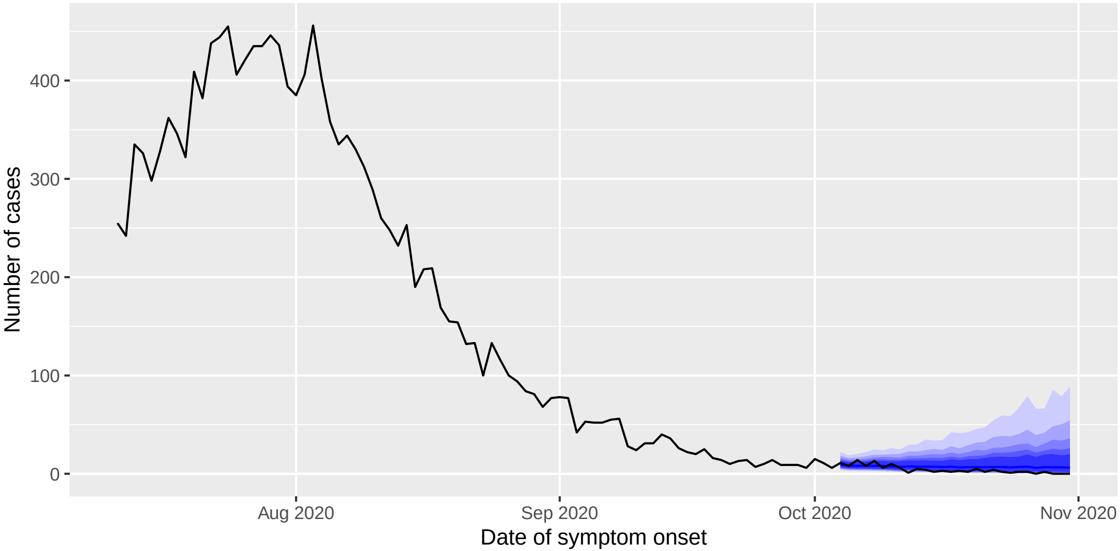

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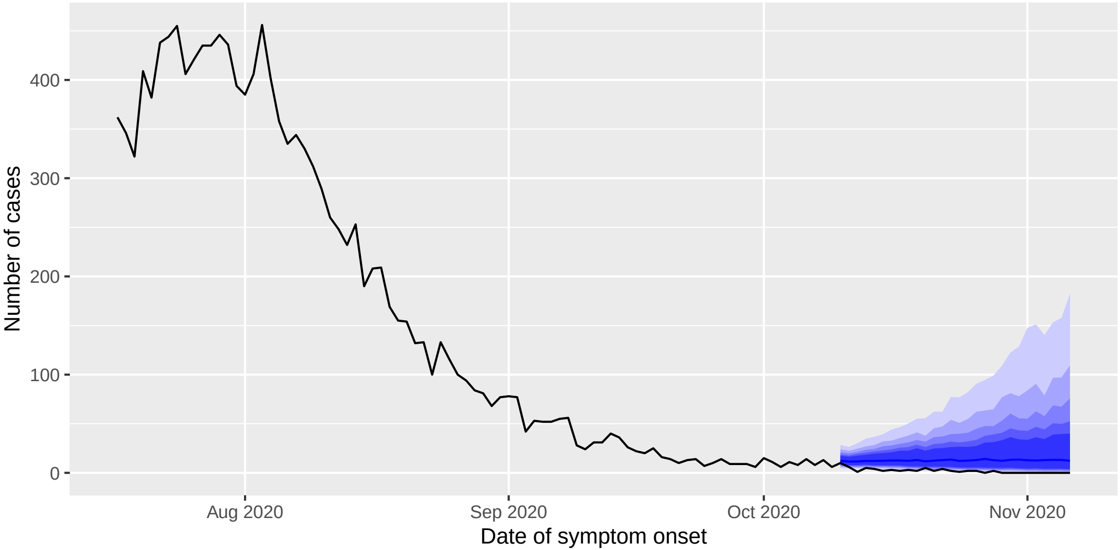

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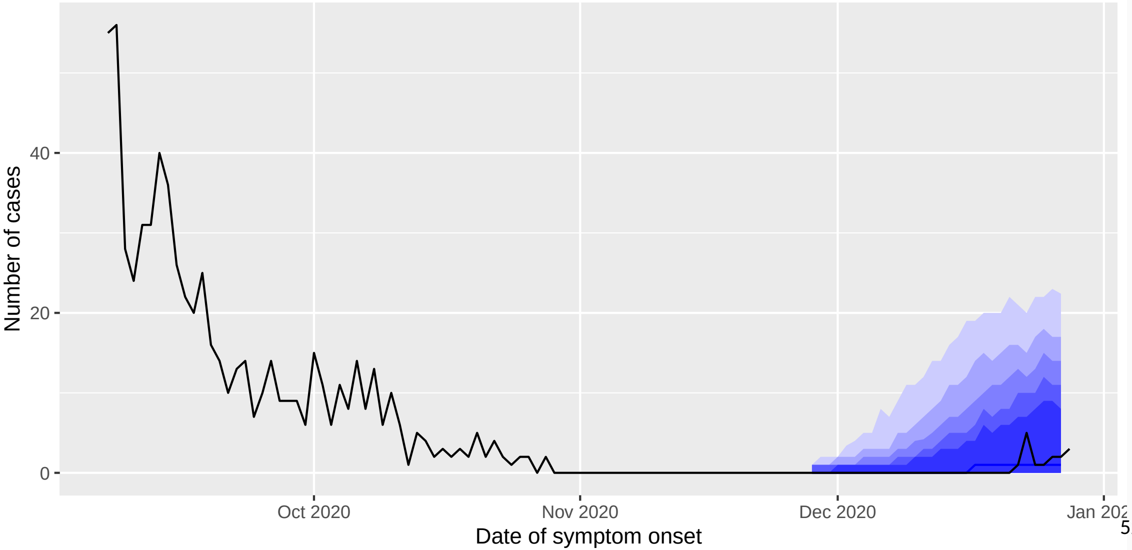

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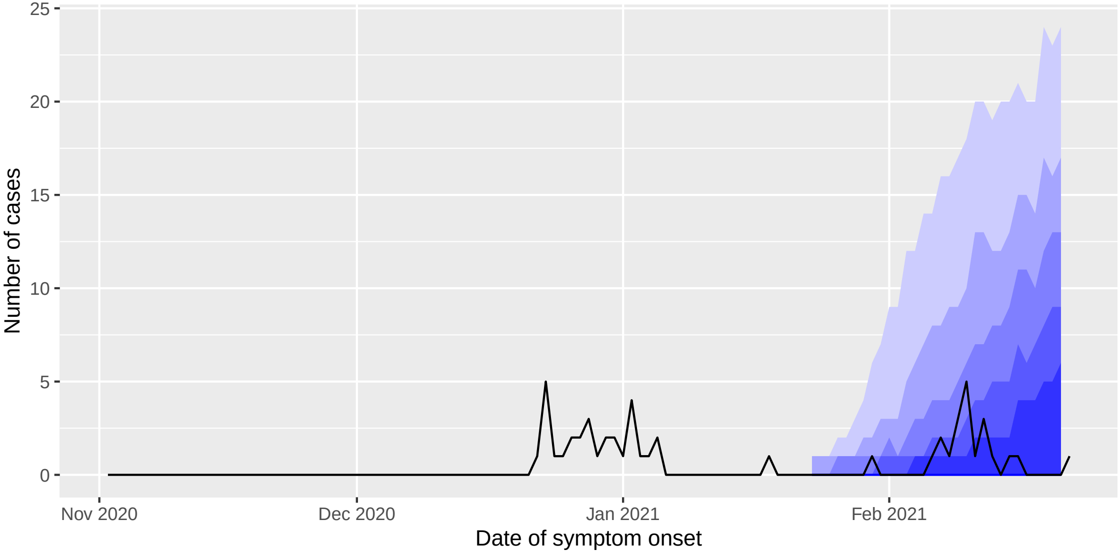

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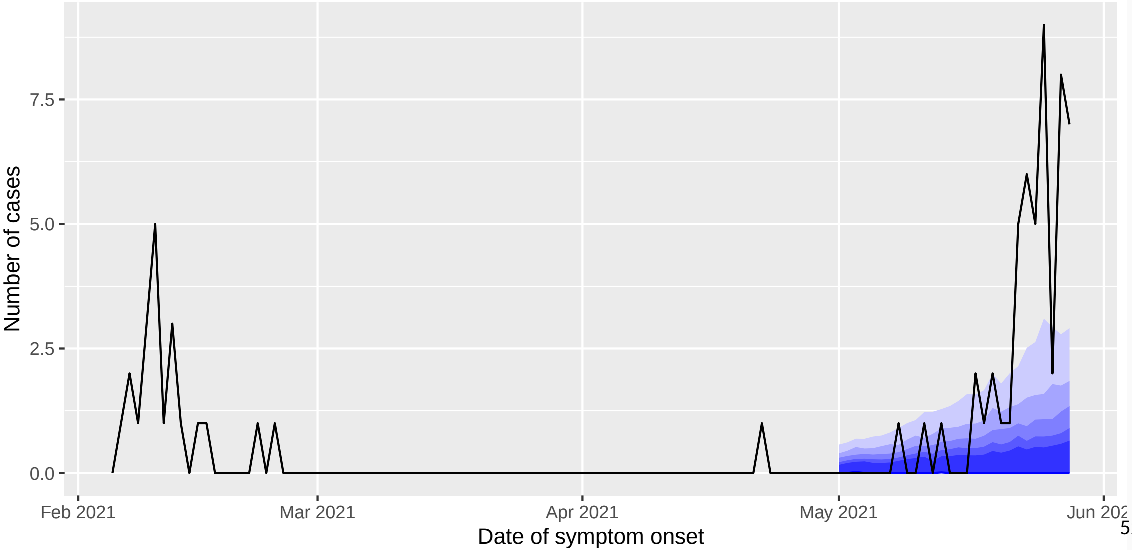

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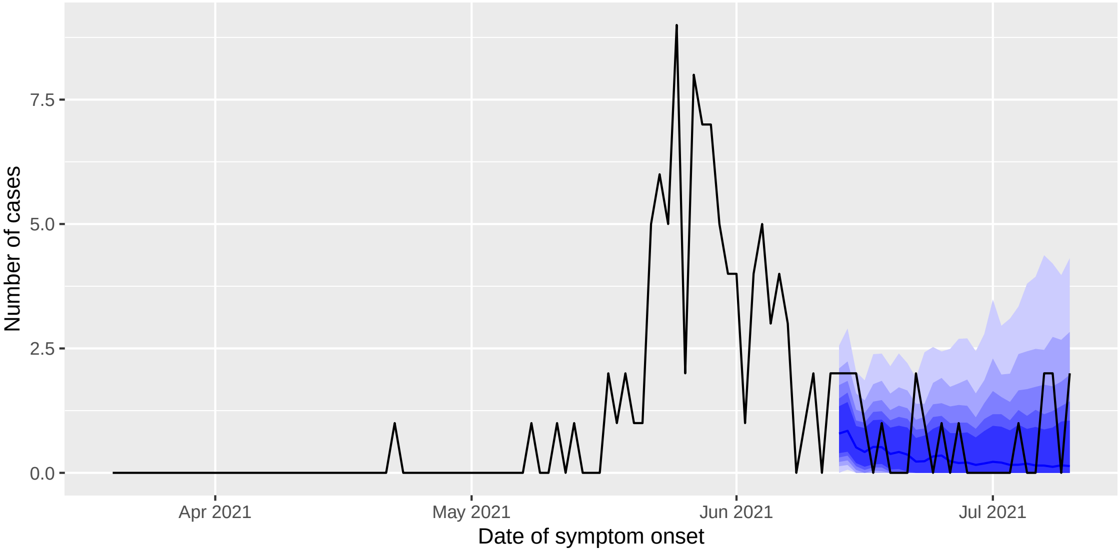

Evaluating probabilistic forecasts

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y_t = observation at time t

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Quantile score

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

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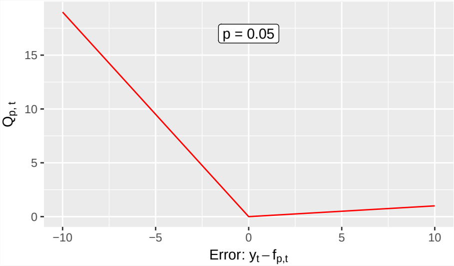

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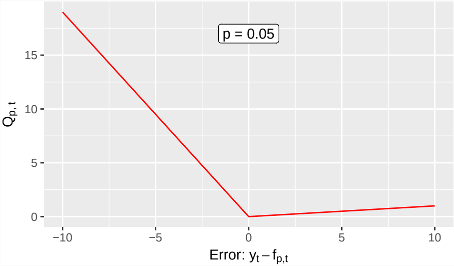


- Low $Q_{p,t}$ is good
- Multiplier of 2 often omitted, but useful for interpretation
- $Q_{p,t}$ like absolute error (weighted to account for likely exceedance)
- Average $Q_{p,t}$ over p = CRPS (Continuous Ranked Probability Score)

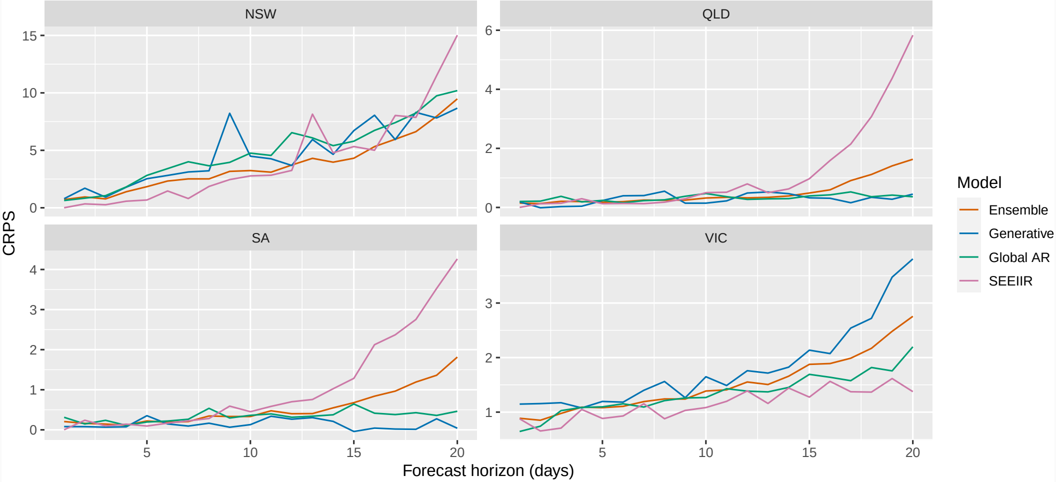
CRPS: Continuous Ranked Probability Score

$$y_t = \text{observation at time } t$$
$$F_t(u) = \Pr(Y_t \leq u) = \text{forecast distribution}$$
$$f_{p,t} = F_t^{-1}(p) = \text{quantile forecast with prob. } p$$
$$Q_{p,t} = \begin{cases} 2(1-p)|y_t - f_{p,t}|, & \text{if } y_t < f_{p,t} \\ 2p|y_t - f_{p,t}|, & \text{if } y_t \geq f_{p,t} \end{cases}$$

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.

When should we give up?

- When there is insufficient data?
- When the models give implausible forecasts?
- When the forecast uncertainty is too large to assist decision making?

More information

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