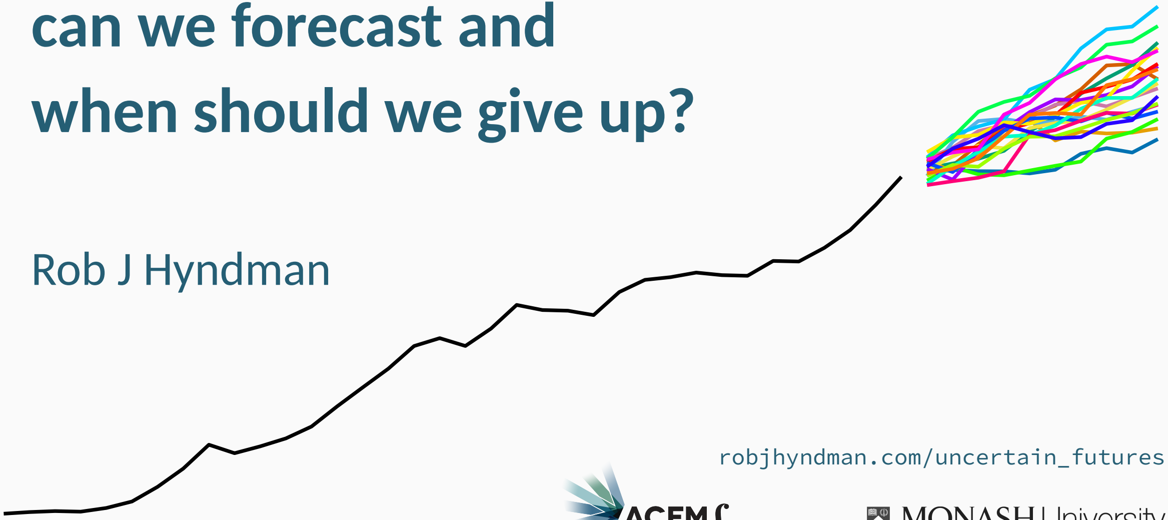
Uncertain futures: what can we forecast and when should we give up?

Rob J Hyndman



robjhyndman.com/uncertain_futures

ACEMS
AUSTRALIAN RESEARCH COUNCIL CENTRE OF EXCELLENCE FOR
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MONASH University

Outline

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Reputations can be made and lost

> “I think there is a world market for maybe five computers.”
>
> (Chairman of IBM, 1943)

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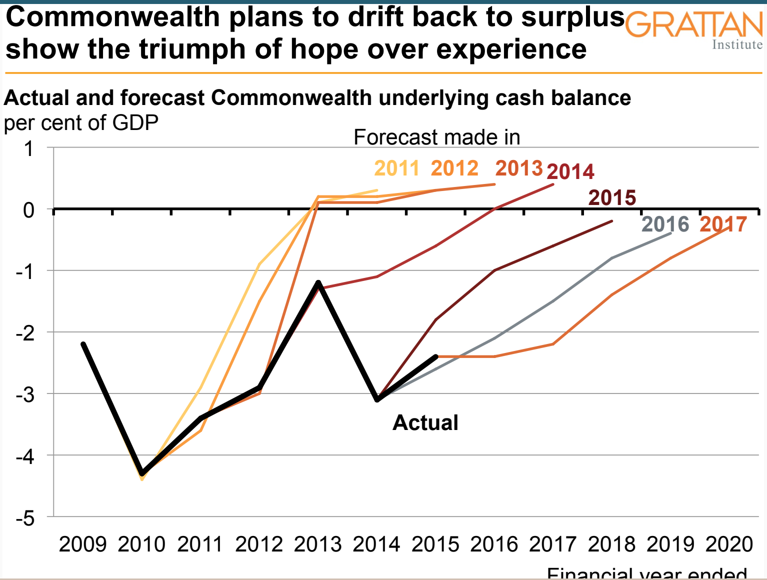
"We're going to be opening relatively soon . . . The virus . . . will go away in April."

(Donald Trump, February 2020)

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

(Scott Morrison, December 2020)

Forecasting is difficult



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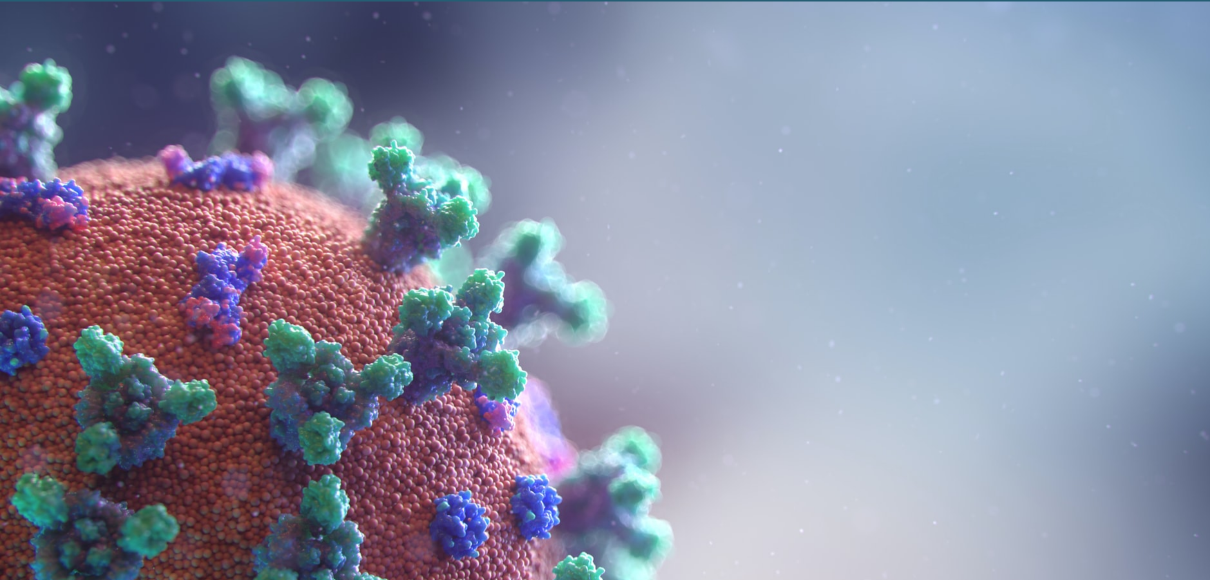

What can we forecast?

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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- 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, and can measure them.
2. there is lots of data available;
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A forecast is an estimate of the probability distribution of a variable to be observed in the future.

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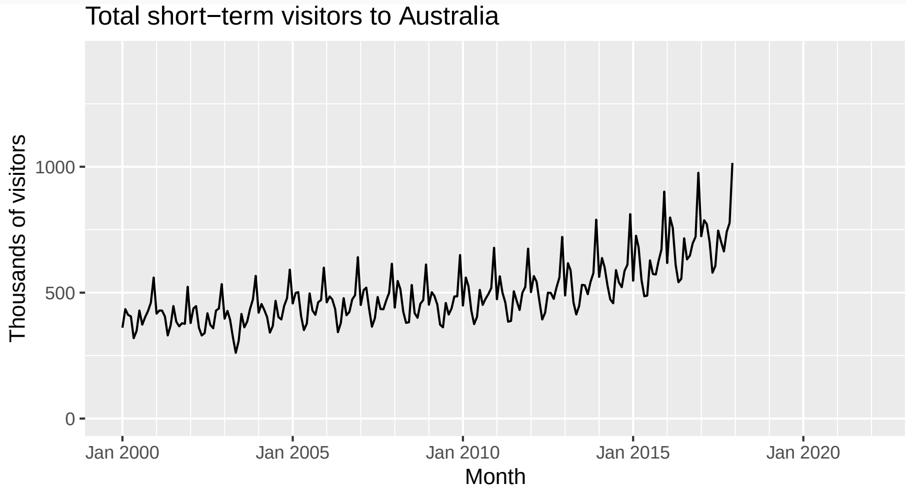

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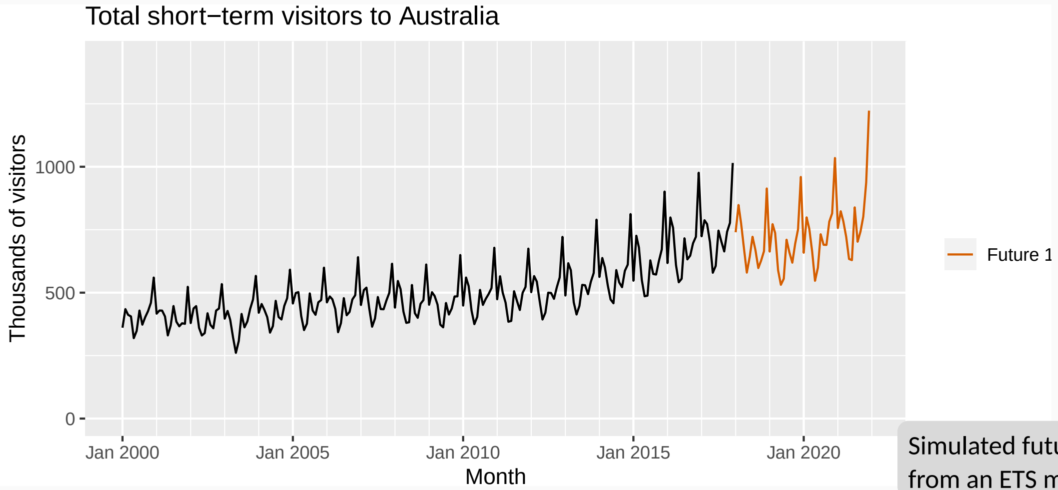

Simulated futures from an ETS model

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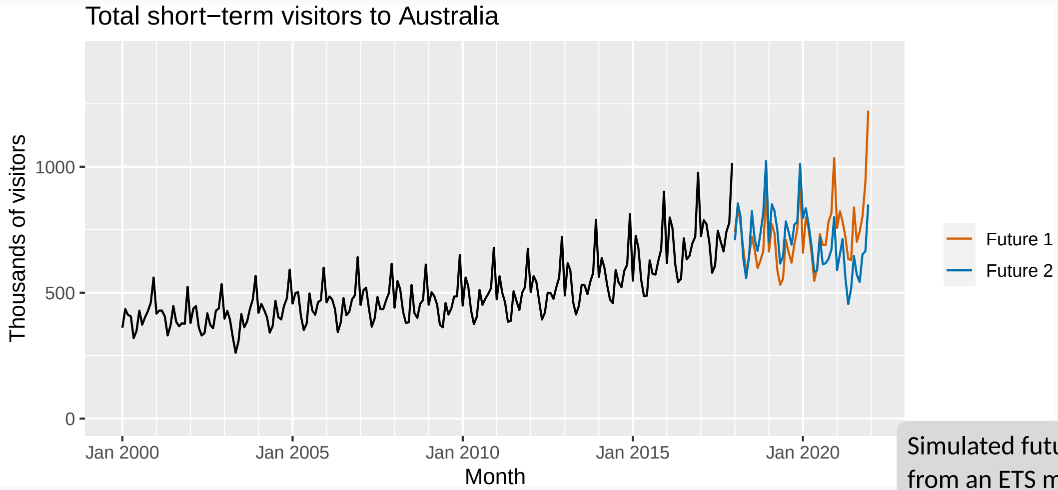

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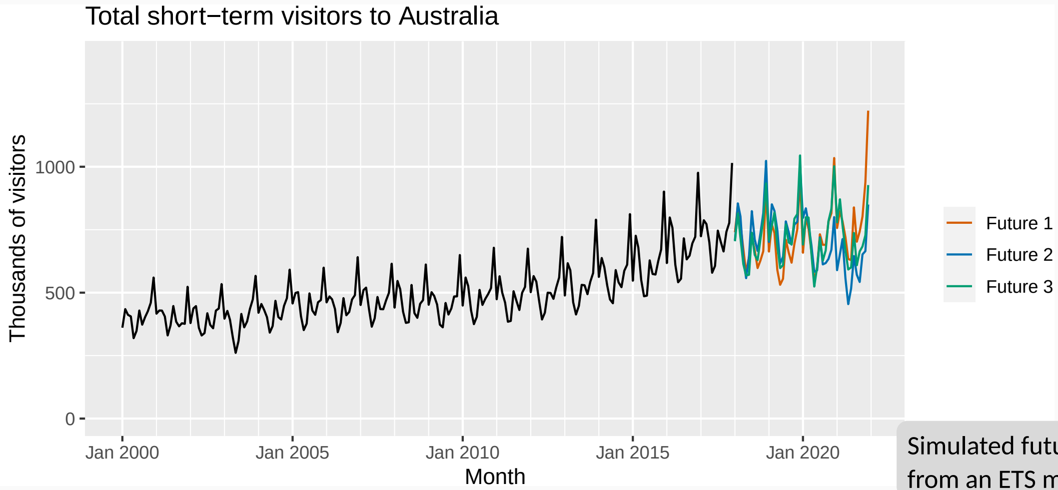

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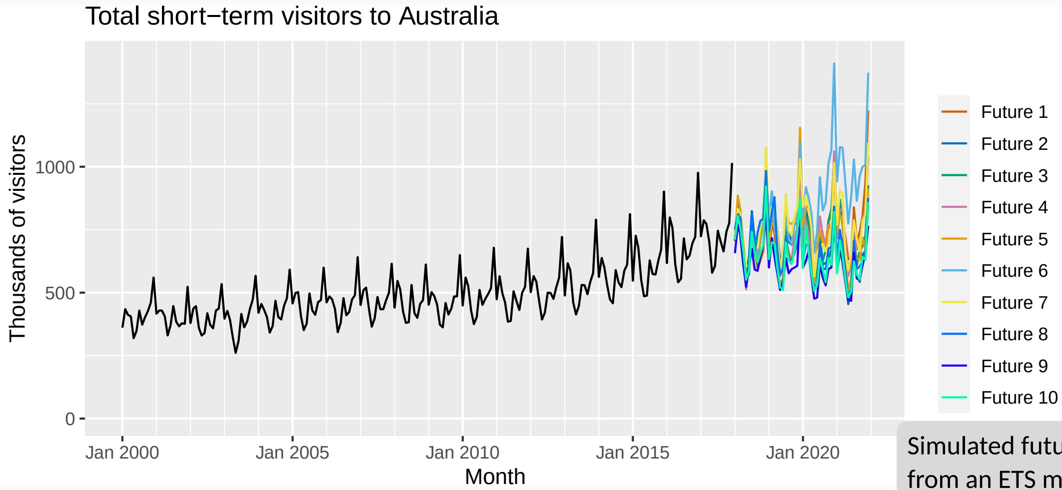

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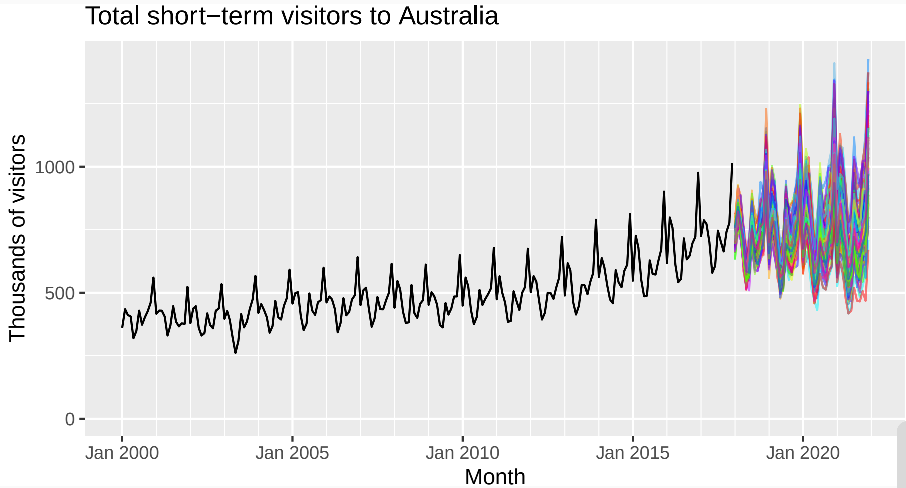

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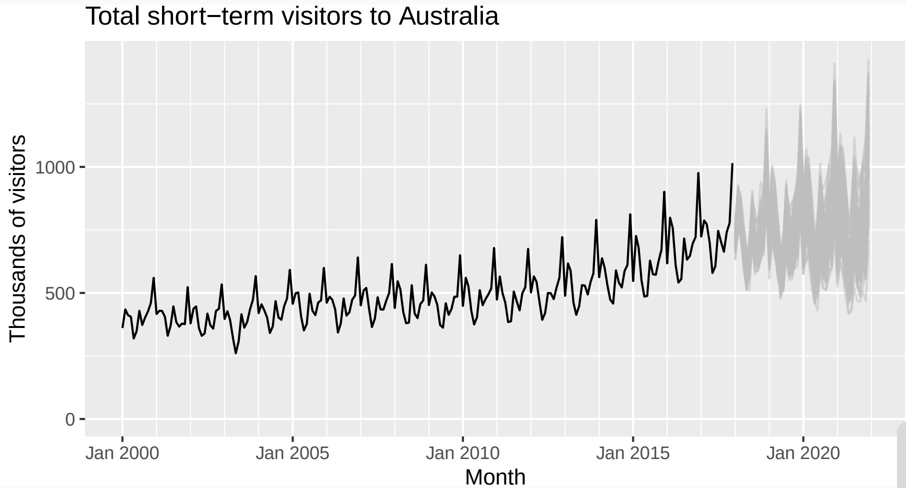

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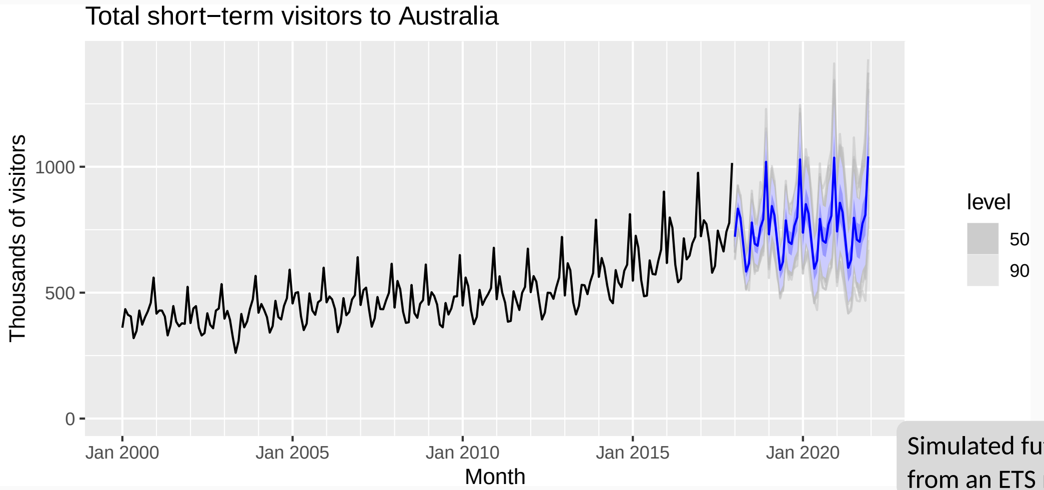

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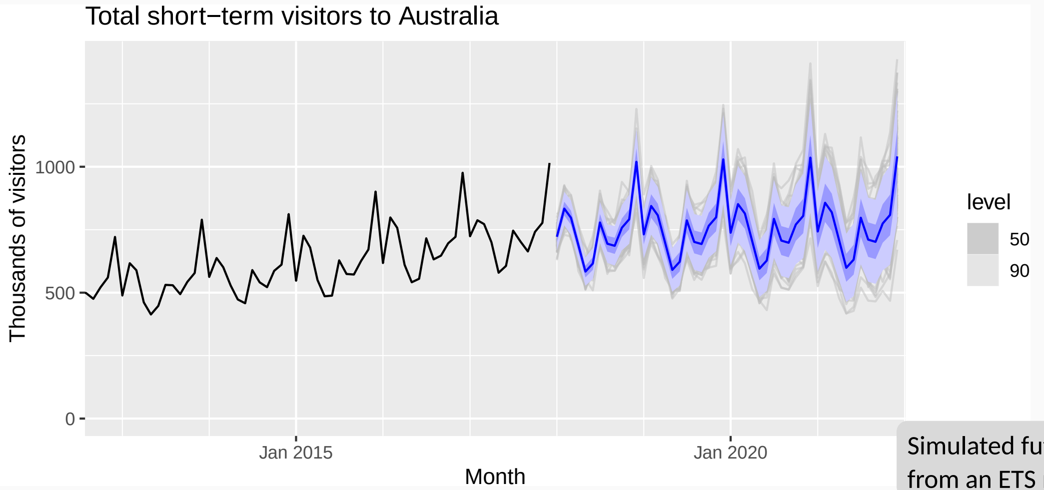

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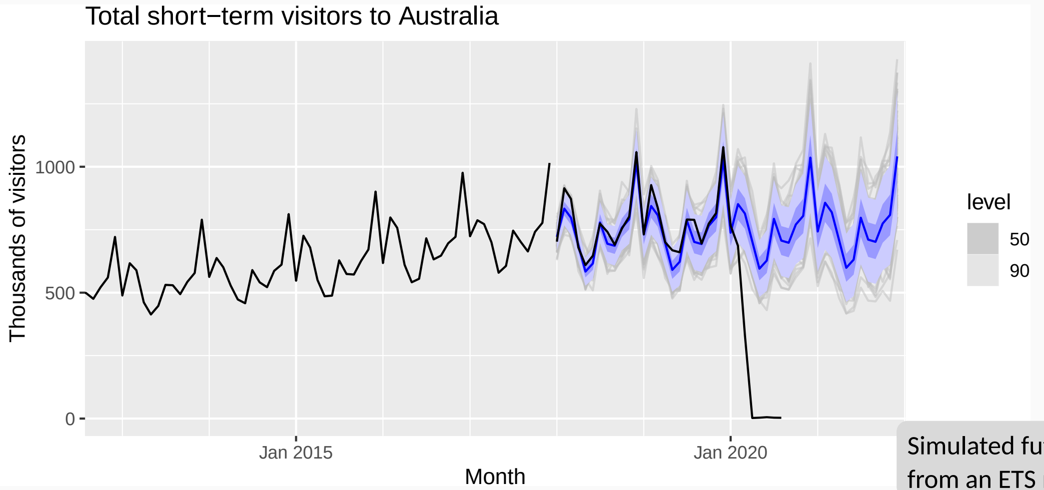

Simulated futures from an ETS model

Outline

Forecasting PBS expenditure

Forecasting PBS expenditure

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.

Forecasting PBS expenditure

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POLITICS

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

the Public Record
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FEATURES

the Public Record
Federal Election 2001

For a fresh perspective on the federal election, reach into ABC Online's campaign weblog, The Poll Vault.

Forecasting PBS expenditure

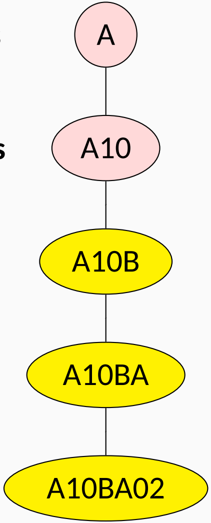
The phone call (2001)

- \$4.5 billion PBS 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

84 classes



Alimentary tract and metabolism

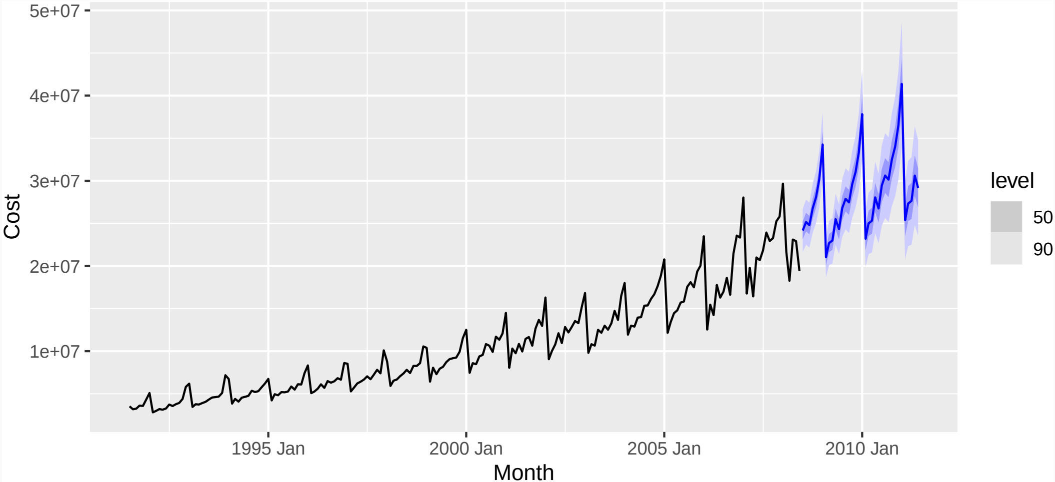
Drugs used in diabetes

Blood glucose lowering drugs

Biguanides

Metformin

ETS forecasts of PBS data



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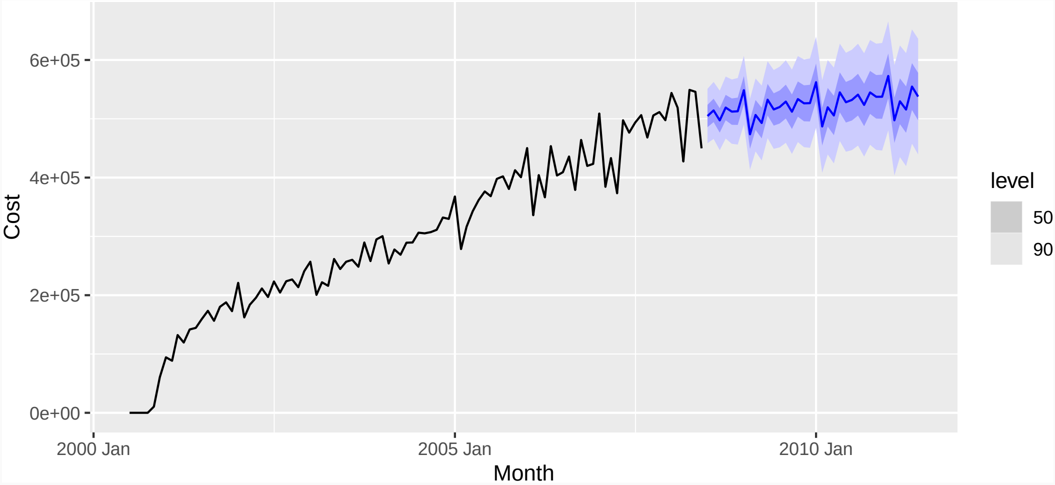

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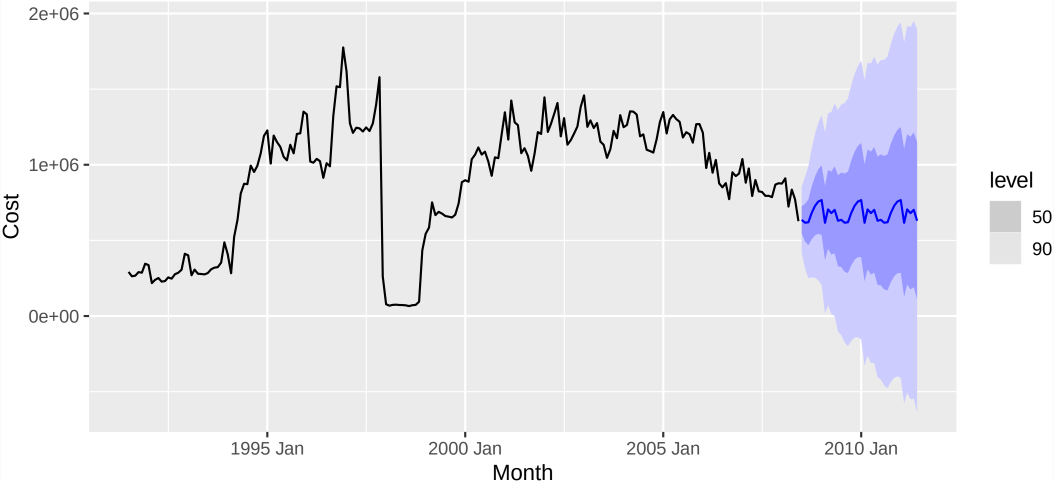

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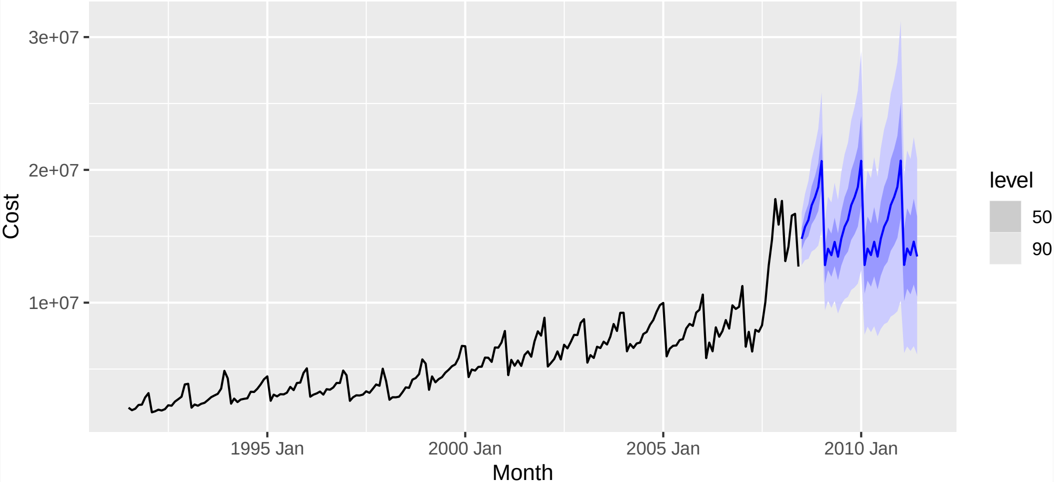

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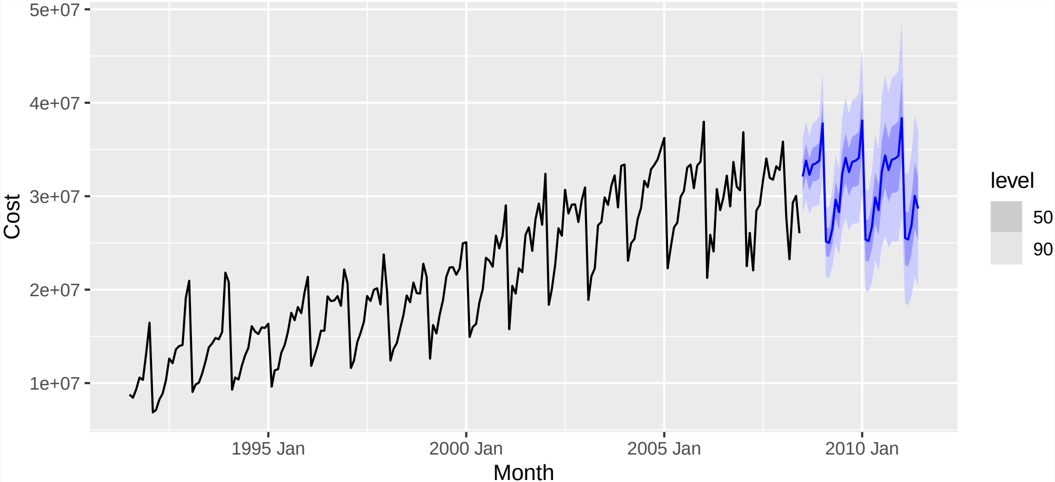

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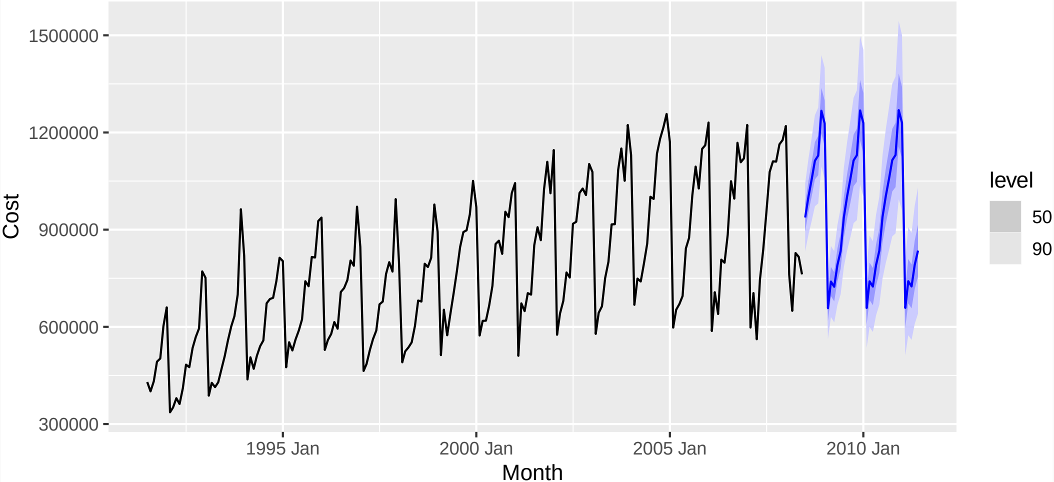

Forecasting PBS expenditure

- 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.

Forecastability factors

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Forecasting peak electricity demand

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The phone call (2006)

- We want to forecast the peak electricity demand in a half-hour period in twenty years time.
- We have fifteen years of half-hourly electricity data, temperature data and some economic and demographic data.
- The location is South Australia: home to the most volatile electricity demand in the world.

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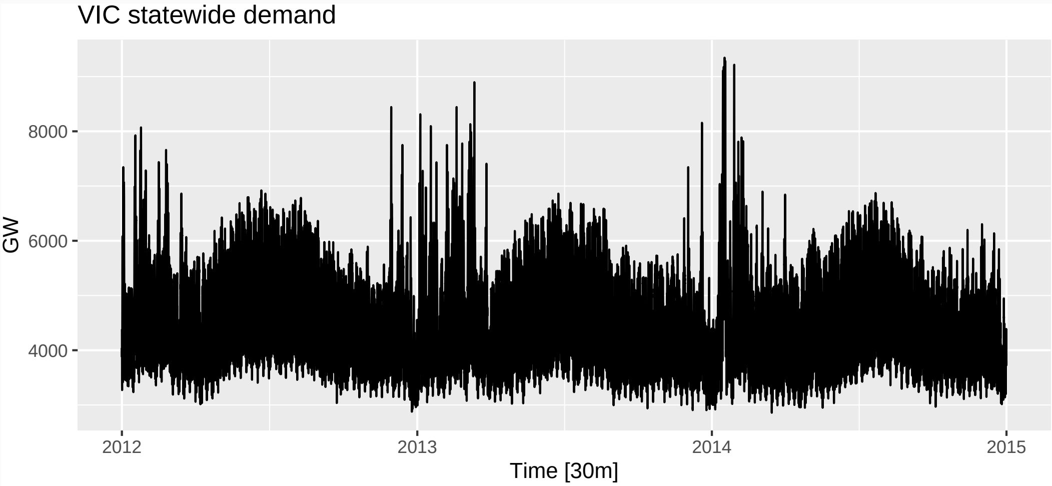
Sounds impossible?

Forecasting peak electricity demand



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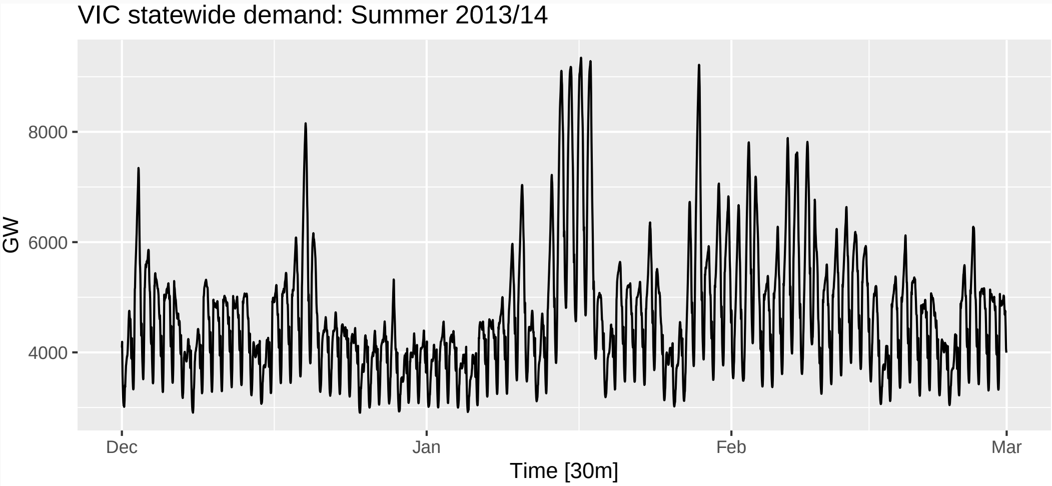

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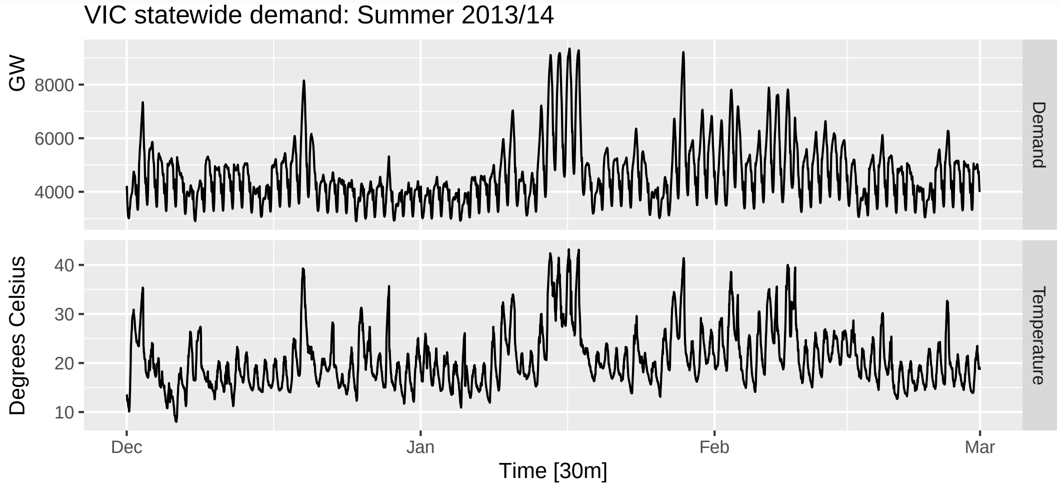

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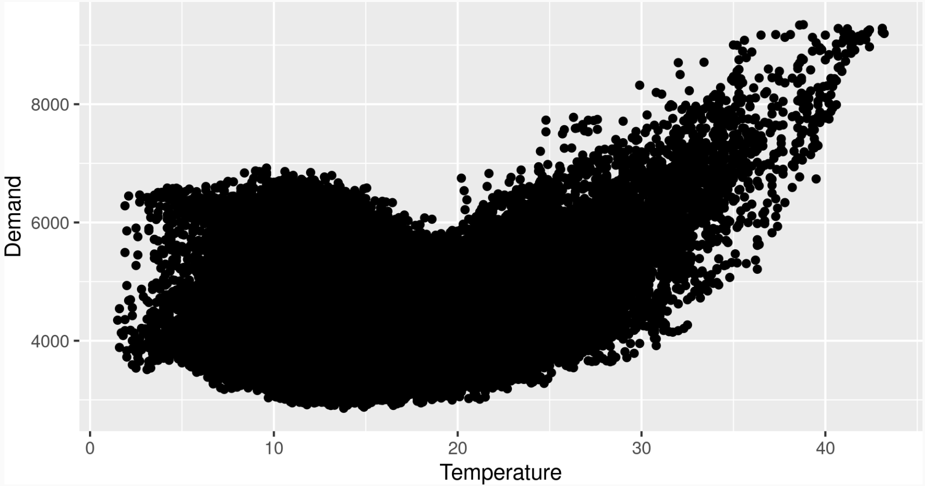

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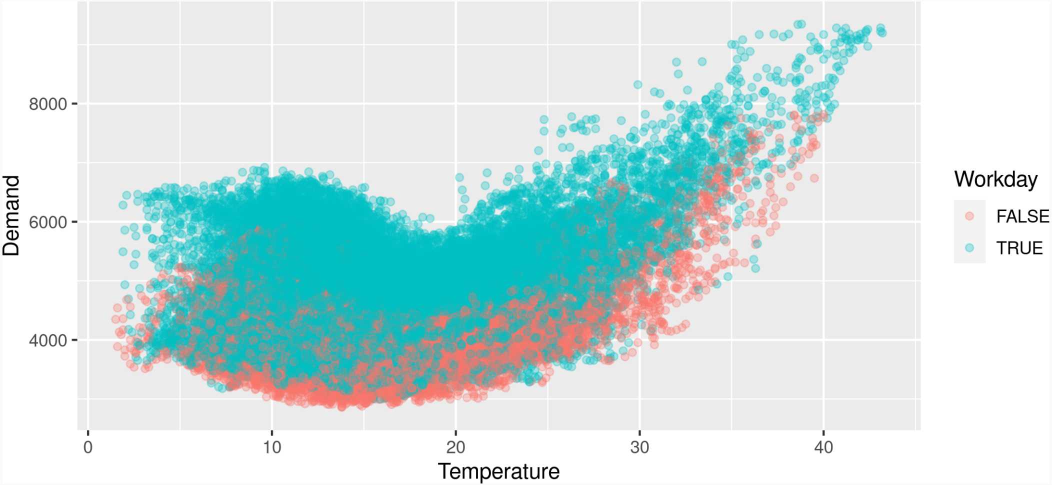

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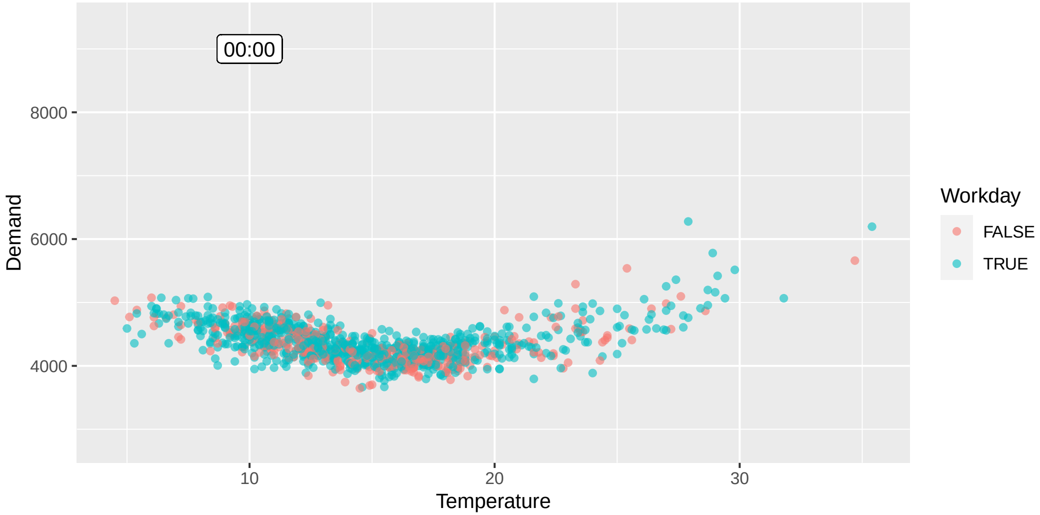

Forecasting peak electricity demand

Predictors

- calendar effects: time of day, day of week, time of year, holidays, etc.
- prevailing and recent weather conditions
- climate change
- demand response incentives
- changing technology
- economic and demographic changes

We build a nonparametric stochastic model of demand as a function of these predictors.

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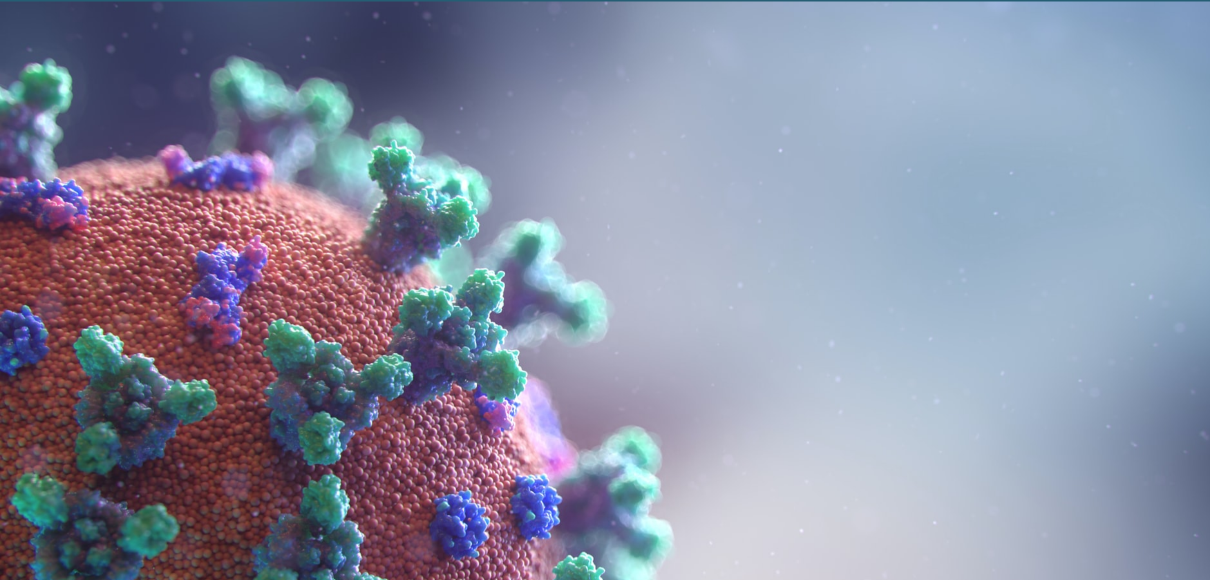
Outline

Forecasting COVID19 cases



Australian Health Protection Principal Committee

The **Australian Health Protection Principal Committee** is the key decision-making committee for national health emergencies. It comprises all state and territory Chief Health Officers and is chaired by the Australian Chief Medical Officer.

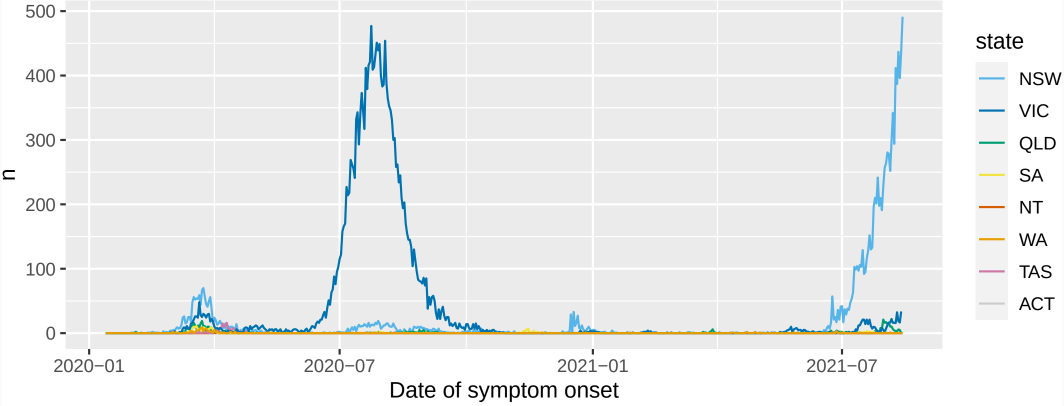
COVID-19 forecasting group

- Peter Dawson
- Nick Golding
- Rob J Hyndman
- Dennis Liu
- Michael Lydeamore
- James M McCaw
- Jodie McVernon
- Pablo Montero-Manso
- Robert Moss
- Mitchell O'Hara-Wild
- David J Price
- Joshua V Ross
- Gerry Ryan
- Freya M Shearer
- Tobin South
- Nicholas Tierney
- Ruarai Tobin

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



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

A model ensemble

Model 1: SEEIIR (Uni Melbourne/Doherty Institute)

- Stochastic compartmental model with time-varying effective reproduction number.

Model 2: Generative model (Uni Adelaide)

- Simulation with three types of infectious individuals: imported, asymptomatic, symptomatic

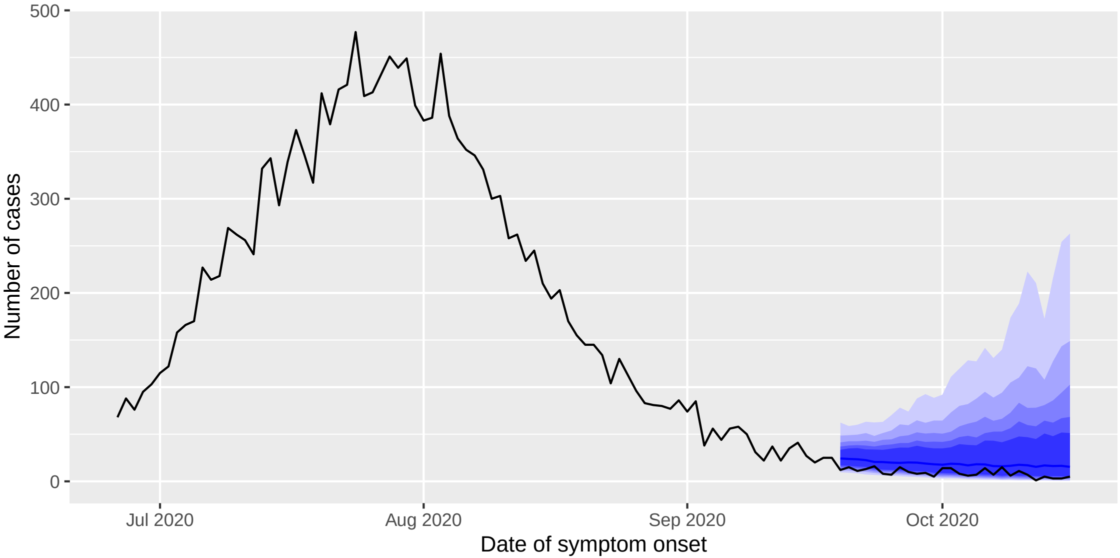
Model 3: Global AR model (Monash)

- Single model fitted to all Johns Hopkins data from countries and regions with sufficient data.
- Series with obvious anomalies removed.

Forecasting ensemble

- Forecasts obtained from a equally-weighted mixture distribution of the component forecasts.
- Also known as “linear pooling”
- Works best when individual models are over-confident and use different data sources.

Ensemble forecasts: Victoria



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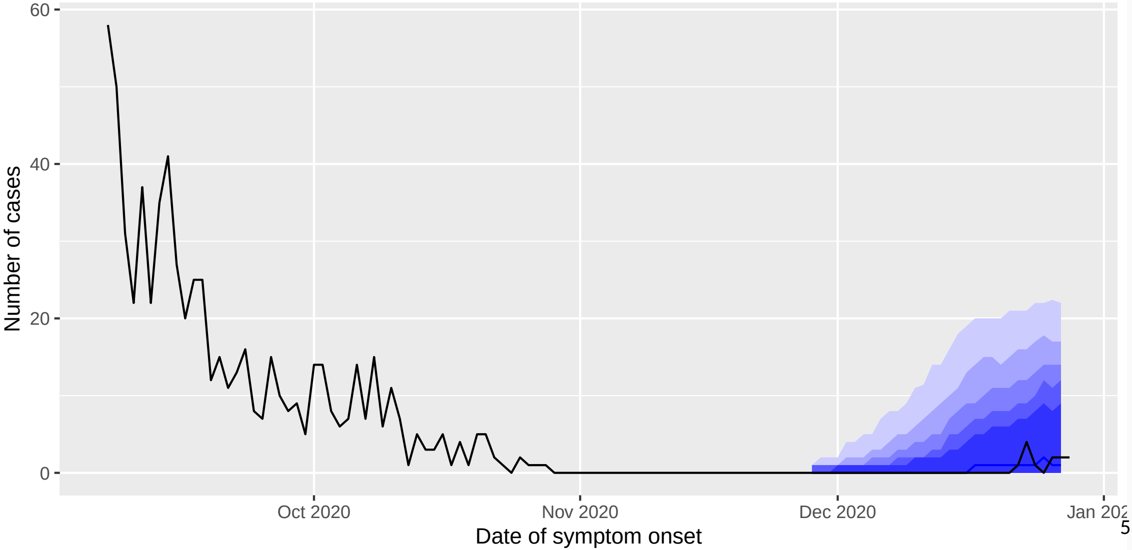

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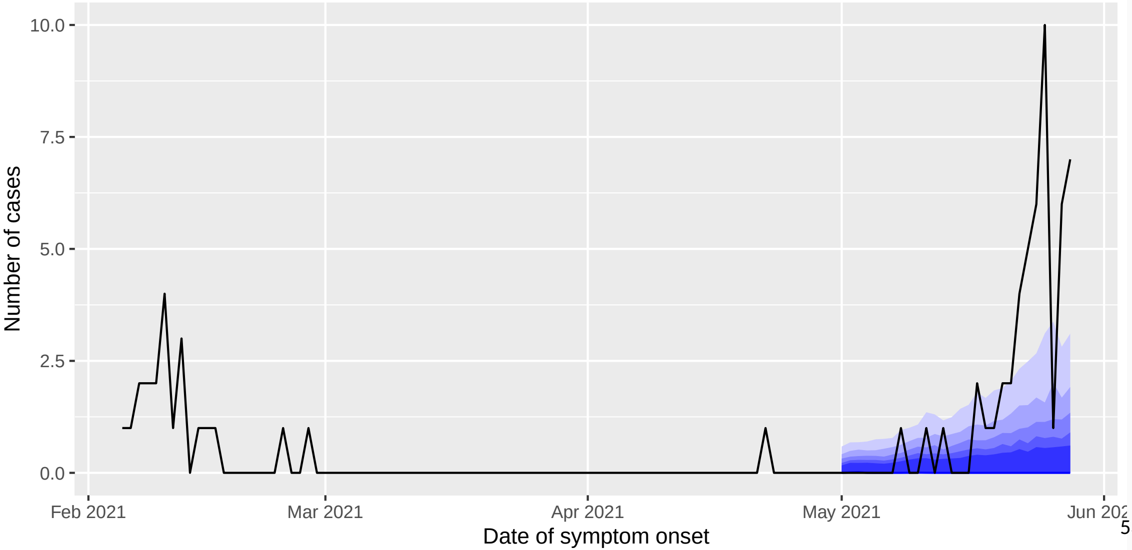

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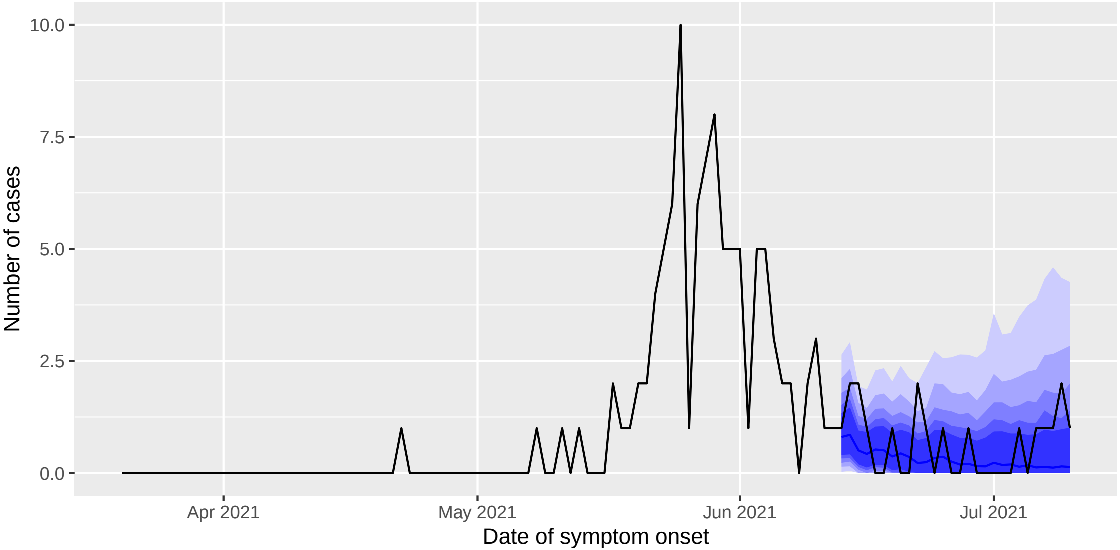

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3 Forecasting PBS expenditure

4 Forecasting peak electricity demand

5 Forecasting COVID19 cases

6 Forecasting post-pandemic tourism

7 Assessing forecast uncertainty

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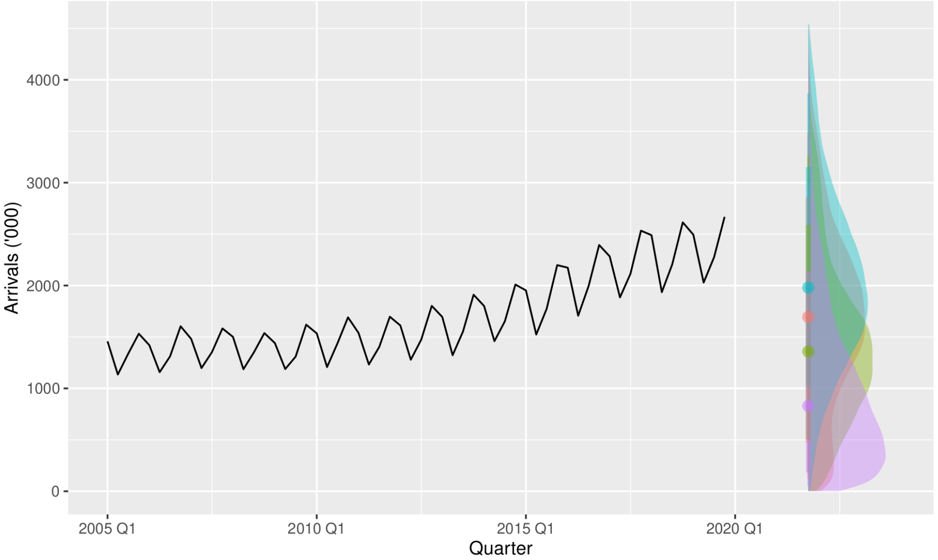

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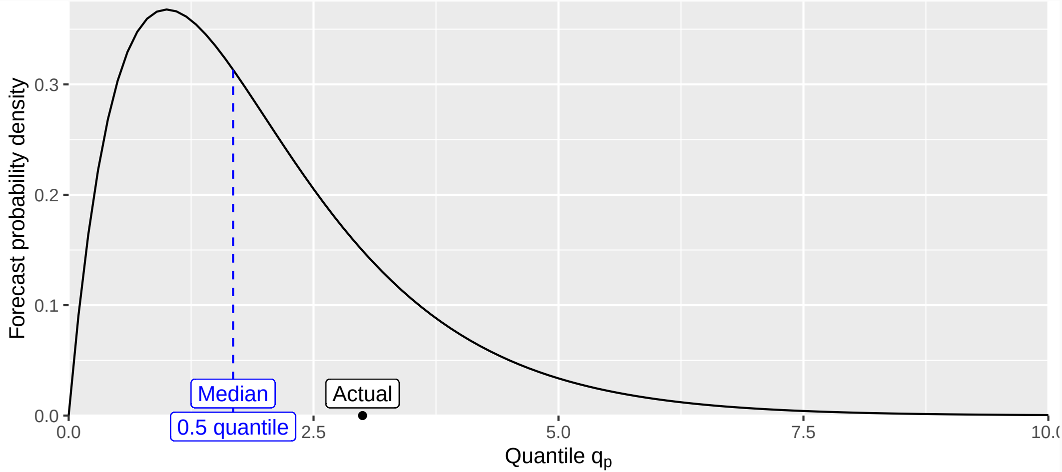

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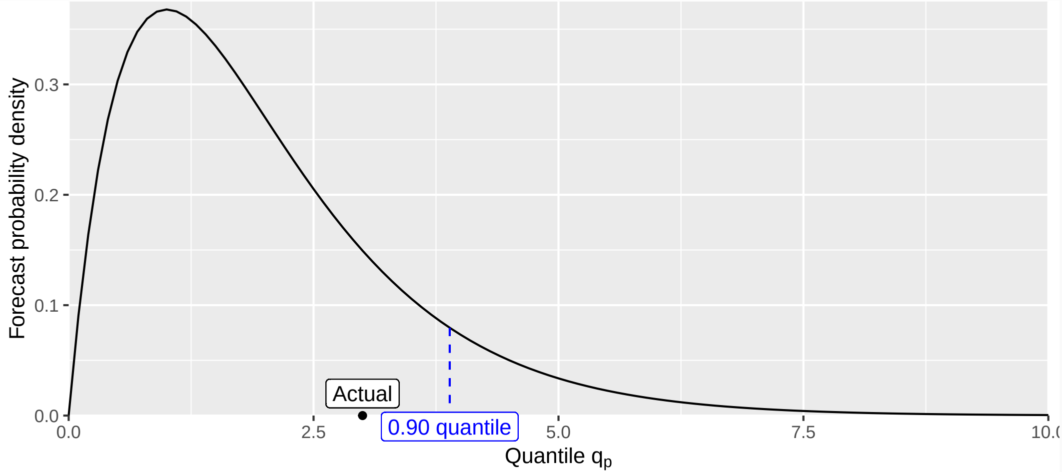

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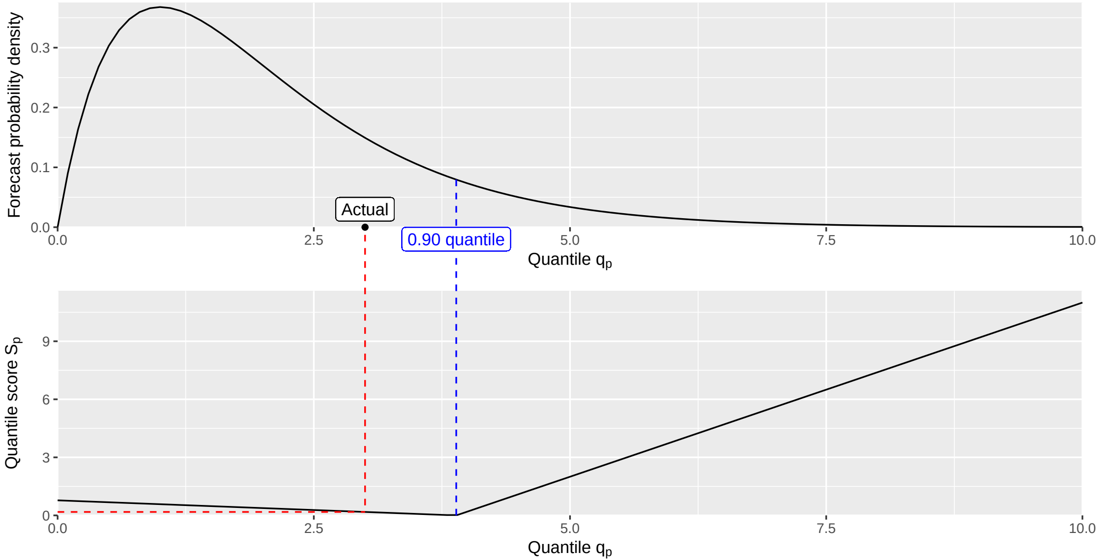

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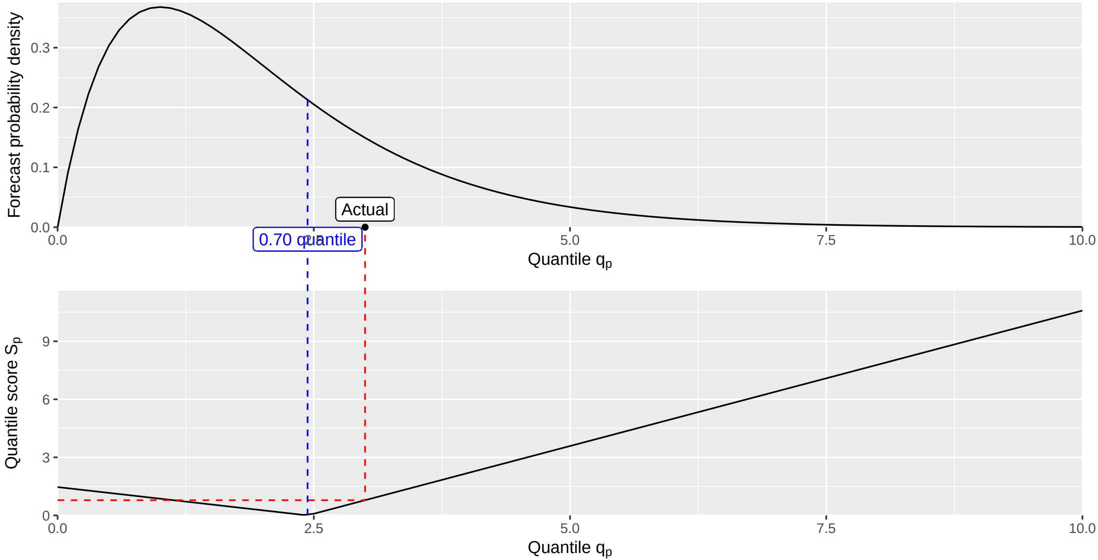

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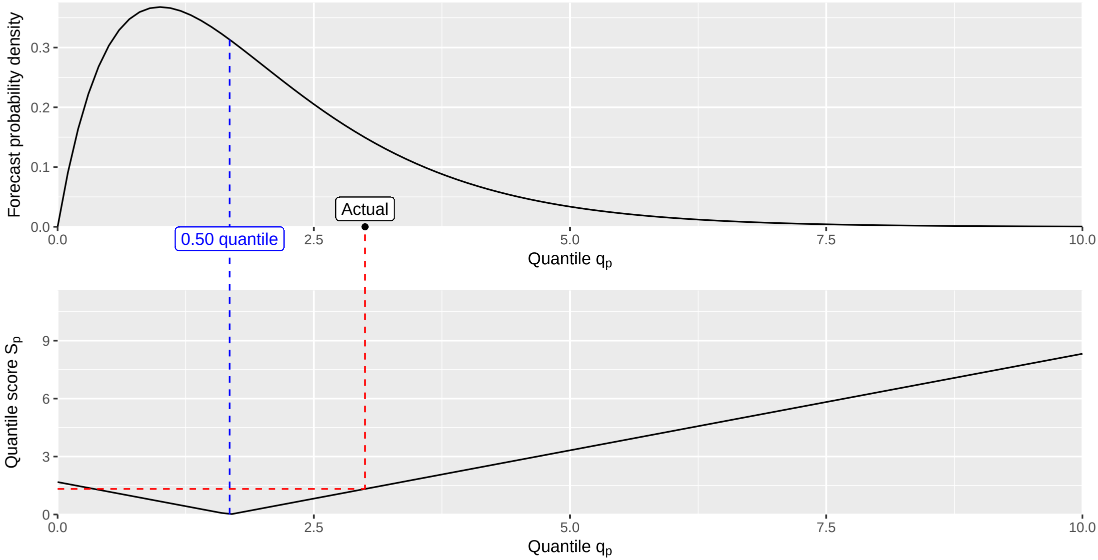

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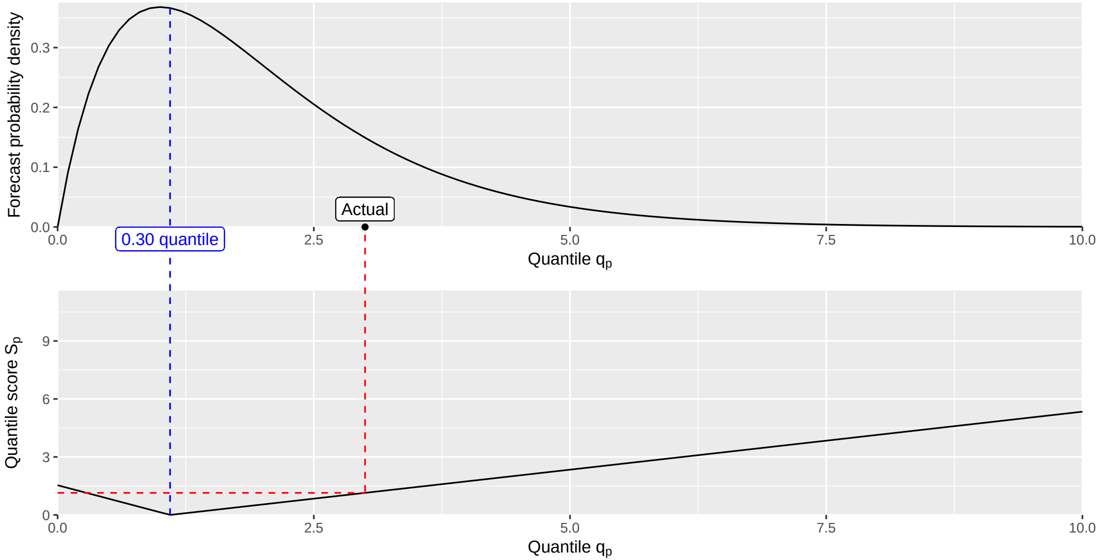

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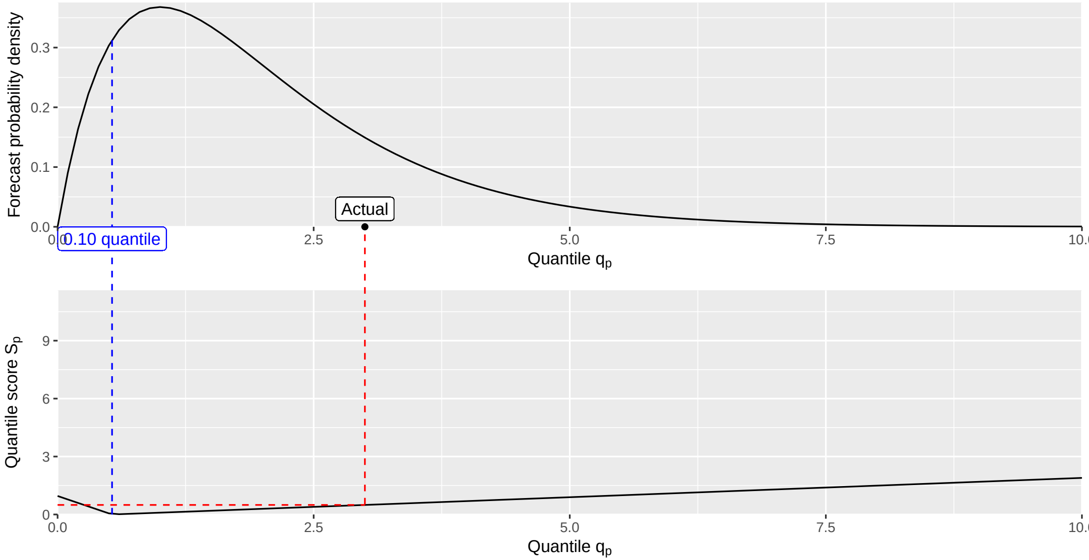

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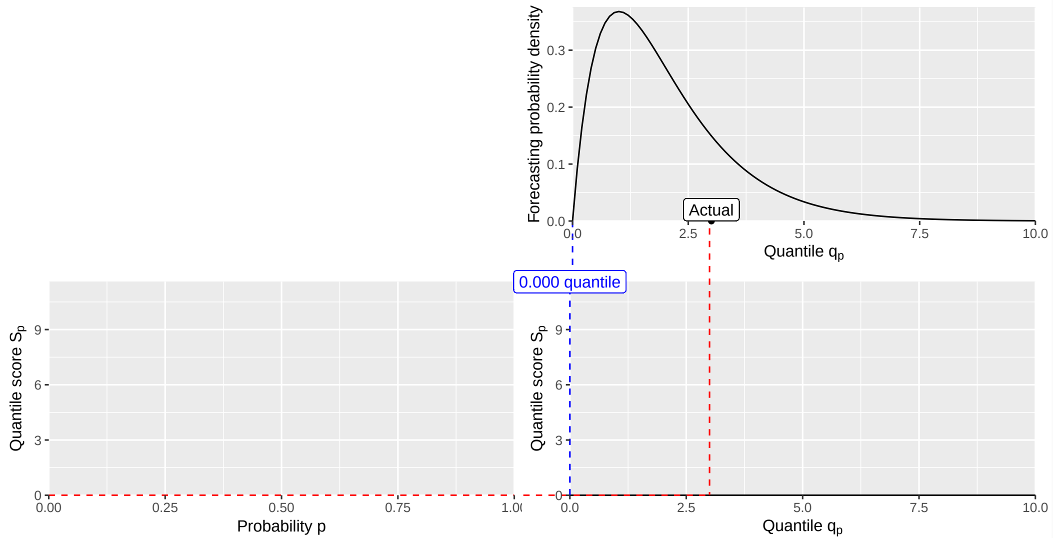

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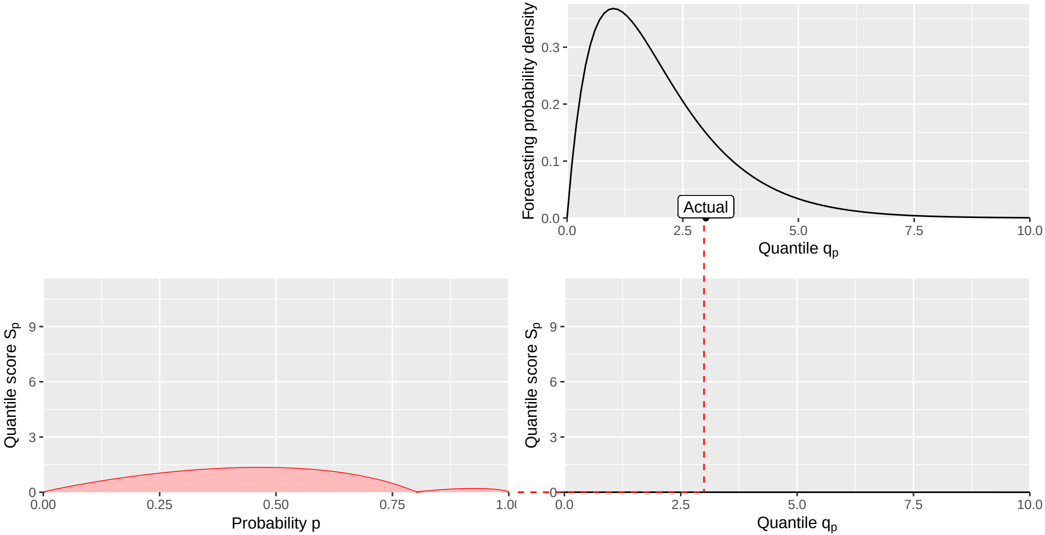

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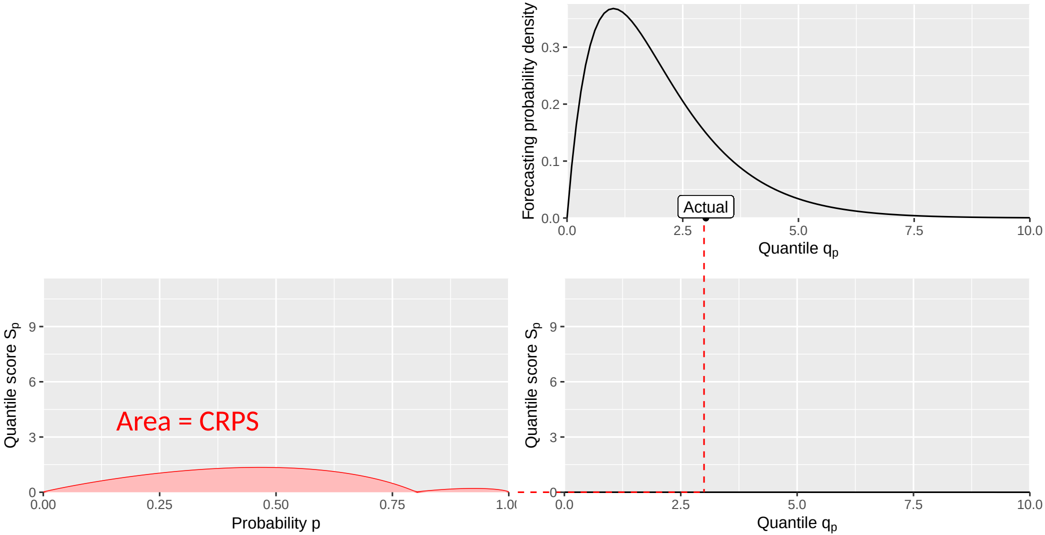

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Quantile score

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

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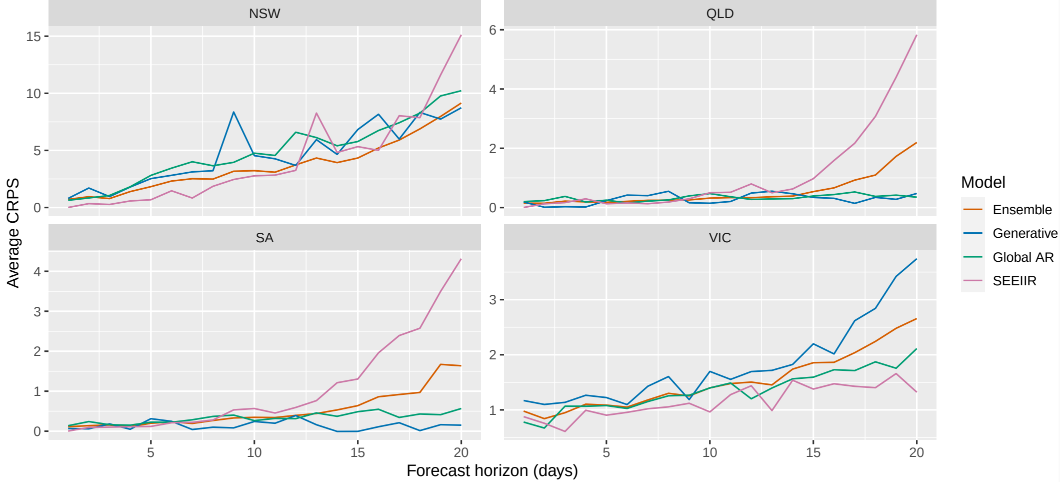
- Low $S_{p,t}$ is good
- Multiplier of 2 often omitted, but useful for interpretation
- $S_{p,t}$ like absolute error (weighted to account for likely exceedance)
- Average $S_{p,t}$ over p = CRPS (Continuous Ranked Probability Score)

CRPS: Continuous Ranked Probability Score



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

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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