

Probabilistic ensemble forecasting of Australian COVID-19 cases

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MONASH University

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 | ■ Jodie McVernon | ■ Joshua V Ross |
| ■ Nick Golding | ■ Pablo Montero-Manso | ■ Gerry Ryan |
| ■ Rob J Hyndman | ■ Robert Moss | ■ Freya M Shearer |
| ■ Dennis Liu | ■ Mitchell O'Hara-Wild | ■ Tobin South |
| ■ James M McCaw | ■ David J Price | ■ 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

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

```
## # A tsibble: 360 x 3 [1D]
```

```
## # Key:           state [1]
```

```
##   date      state      n
```

```
##   <date>    <chr> <dbl>
```

```
## 1 2020-07-01 VIC      122
```

```
## 2 2020-07-02 VIC      118
```

```
## 3 2020-07-03 VIC      173
```

```
## 4 2020-07-04 VIC      167
```

```
## 5 2020-07-05 VIC      162
```

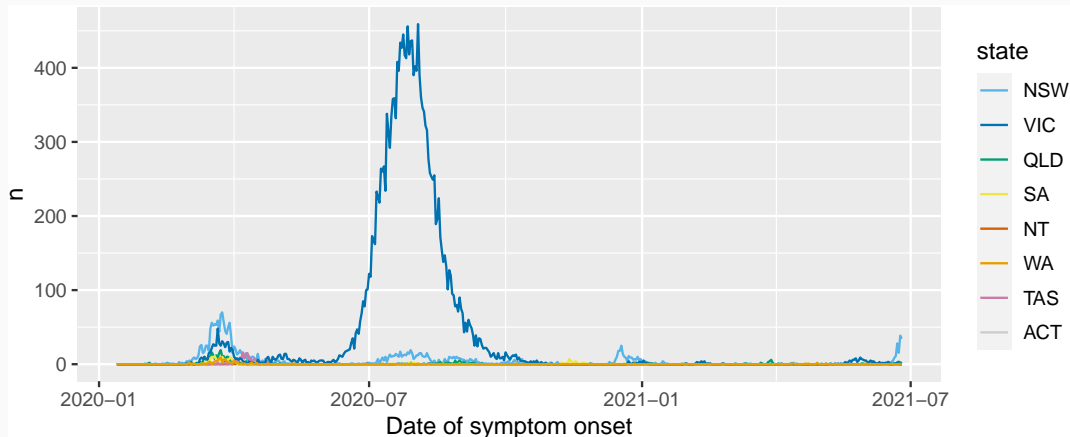
```
## 6 2020-07-06 VIC      233
```

```
## 7 2020-07-07 VIC      226
```

```
## 8 2020-07-08 VIC      218
```

```
## 9 2020-07-09 VIC      264
```

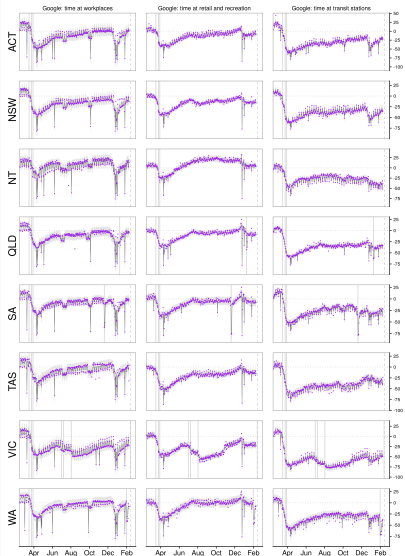
Case numbers



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

Google mobility data

Percentage change in selected mobility datastreams up to February 14, 2021



Percentage change compared to pre-COVID-19 baseline for:

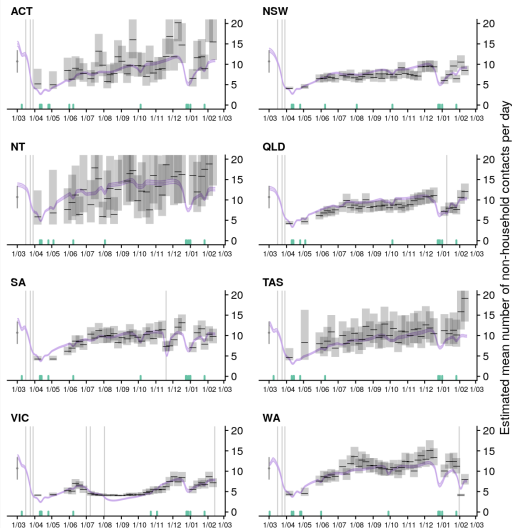
- (a) time at workplace;
- (b) time at retail/recreation;
- (c) time at transit stations.

Vertical lines: physical distancing measures implemented.

Macrodistancing

Macro-distancing trend

Rate of non-household contacts

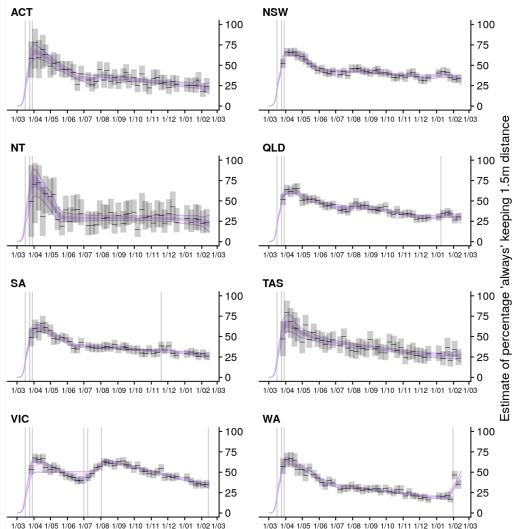


Estimated # non-household contacts per day based on nationwide weekly surveys (gray) and Google mobility data. Green: public holidays.

Microdistancing

Micro-distancing trend

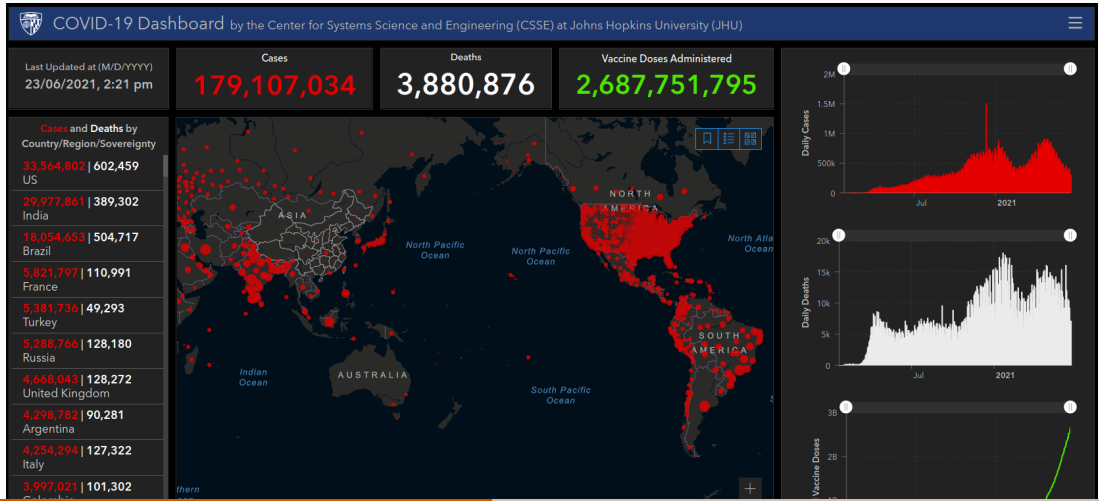
Calibrated against self-reported adherence to physical distancing



Estimated % keeping 1.5m distance from non-household contacts based on nationwide weekly surveys (gray).

Global daily cases by region from Johns Hopkins

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



Model 1: SEIIR (Uni Melbourne/Doherty Institute)

- Stochastic susceptible-exposed-infectious-recovered compartmental model that incorporates changes in local transmission potential via a time-varying effective reproduction number.
- Uses mobility and survey data and case onset and detection times.
- Daily counts \sim Negative Binomial.
- Time in class \sim Gamma.
- Forecasts obtained using a bootstrap particle filter.

Model 2: Generative model (Uni Adelaide)

- Uses mobility and survey data and case onset and detection times.
- Three types of infectious individuals: imported, asymptomatic, symptomatic
- Class counts \sim Negative Binomial.
- Incubation times \sim Gamma.
- Estimation via Hamilton Monte Carlo
- Forecasts obtained via simulation

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).
- $y_{t,i} = \phi_1 y_{t-1,i} + \dots + \phi_p y_{t-p,i} + \varepsilon_{t,i}$
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

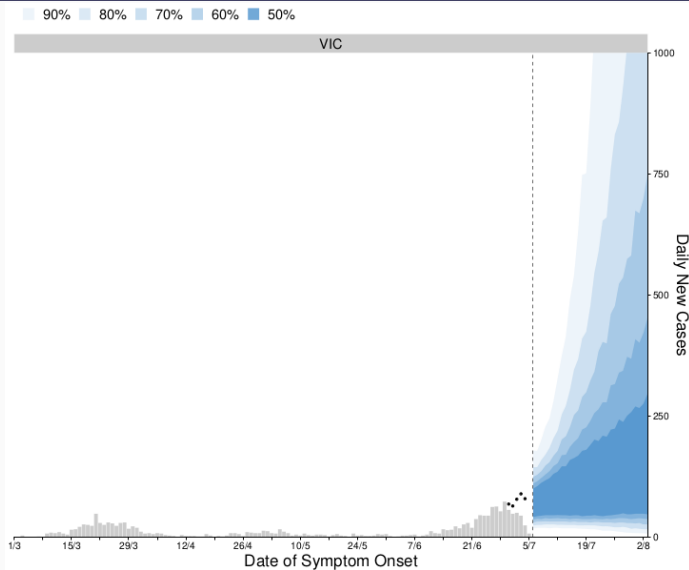
- Forecasts obtained from a mixture distribution of the component models.

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

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 $w_{t+h|t,k} = 1/3$.

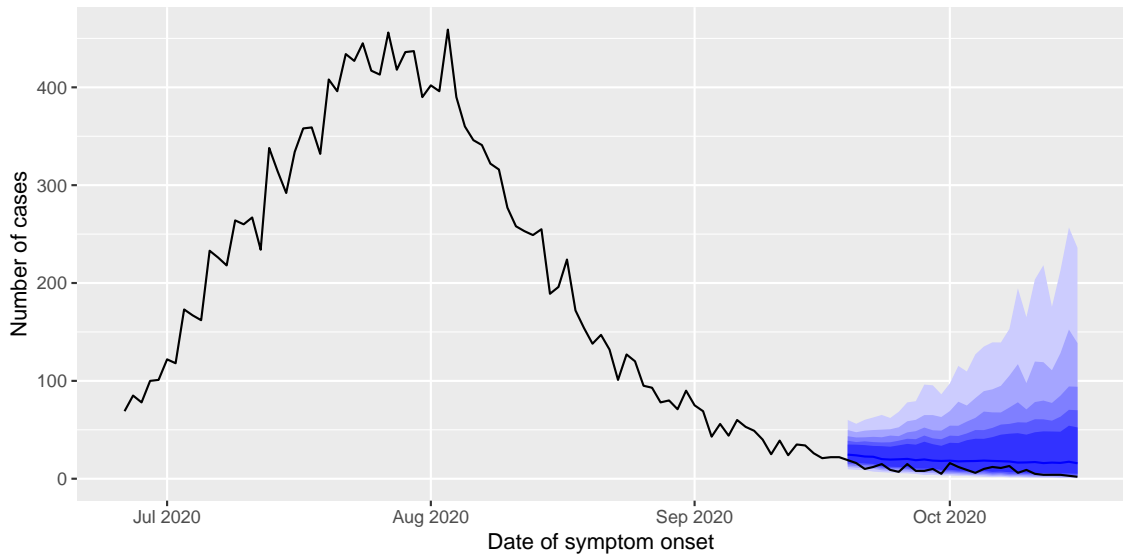
Ensemble forecasts: Victoria



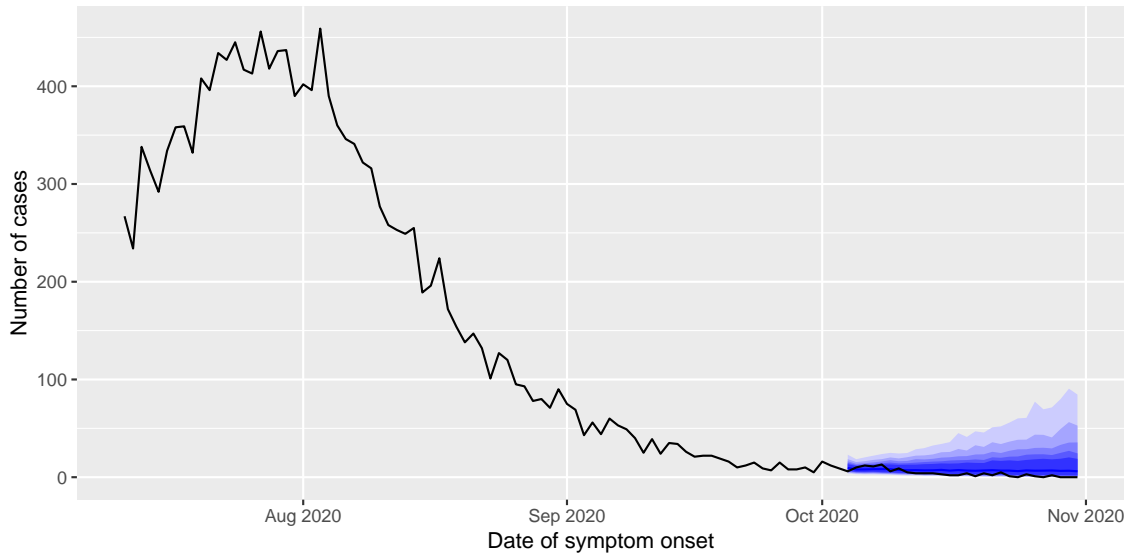
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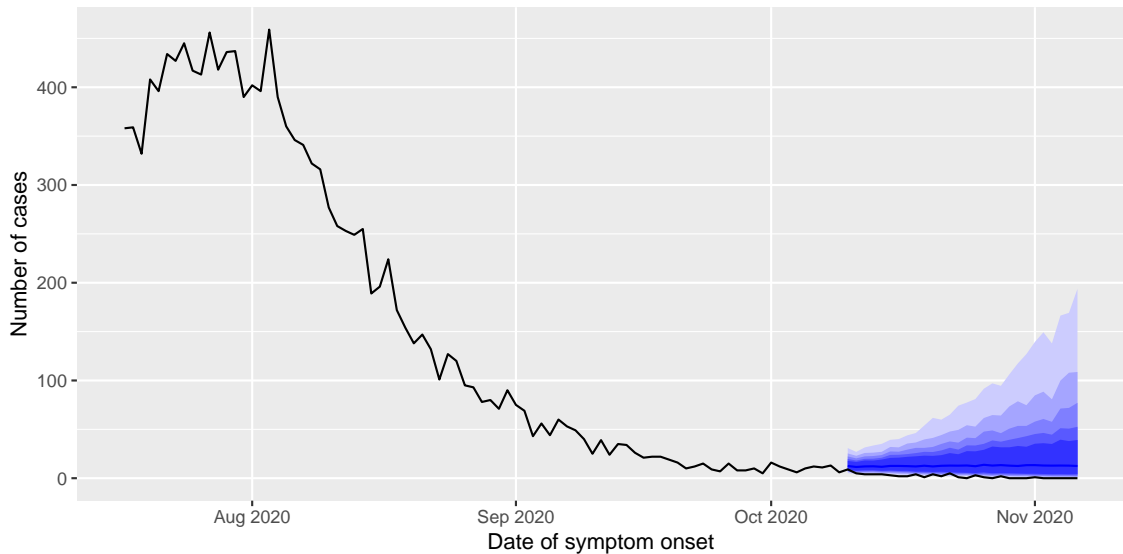
Ensemble forecasts: Victoria



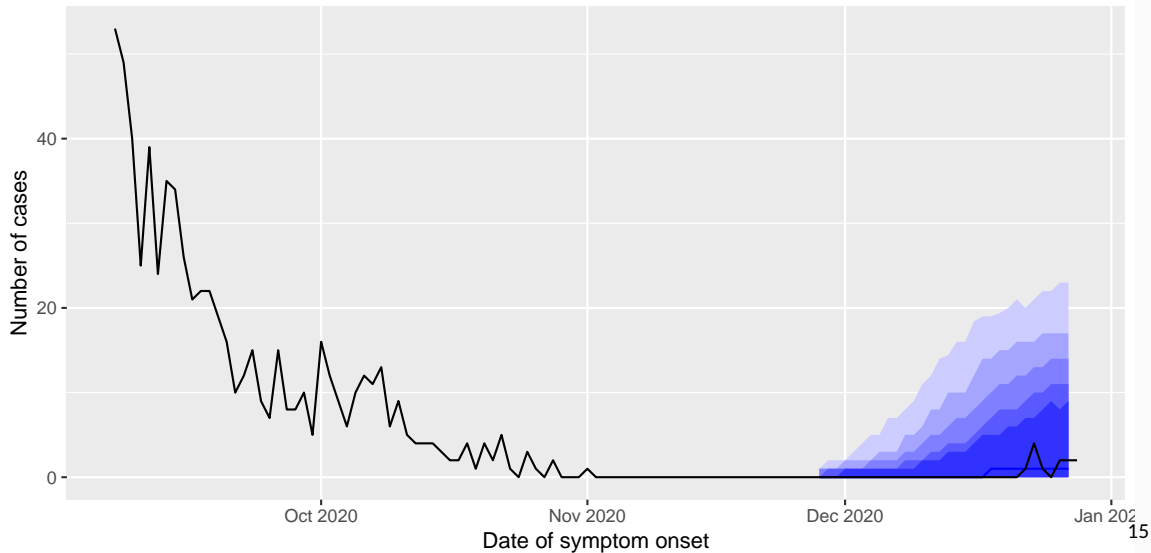
Ensemble forecasts: Victoria



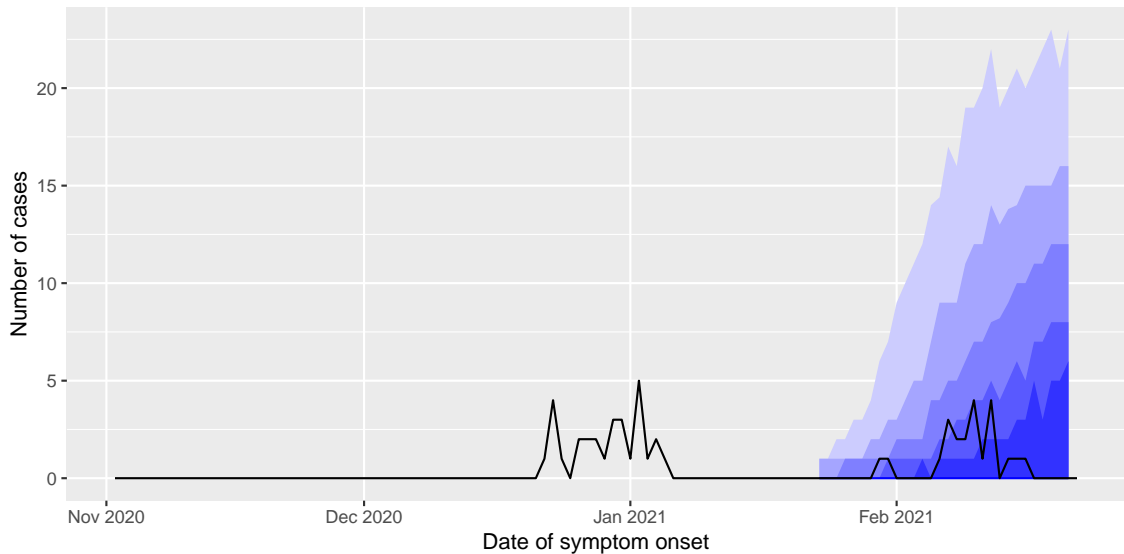
Ensemble forecasts: Victoria



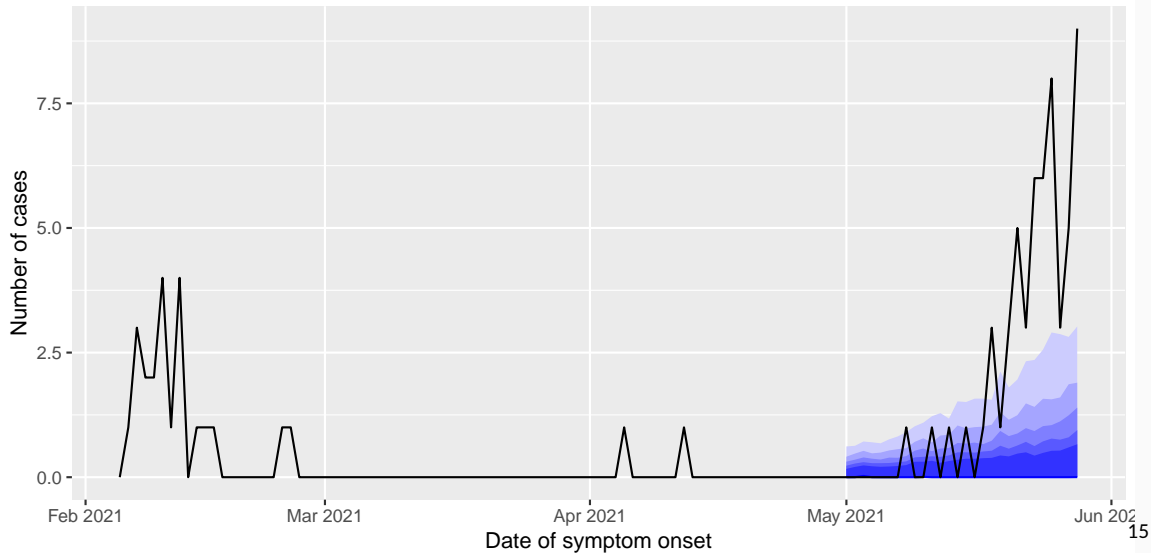
Ensemble forecasts: Victoria



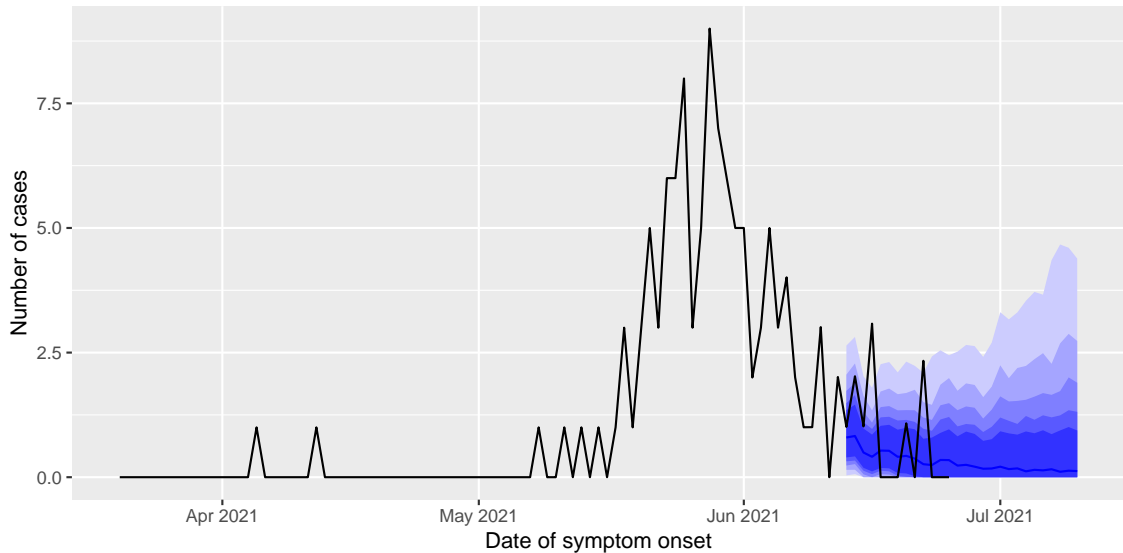
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Ensemble forecasts: Victoria



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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- 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

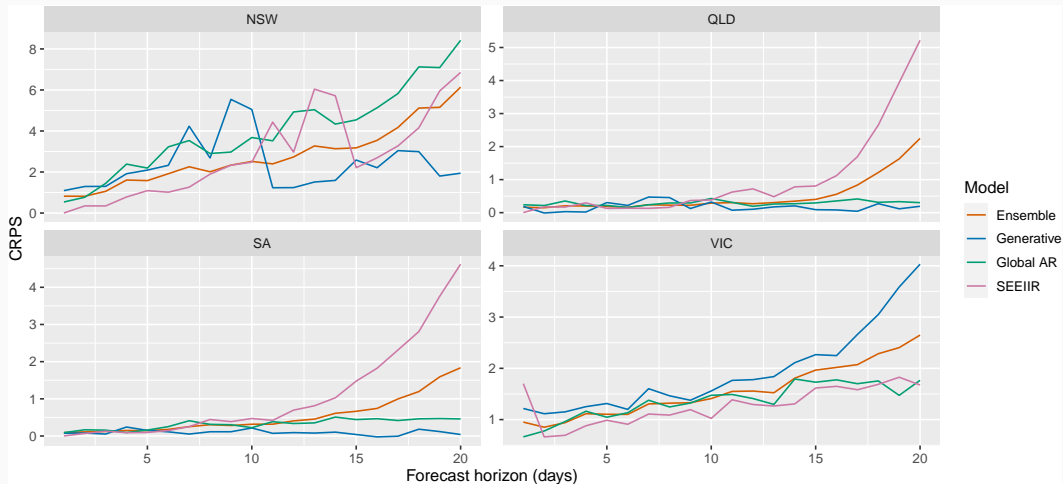
$f_{p,t} = F_t^{-1}(p)$ = quantile forecast with prob. p

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

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

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

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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