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Time Series Analysis & Forecasting Using R

6. Introduction to forecasting

tsibble feasts Fable

Outline

1 Statistical forecasting

2 Benchmark methods

3 Lab Session 11

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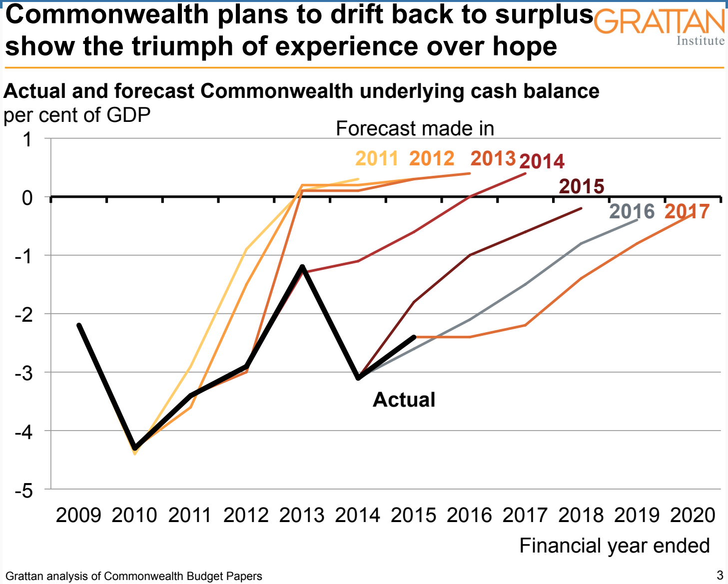
1. Statistical forecasting
2. Benchmark methods
3. Lab Session 11

Forecasting is difficult



What can we forecast?

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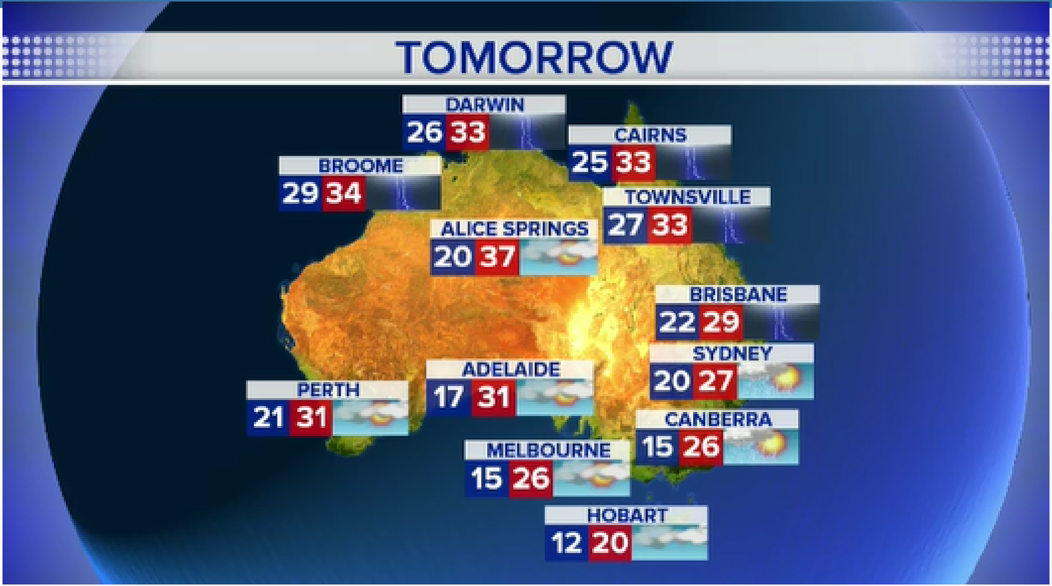

What can we forecast?

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Which is easiest to forecast?

1. daily electricity demand in 3 days time
2. timing of next Halley's comet appearance
3. time of sunrise this day next year
4. Google stock price tomorrow
5. Google stock price in 6 months time
6. maximum temperature tomorrow
7. exchange rate of $US/AUS next week
8. 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?

Factors affecting forecastability

Something is easier to forecast if:

- we have a good understanding of the factors that contribute to it
- there is lots of data available;
- the forecasts cannot affect the thing we are trying to forecast.
- there is relatively low natural/unexplainable random variation.
- the future is somewhat similar to the past

Random futures

A forecast is an estimate of the probabilities of possible futures.

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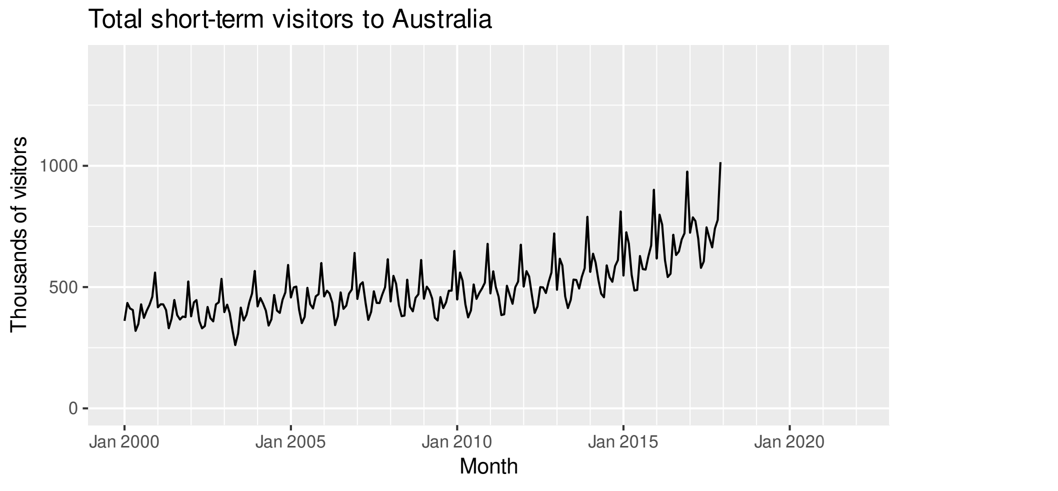

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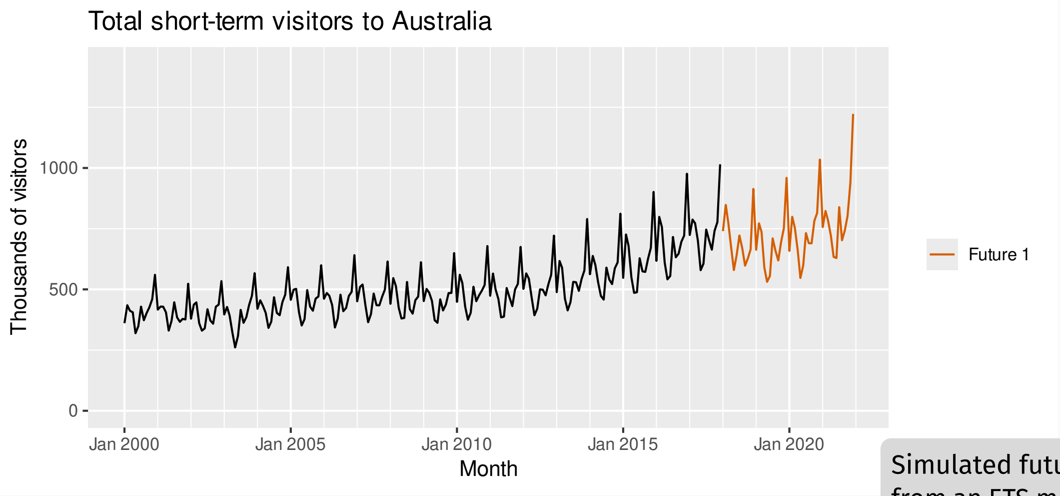

Simulated futures from an ETS model

Random futures

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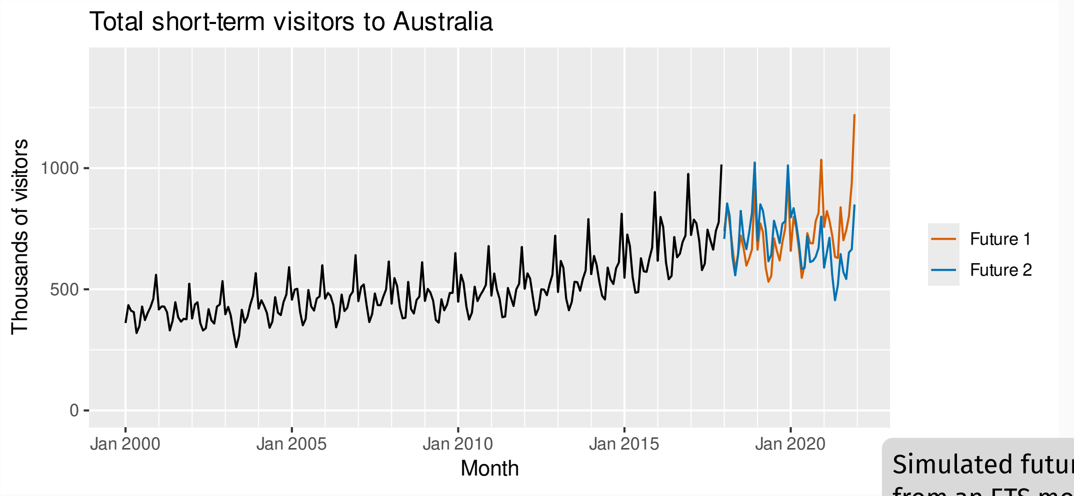

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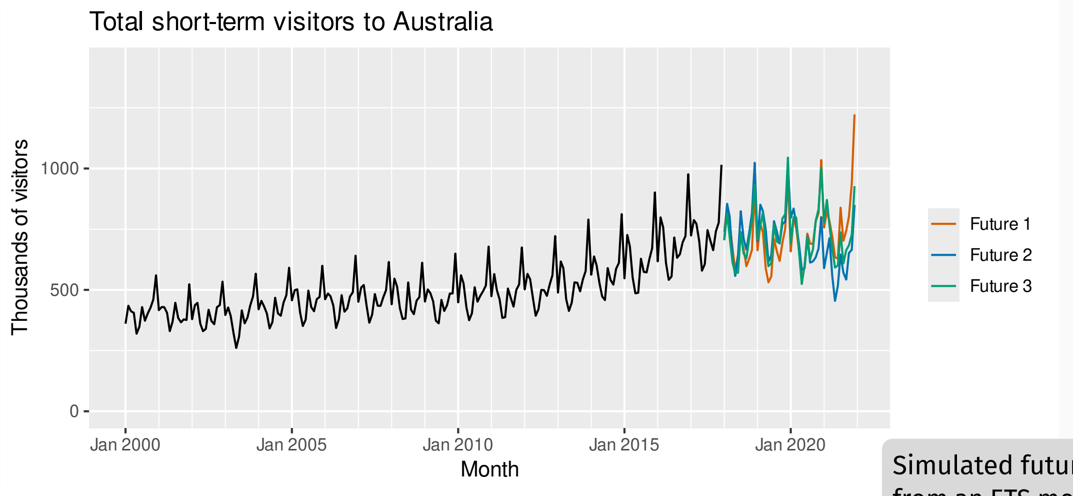

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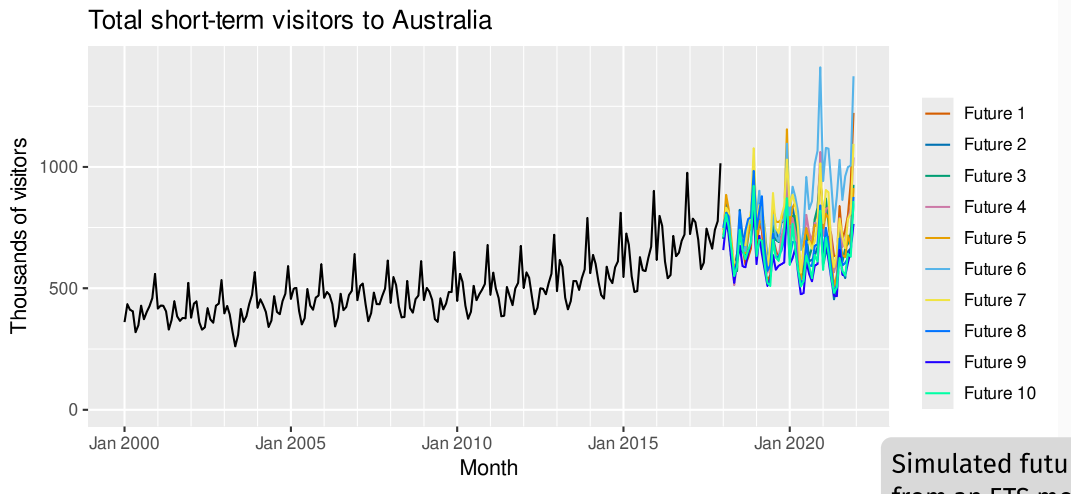

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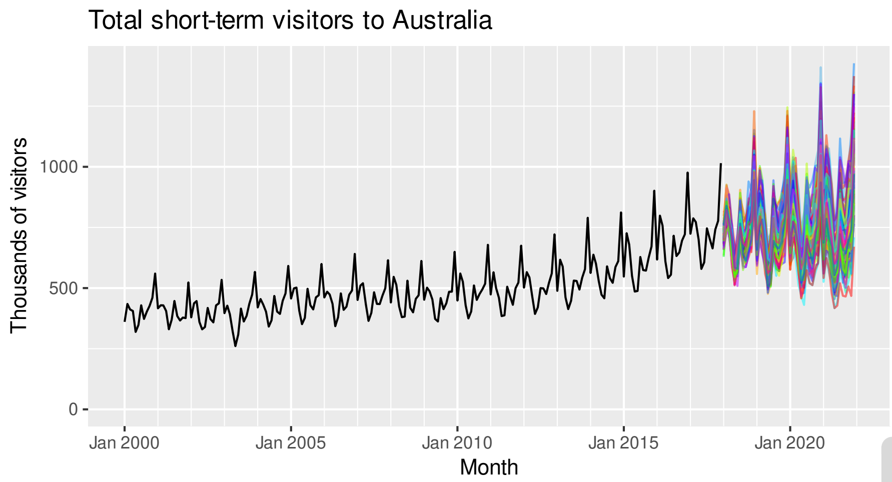

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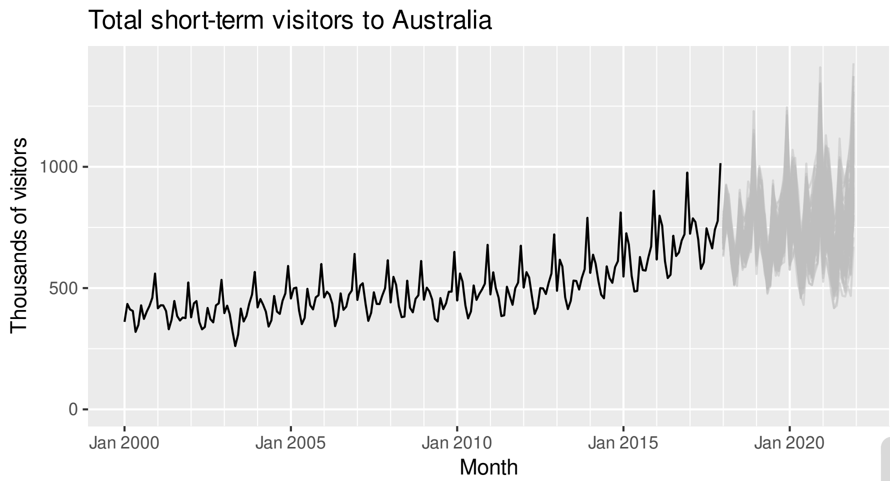

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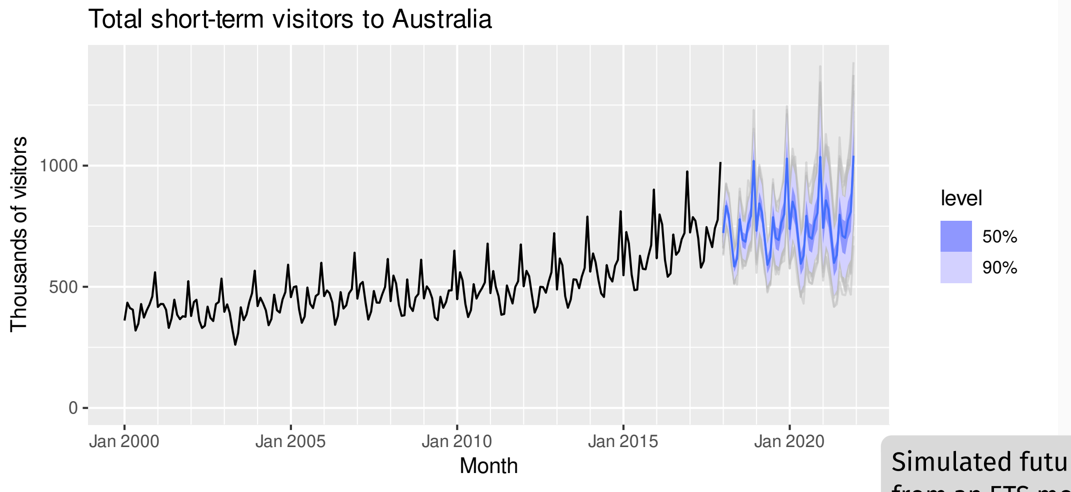

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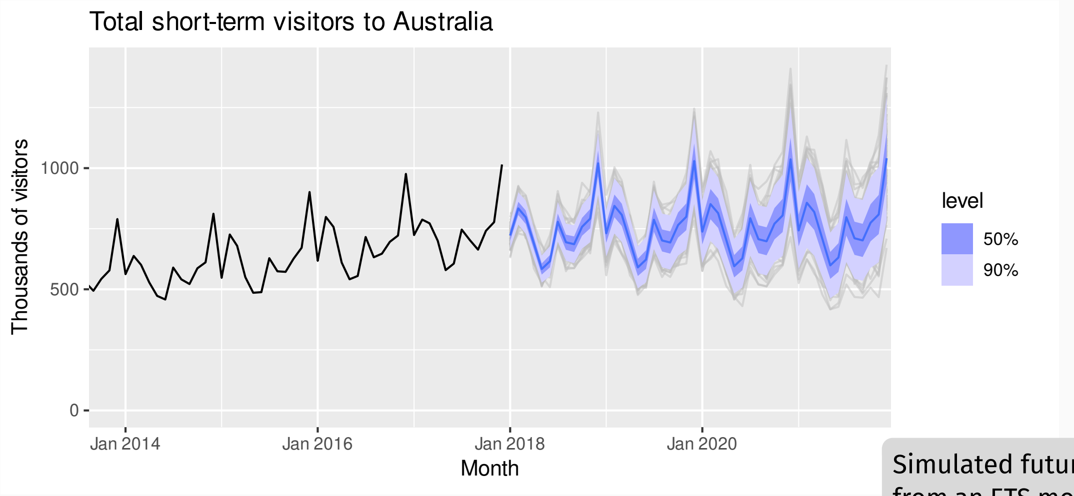

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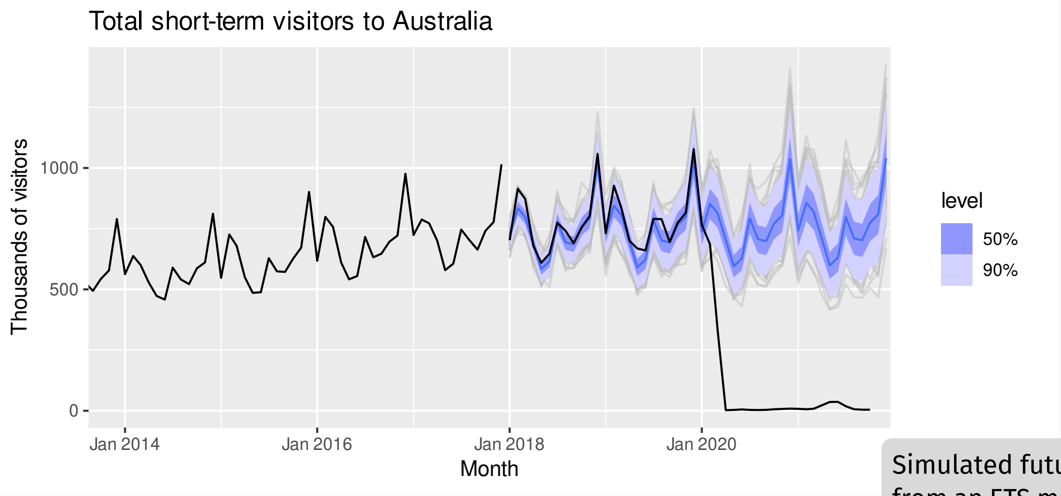

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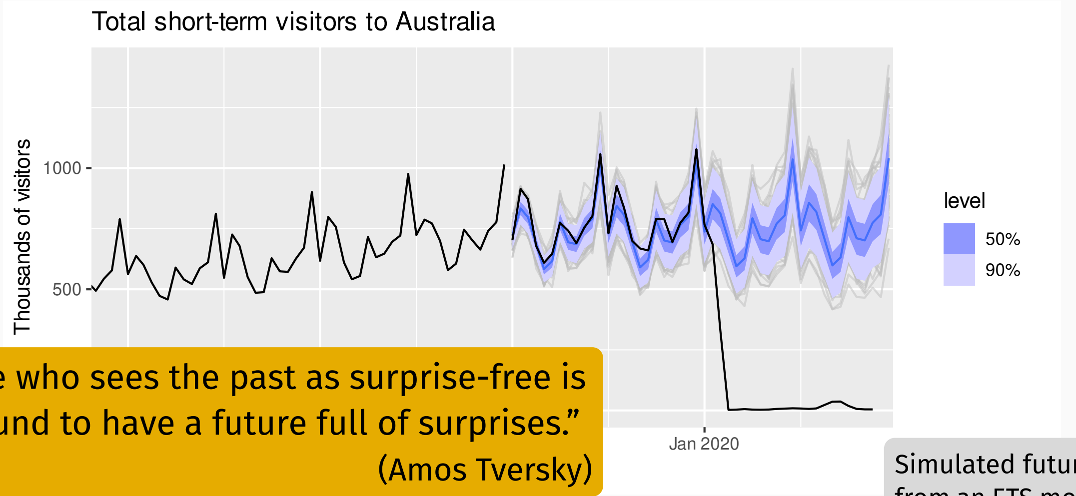

“He who sees the past as surprise-free is bound to have a future full of surprises.”

(Amos Tversky)

Simulated futures from an ETS model

Statistical forecasting

- Thing to be forecast: y_{T+h}.
- What we know: $y_1, \dots, y_T$.
- Forecast distribution: $y_{T+h|t} = y_{T+h} \mid \{y_1, y_2, \dots, y_T\}$.
- Point forecast: $\hat{y}_{T+h|T} = \text{E}[y_{T+h} \mid y_1, \dots, y_T]$.
- Forecast variance: $\text{Var}[y_t \mid y_1, \dots, y_T]$
- Prediction interval is a range of values of y_{T+h} with high probability.

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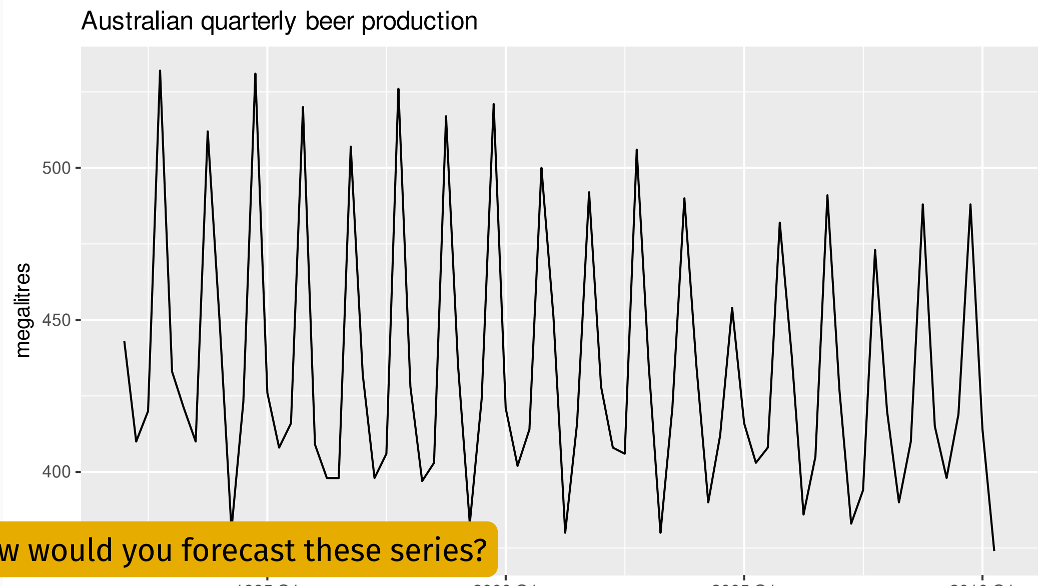
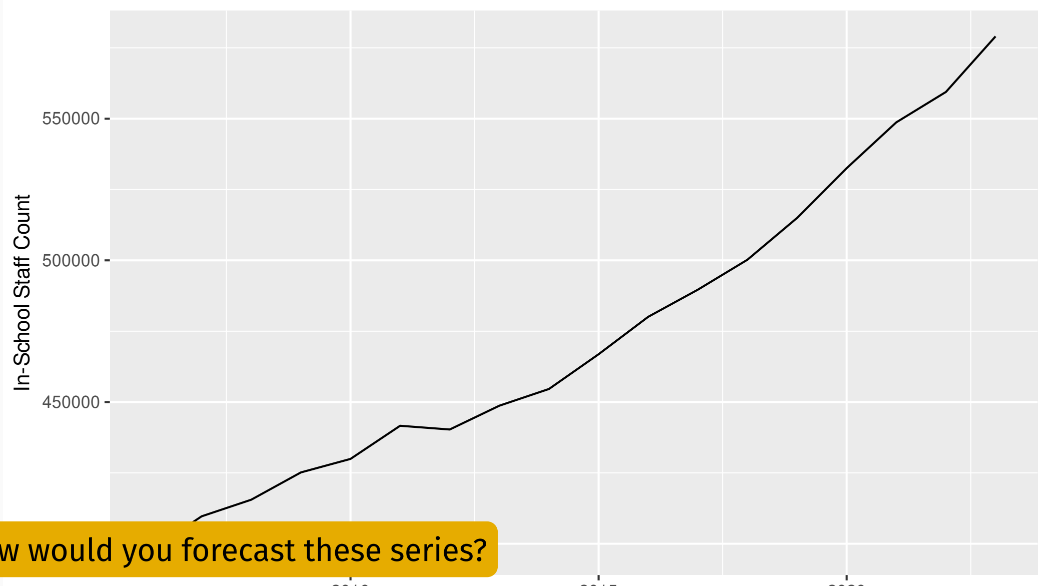
Some simple forecasting methods



How would you forecast these series?

Some simple forecasting methods



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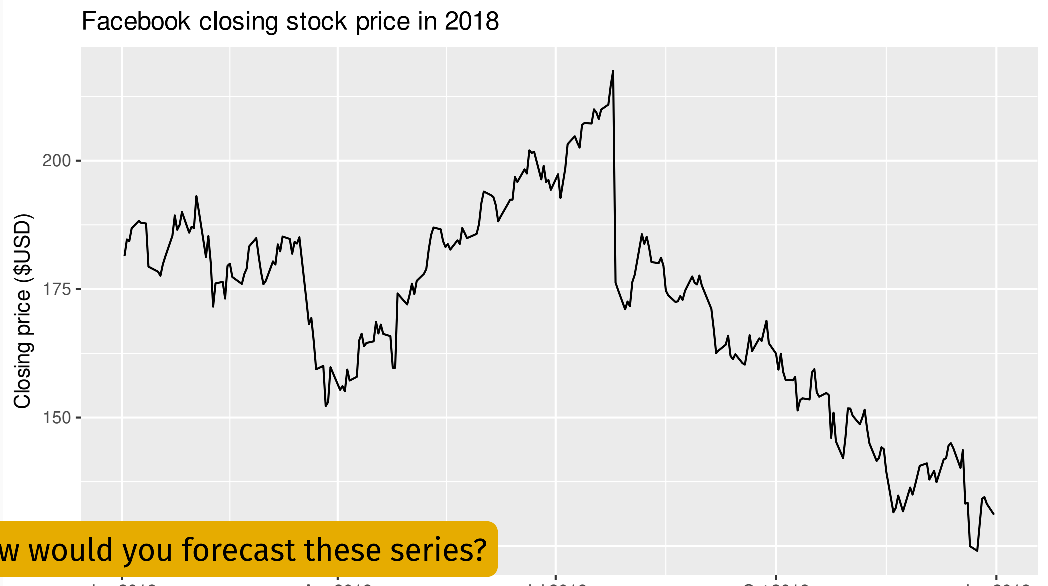
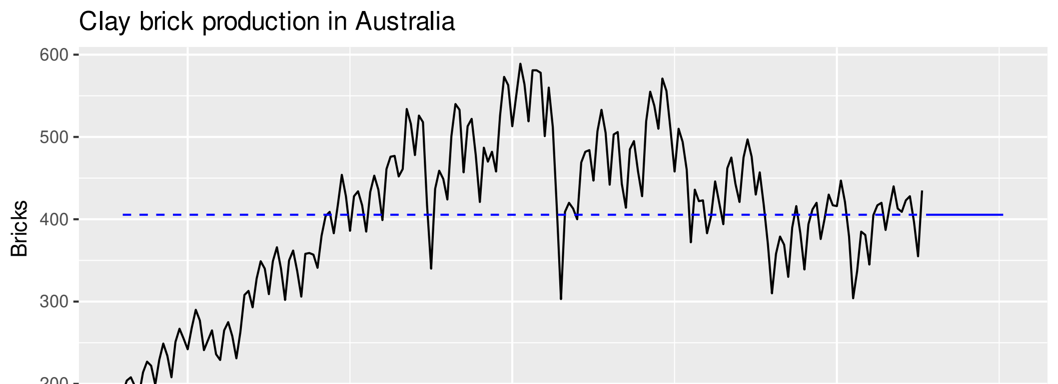


How would you forecast these series?

Some simple forecasting methods

`MEAN(y)`: Average method

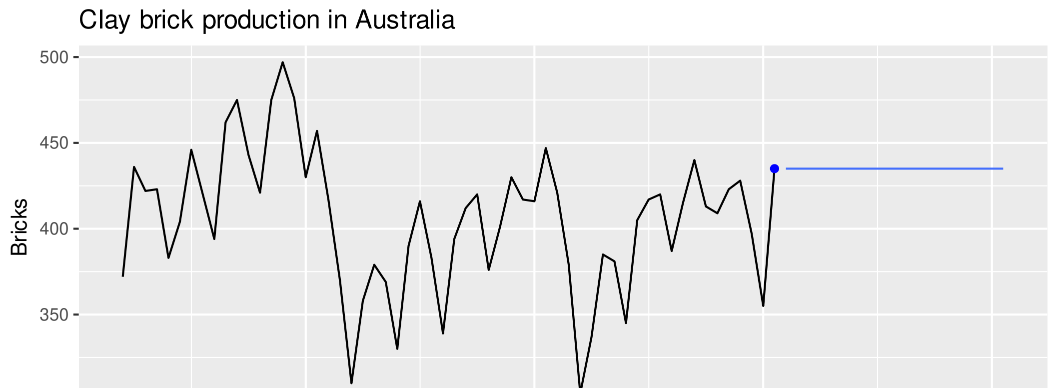
- Forecast of all future values is equal to mean of historical data $\{y_1, \dots, y_T\}$.
- Forecasts: $\hat{y}_{T+h|T} = \bar{y} = (y_1 + \cdots + y_T)/T$



Some simple forecasting methods

NAIVE(y): Naive method

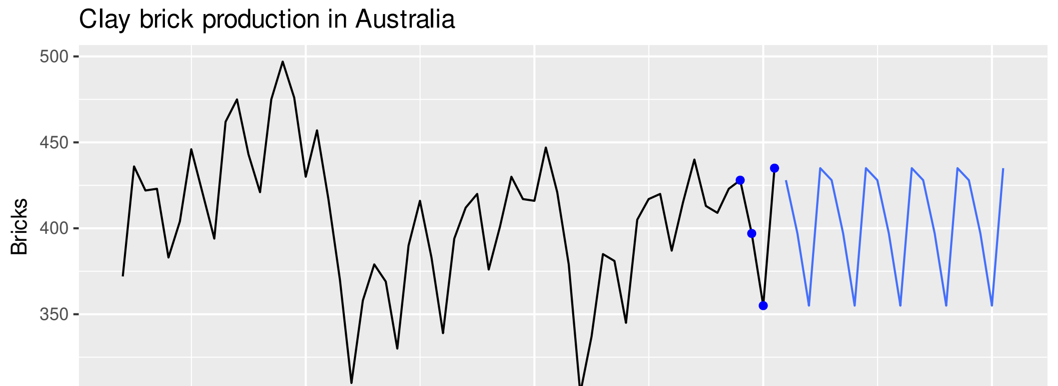
- Forecasts equal to last observed value.
- Forecasts: $\hat{y}_{T+h|T} = y_T$.
- Consequence of efficient market hypothesis.



Some simple forecasting methods

`SNAIVE(y ~ lag(m))`: Seasonal naive method

- Forecasts equal to last value from same season.
- Forecasts: $\hat{y}_{T+h|T} = y_{T+h-m(k+1)}$, where m = seasonal period and k is the integer part of $(h-1)/m$.



Some simple forecasting methods

`RW(y ~ drift())`: Drift method

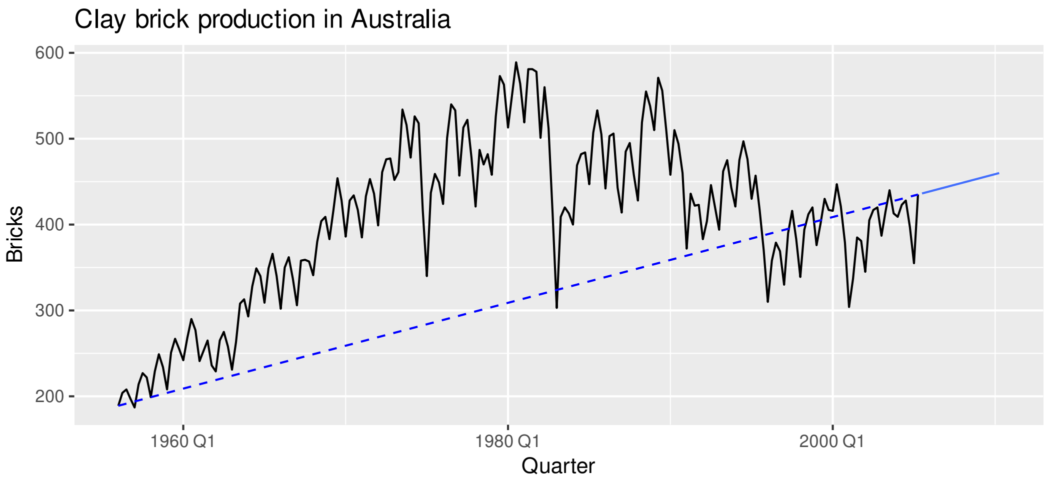
- Forecasts equal to last value plus average change.
- Forecasts:

$$\hat{y}_{T+h|T} = y_T + \frac{h}{T-1}\sum_{t=2}^{T}(y_t - y_{t-1})$$
$$= y_T + \frac{h}{T-1}(y_T - y_1).$$

- Equivalent to extrapolating a line drawn between first and last observations.

Some simple forecasting methods

Drift method



Model fitting

The `model()` function trains models to data.

```
brick_fit <- aus_production |>
  filter(!is.na(Bricks)) |>
  model(
    `Seasonal_naive` = SNAIVE(Bricks),
    `Naive` = NAIVE(Bricks),
    Drift = RW(Bricks ~ drift()),
    Mean = MEAN(Bricks)
  )
```

```
# A mable: 1 x 4
  Seasonal_naive   Naive          Drift    Mean
         <model> <model>        <model> <model>
1       <SNAIVE> <NAIVE> <RW w/ drift>  <MEAN>
```

A `mable` is a model table, each cell corresponds to a fitted model.

Producing forecasts

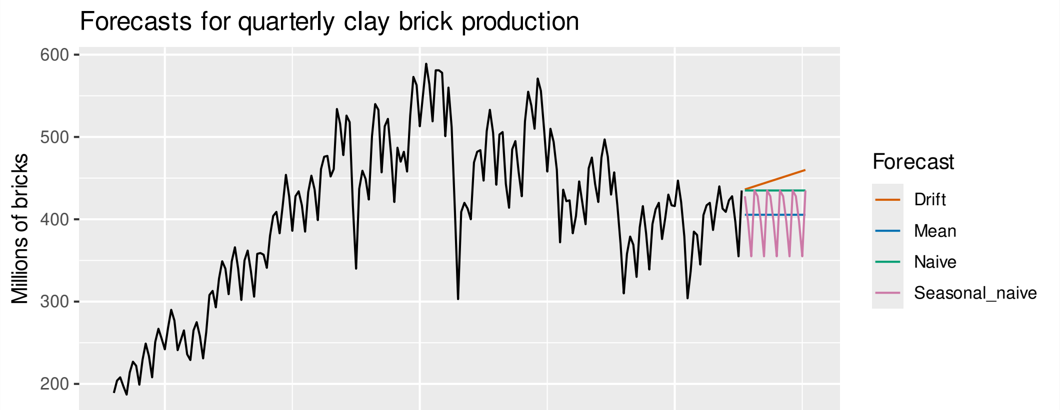
```
brick_fc <- brick_fit |>
  forecast(h = "5 years")
```

```
# A fable: 80 x 4 [1Q]
# Key:     .model [4]
  .model         Quarter
  <chr>            <qtr>
1 Seasonal_naive 2005 Q3
2 Seasonal_naive 2005 Q4
3 Seasonal_naive 2006 Q1
4 Seasonal_naive 2006 Q2
# i 76 more rows
# i 2 more variables: Bricks <dist>, .mean <dbl>
```

A `fable` is a forecast table with point forecasts and distributions.

Visualising forecasts

```
brick_fc |>
  autoplot(aus_production, level = NULL) +
  labs(title = "Forecasts for quarterly clay brick production",
       x = "Year", y = "Millions of bricks") +
  guides(colour = guide_legend(title = "Forecast"))
```



Prediction intervals

```r
brick_fc |>
  hilo(level = c(50, 75))
```

```
# A tsibble: 80 x 6 [1Q]
# Key:       .model [4]
   .model          Quarter
   <chr>             <qtr>
 1 Seasonal_naive 2005 Q3
 2 Seasonal_naive 2005 Q4
 3 Seasonal_naive 2006 Q1
 4 Seasonal_naive 2006 Q2
 5 Seasonal_naive 2006 Q3
 6 Seasonal_naive 2006 Q4
 7 Seasonal_naive 2007 Q1
 8 Seasonal_naive 2007 Q2
 9 Seasonal_naive 2007 Q3
10 Seasonal_naive 2007 Q4
```

Prediction intervals

```
brick_fc |>
  hilo(level = c(50, 75)) |>
  mutate(lower = `50%`$lower, upper = `50%`$upper)
```

```
# A tsibble: 80 x 8 [1Q]
# Key:       .model [4]
   .model         Quarter
   <chr>            <qtr>
 1 Seasonal_naive 2005 Q3
 2 Seasonal_naive 2005 Q4
 3 Seasonal_naive 2006 Q1
 4 Seasonal_naive 2006 Q2
 5 Seasonal_naive 2006 Q3
 6 Seasonal_naive 2006 Q4
 7 Seasonal_naive 2007 Q1
 8 Seasonal_naive 2007 Q2
 9 Seasonal_naive 2007 Q3
```

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Lab Session 11

Produce forecasts using an appropriate benchmark method, and plot the results using `autoplot()` for the following time series:

1. Total in-school staff in Australia (`staff`)
2. Preschool and School education payroll jobs (`payroll_education`)
3. Total Australian retail turnover (aggregate `aus_retail`)