Tidy Time Series & Forecasting in R

6. Introduction to forecasting

bit.ly/fable2020

Outline

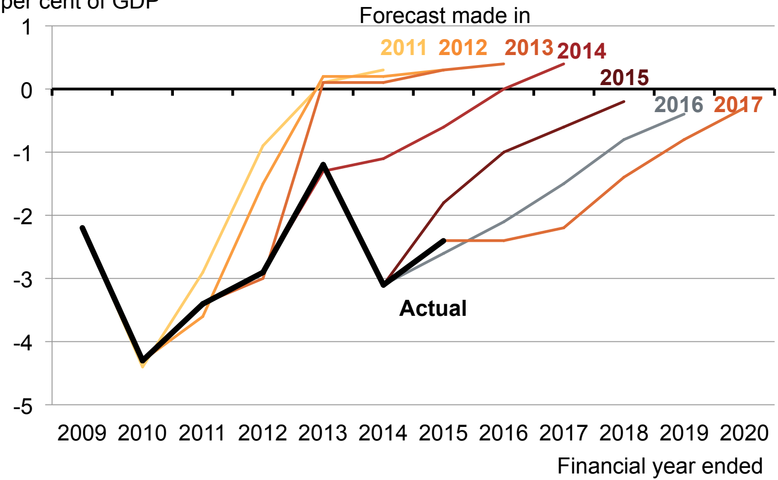
Outline

Forecasting is difficult

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

GRATTAN Institute

Actual and forecast Commonwealth underlying cash balance
per cent of GDP



What can we forecast?

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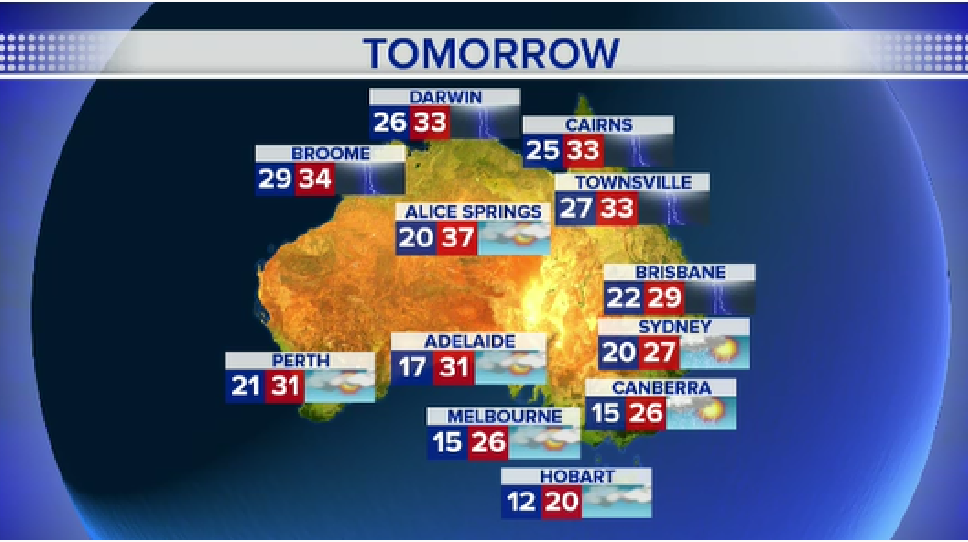

What can we forecast?

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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

Which is easiest to forecast?

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7. exchange rate of $US/AUS next week
8. total sales of drugs in Australian pharmacies next month

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

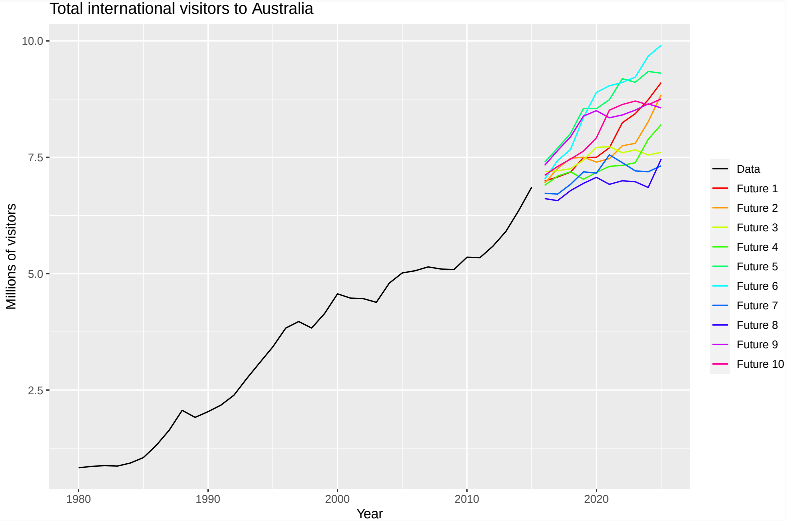
Factors affecting forecastability

Something is easier to forecast if:

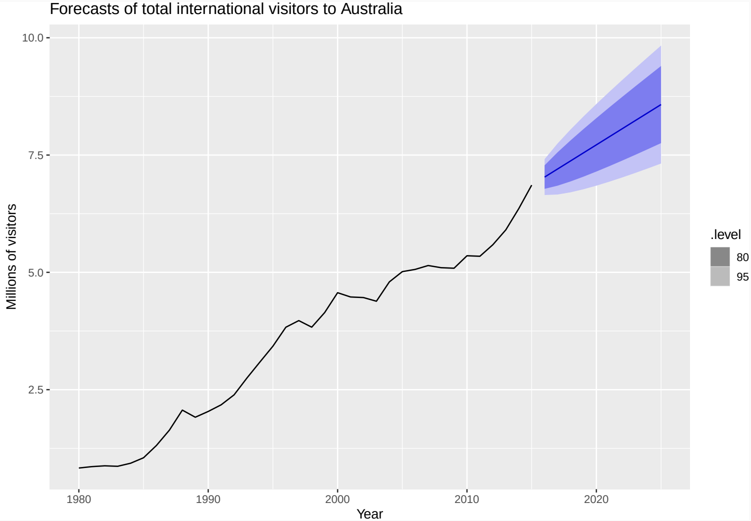
- we have a good understanding of the factors that contribute to it
- there is lots of data available;
- the forecasts cannot affect the thing we are trying to forecast.
- there is relatively low natural/unexplainable random variation.
- the future is somewhat similar to the past

Outline

Sample futures



Forecast intervals

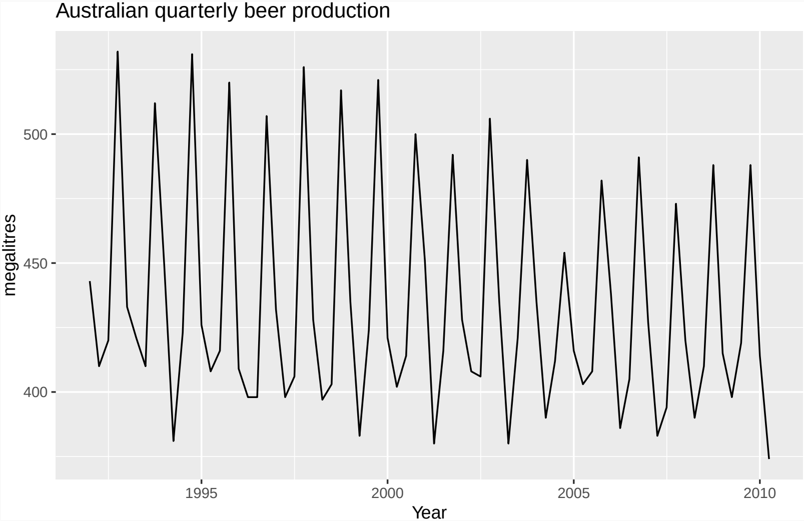


Statistical forecasting

- 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: $\hat{y}_{T+h|T} = \mathrm{E}[y_{T+h} \mid y_1, \dots, y_T]$.
- Forecast variance: $\mathrm{Var}[y_t \mid y_1, \dots, y_T]$
- Prediction interval is a range of values of y_{T+h} with high probability.

Outline

Some simple forecasting methods

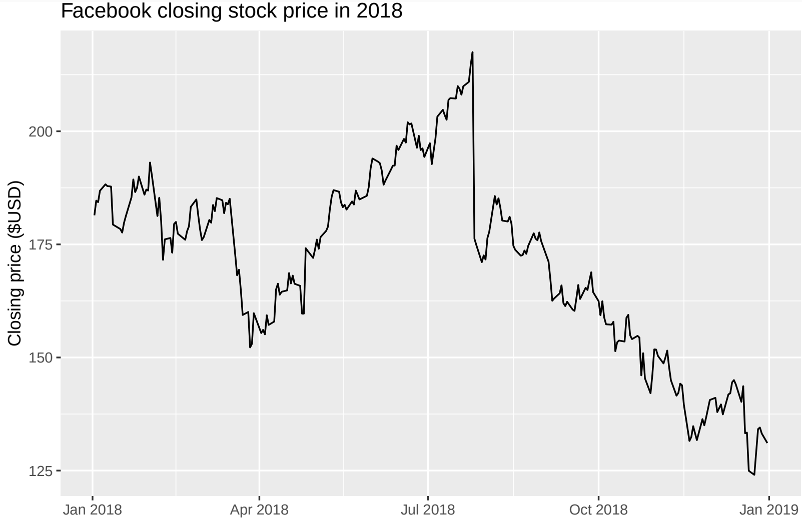


How would you forecast these series?

Some simple forecasting methods

How would you forecast these series?

Some simple forecasting methods

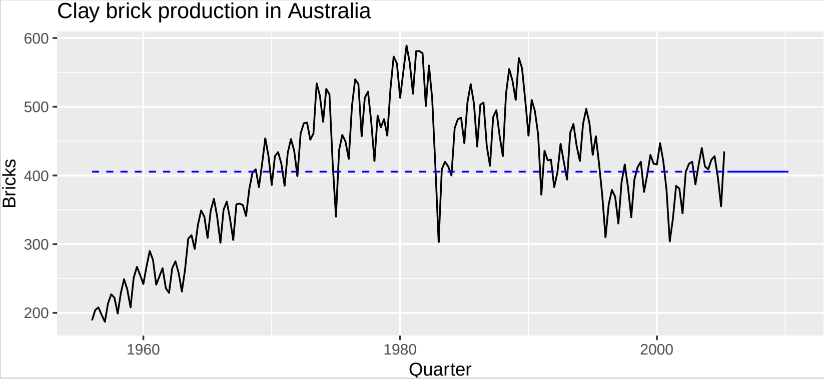


How would you forecast these series?

Some simple forecasting methods

`MEAN(y)`: Average method

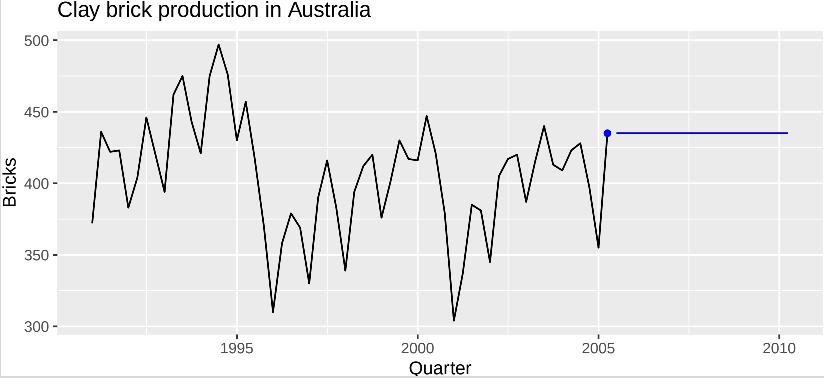
- Forecast of all future values is equal to mean of historical data $\{y_1, \dots, y_T\}$.
- Forecasts: $\hat{y}_{T+h|T} = \bar{y} = (y_1 + \cdots + y_T)/T$



Some simple forecasting methods

`NAIVE(y)`: Naïve method

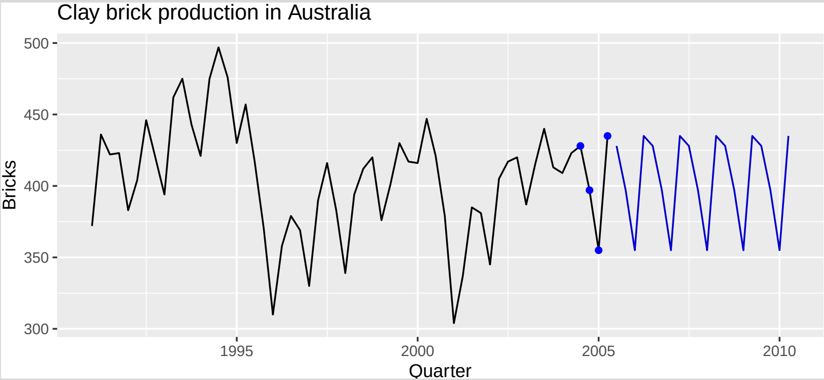
- Forecasts equal to last observed value.
- Forecasts: $\hat{y}_{T+h|T} = y_T$.
- Consequence of efficient market hypothesis.



Some simple forecasting methods

`SNAIVE(y ~ lag(m))`: Seasonal naïve 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

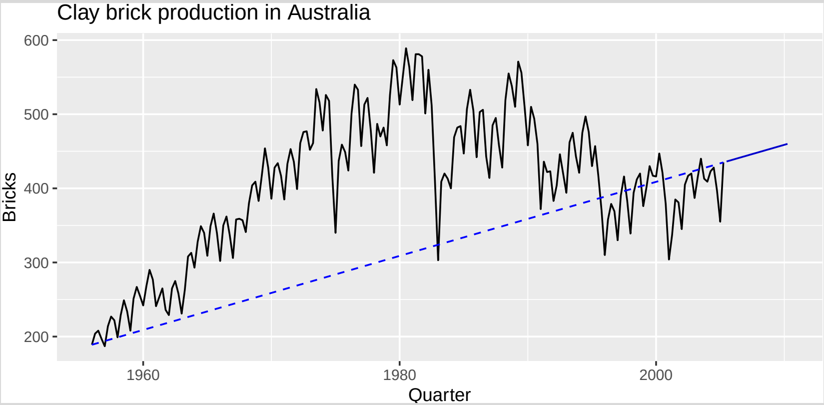
- Forecasts equal to last value plus average change.
- Forecasts:

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

- 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 naïve = SNAIVE(Bricks),
    Naïve = NAIVE(Bricks),
    Drift = RW(Bricks ~ drift()),
    Mean = MEAN(Bricks)
  )
```

```
## # A mable: 1 x 4
##   Seasonal naïve Naïve   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

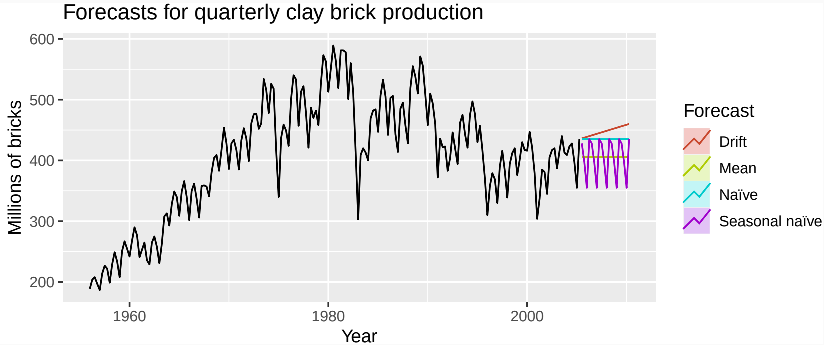
```r
brick_fc <- brick_fit %>%
  forecast(h = "5 years")
```

```
## # A fable: 80 x 4 [1Q]
## # Key:     .model [4]
##   .model         Quarter Bricks .distribution
##   <chr>            <qtr>  <dbl> <dist>
## 1 Seasonal naïve 2005 Q3    428 N(428, 2336)
## 2 Seasonal naïve 2005 Q4    397 N(397, 2336)
## 3 Seasonal naïve 2006 Q1    355 N(355, 2336)
## 4 Seasonal naïve 2006 Q2    435 N(435, 2336)
## # ... with 76 more rows
```

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

Visualising forecasts

```
brick_fc %>%
  autoplot(aus_production, level = NULL) +
  ggtitle("Forecasts for quarterly clay brick production") +
  xlab("Year") + ylab("Millions of bricks") +
  guides(colour = guide_legend(title = "Forecast"))
```



Prediction intervals

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

```
## # A tsibble: 80 x 5 [1Q]
## # Key:       .model [4]
##    .model          Quarter Bricks          50%          75%
##    <chr>             <qtr>  <dbl>       <hilo>       <hilo>
##  1 Seasonal naïve 2005 Q3    428 [395, 461]50 [372, 484]75
##  2 Seasonal naïve 2005 Q4    397 [364, 430]50 [341, 453]75
##  3 Seasonal naïve 2006 Q1    355 [322, 388]50 [299, 411]75
##  4 Seasonal naïve 2006 Q2    435 [402, 468]50 [379, 491]75
##  5 Seasonal naïve 2006 Q3    428 [382, 474]50 [349, 507]75
##  6 Seasonal naïve 2006 Q4    397 [351, 443]50 [318, 476]75
##  7 Seasonal naïve 2007 Q1    355 [309, 401]50 [276, 434]75
##  8 Seasonal naïve 2007 Q2    435 [389, 481]50 [356, 514]75
##  9 Seasonal naïve 2007 Q3    428 [372, 484]50 [332, 524]75
## 10 Seasonal naïve 2007 Q4    397 [341, 453]50 [301, 493]75
```

Prediction intervals

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

```
## # A tibble: 80 x 9
##    .model    Quarter Bricks .lower .upper .level .lower1 .upper
##    <chr>       <qtr>  <dbl>  <dbl>  <dbl>  <dbl>   <dbl>   <dbl
##  1 Seaso~    2005 Q3    428   395.   461.     50    372.    484
##  2 Seaso~    2005 Q4    397   364.   430.     50    341.    453
##  3 Seaso~    2006 Q1    355   322.   388.     50    299.    411
##  4 Seaso~    2006 Q2    435   402.   468.     50    379.    491
##  5 Seaso~    2006 Q3    428   382.   474.     50    349.    507
##  6 Seaso~    2006 Q4    397   351.   443.     50    318.    476
##  7 Seaso~    2007 Q1    355   309.   401.     50    276.    434
##  8 Seaso~    2007 Q2    435   389.   481.     50    356.    514
##  9 Seaso~    2007 Q3    428   372.   484.     50    332.    524
## 10 Seaso~    2007 Q4    397   341.   453.     50    301.    493
## # ... with 70 more rows, and 1 more variable: .level1 <dbl>
```

Outline

Lab Session 11

- Produce forecasts using an appropriate benchmark method for household wealth (`hh_budget`). Plot the results using `autoplot()`.
- Produce forecasts using an appropriate benchmark method for Australian takeaway food turnover (`aus_retail`). Plot the results using `autoplot()`.

Outline

Fitted values

- $\hat{y}_{t|t-1}$ is the forecast of y_t based on observations $y_1, \dots, y_t$.
- We call these "fitted values".
- Sometimes drop the subscript: $\hat{y}_t \equiv \hat{y}_{t|t-1}$.
- Often not true forecasts since parameters are estimated on all data.

For example:

- $\hat{y}_t = \bar{y}$ for average method.
- $\hat{y}_t = y_{t-1} + (y_T - y_1)/(T - 1)$ for drift method.

Forecasting residuals

Residuals in forecasting: difference between observed value and its fitted value: $e_t = y_t - \hat{y}_{t|t-1}$.

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Assumptions

1. $\{e_t\}$ uncorrelated. If they aren't, then information left in residuals that should be used in computing forecasts.
2. $\{e_t\}$ have mean zero. If they don't, then forecasts are biased.

Forecasting residuals

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Assumptions

1. $\{e_t\}$ uncorrelated. If they aren't, then information left in residuals that should be used in computing forecasts.
2. $\{e_t\}$ have mean zero. If they don't, then forecasts are biased.

Useful properties (for prediction intervals)

3. $\{e_t\}$ have constant variance.
4. $\{e_t\}$ are normally distributed.

Facebook closing stock price

```
fb_stock <- gafa_stock %>%
  filter(Symbol == "FB") %>%
  mutate(trading_day = row_number()) %>%
  update_tsibble(index = trading_day, regular = TRUE)
fb_stock %>% autoplot(Close)
```

Facebook closing stock price

```r
fit <- fb_stock %>% model(NAIVE(Close))
augment(fit)
```

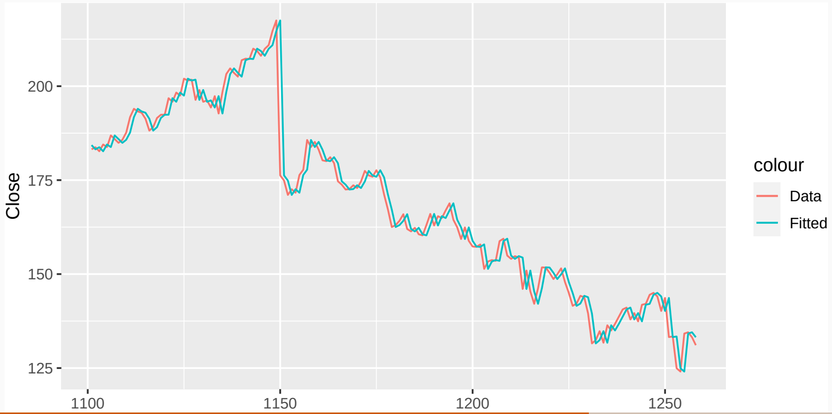
```
## # A tsibble: 1,258 x 6 [1]
## # Key:       Symbol, .model [1]
##    Symbol .model        trading_day Close .fitted .resid
##    <chr>  <chr>               <int> <dbl>   <dbl>  <dbl>
##  1 FB     NAIVE(Close)            1  54.7    NA    NA
##  2 FB     NAIVE(Close)            2  54.6    54.7 -0.150
##  3 FB     NAIVE(Close)            3  57.2    54.6  2.64
##  4 FB     NAIVE(Close)            4  57.9    57.2  0.720
##  5 FB     NAIVE(Close)            5  58.2    57.9  0.310
##  6 FB     NAIVE(Close)            6  57.2    58.2 -1.01
##  7 FB     NAIVE(Close)            7  57.9    57.2  0.720
##  8 FB     NAIVE(Close)            8  55.9    57.9 -2.03
##  9 FB     NAIVE(Close)            9  57.7    55.9  1.83
## 10 FB     NAIVE(Close)           10  57.6    57.7 -0.140
## # ... with 1,248 more rows
```

Facebook closing stock price

```
augment(fit) %>%
  ggplot(aes(x = trading_day)) +
  geom_line(aes(y = Close, colour = "Data")) +
  geom_line(aes(y = .fitted, colour = "Fitted"))
```

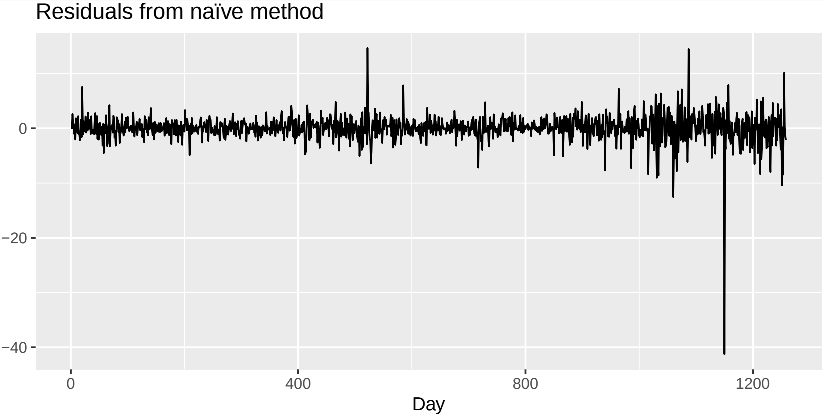
Facebook closing stock price

```r
augment(fit) %>%
  filter(trading_day > 1100) %>%
  ggplot(aes(x = trading_day)) +
  geom_line(aes(y = Close, colour = "Data")) +
  geom_line(aes(y = .fitted, colour = "Fitted"))
```



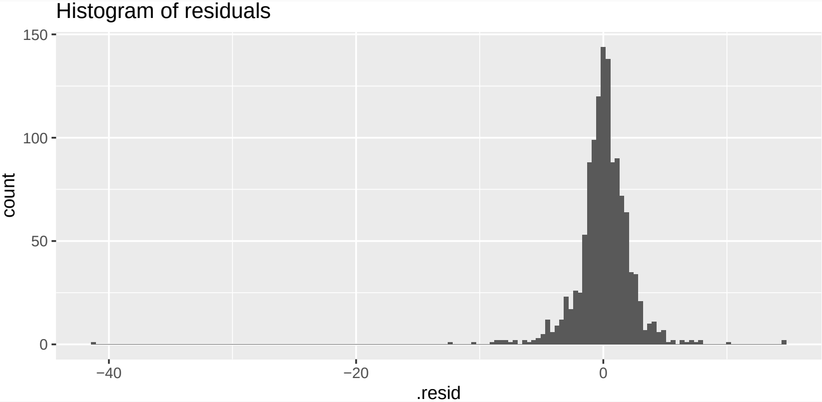
Facebook closing stock price

```r
augment(fit) %>%
  autoplot(.resid) + xlab("Day") + ylab("") +
  ggtitle("Residuals from naïve method")
```



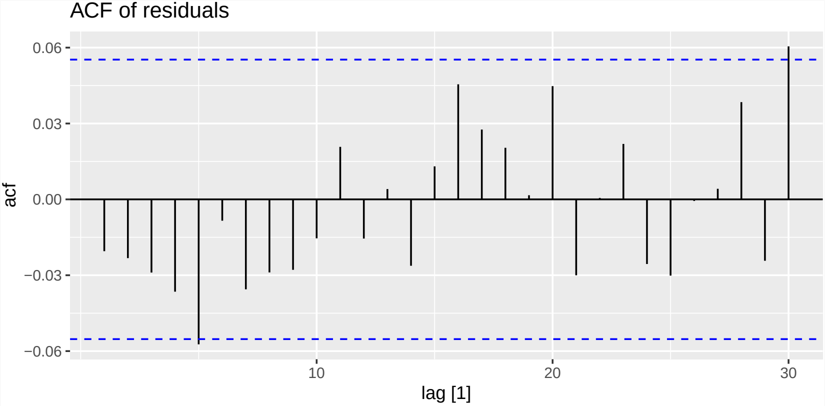
Facebook closing stock price

```
augment(fit) %>%
  ggplot(aes(x = .resid)) +
  geom_histogram(bins = 150) +
  ggtitle("Histogram of residuals")
```



Facebook closing stock price

```r
augment(fit) %>%
  ACF(.resid) %>%
  autoplot() + ggtitle("ACF of residuals")
```

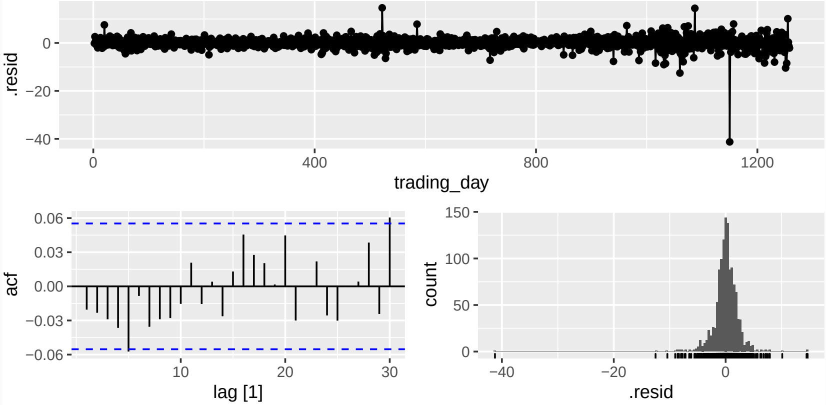


ACF of residuals

- We assume that the residuals are white noise (uncorrelated, mean zero, constant variance). If they aren't, then there is information left in the residuals that should be used in computing forecasts.
- So a standard residual diagnostic is to check the ACF of the residuals of a forecasting method.
- We *expect* these to look like white noise.

Combined diagnostic graph

```
fit %>% gg_tsresiduals()
```



Ljung-Box test

Test whether *whole set* of r_k values is significantly different from zero set.

$$Q = T(T+2)\sum_{k=1}^{h}(T-k)^{-1}r_k^2$$

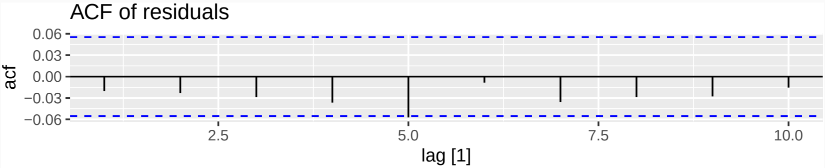
where h = max lag and T = # observations.

- If each r_k close to zero, Q will be **small**.
- If some r_k values large (+ or $-$), Q will be **large**.
- My preferences: $h = 10$ for non-seasonal data, $h = 2m$ for seasonal data.
- If data are WN, $Q \sim \chi^2$ with $(h - K)$ degrees of freedom where K = no. parameters in model.
- When applied to raw data, set $K = 0$.

Ljung-Box test

$$Q = T(T+2)\sum_{k=1}^{h}(T-k)^{-1}r_k^2$$

where h = max lag and T = # observations.




```
# lag=h and dof=K
augment(fit) %>%
  features(.resid, ljung_box, dof = 0, lag = 10)
```

```
## # A tibble: 1 x 4
##   Symbol .model       lb_stat lb_pvalue
##   <chr>  <chr>          <dbl>     <dbl>
## 1 FB     NAIVE(Close)    12.1     0.276
```

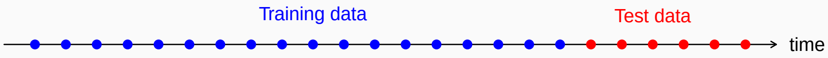
Outline

Lab Session 12

- Compute seasonal naïve forecasts for quarterly Australian beer production.
- Test if the residuals are white noise. What do you conclude?

Outline

Training and test sets



- A model which fits the training data well will not necessarily forecast well.
- Forecast accuracy is based only on the test set.

Forecast errors

Forecast "error": the difference between an observed value and its forecast.

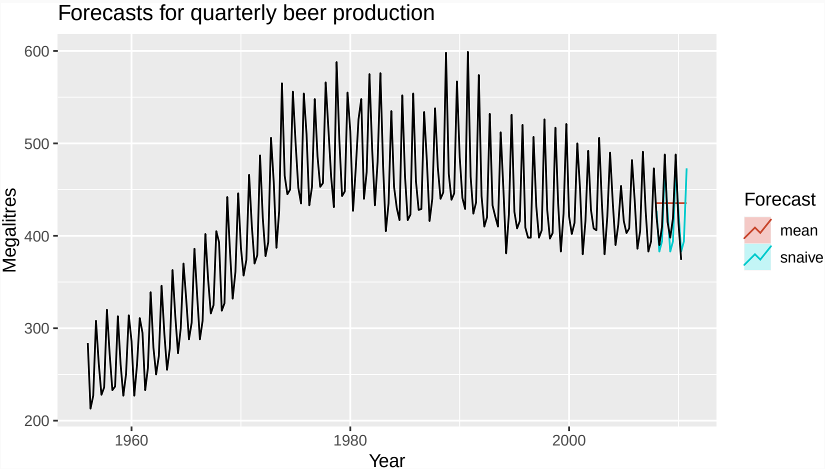
$$e_{T+h} = y_{T+h} - \hat{y}_{T+h|T},$$

where the training data is given by $\{y_1, \dots, y_T\}$

Measures of forecast accuracy

```r
beer_fit <- aus_production %>%
  filter(between(year(Quarter), 1992, 2007)) %>%
  model(
    snaive = SNAIVE(Beer),
    mean = MEAN(Beer)
  )
beer_fit %>%
  forecast(h = "3 years") %>%
  autoplot(aus_production, level = NULL) +
  ggtitle("Forecasts for quarterly beer production") +
  xlab("Year") + ylab("Megalitres") +
  guides(colour = guide_legend(title = "Forecast"))
```

Measures of forecast accuracy



Measures of forecast accuracy

$$
\begin{aligned}
y_{T+h} &= (T+h)\text{th observation, } h = 1, \dots, H \\
\hat{y}_{T+h|T} &= \text{its forecast based on data up to time } T. \\
e_{T+h} &= y_{T+h} - \hat{y}_{T+h|T}
\end{aligned}
$$

$$
\begin{aligned}
\text{MAE} &= \text{mean}(|e_{T+h}|) \\
\text{MSE} &= \text{mean}(e^2_{T+h}) \qquad\qquad \text{RMSE} = \sqrt{\text{mean}(e^2_{T+h})} \\
\text{MAPE} &= 100\text{mean}(|e_{T+h}|/|y_{T+h}|)
\end{aligned}
$$

Measures of forecast accuracy

$$
\begin{aligned}
y_{T+h} &= (T+h)\text{th observation}, h = 1, \dots, H \\
\hat{y}_{T+h|T} &= \text{its forecast based on data up to time } T. \\
e_{T+h} &= y_{T+h} - \hat{y}_{T+h|T}
\end{aligned}
$$

$$
\begin{aligned}
\text{MAE} &= \text{mean}(|e_{T+h}|) \\
\text{MSE} &= \text{mean}(e_{T+h}^2) \qquad \text{RMSE} = \sqrt{\text{mean}(e_{T+h}^2)} \\
\text{MAPE} &= 100\text{mean}(|e_{T+h}|/|y_{T+h}|)
\end{aligned}
$$

- MAE, MSE, RMSE are all scale dependent.
- MAPE is scale independent but is only sensible if $y_t \gg 0$ for all t, and y has a natural zero.

Measures of forecast accuracy

Mean Absolute Scaled Error

$$\text{MASE} = \text{mean}(|e_{T+h}|/Q)$$

where Q is a stable measure of the scale of the time series $\{y_t\}$.

Proposed by Hyndman and Koehler (IJF, 2006).

For non-seasonal time series,

$$Q = (T-1)^{-1}\sum_{t=2}^{T}|y_t - y_{t-1}|$$

works well. Then MASE is equivalent to MAE relative to a naïve method.

Measures of forecast accuracy

Mean Absolute Scaled Error

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where Q is a stable measure of the scale of the time series $\{y_t\}$.

Proposed by Hyndman and Koehler (IJF, 2006).

For seasonal time series,

$$Q = (T-m)^{-1} \sum_{t=m+1}^{T} |y_t - y_{t-m}|$$

works well. Then MASE is equivalent to MAE relative to a seasonal naïve method.

Measures of forecast accuracy

```r
beer_fc <- forecast(beer_fit, h = "3 years")
accuracy(beer_fc, aus_production)
```

```
## # A tibble: 2 x 9
##   .model .type     ME  RMSE   MAE   MPE  MAPE  MASE    ACF1
##   <chr>  <chr>  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>   <dbl>
## 1 mean   Test   -13.8  38.4  34.8 -3.97  8.28 2.20  -0.0691
## 2 snaive Test     5.2  14.3  13.4  1.15  3.17 0.847  0.132
```

Outline

Lab Session 13

- Create a training set for household wealth (`hh_budget`) by witholding the last four years as a test set.
- Fit all the appropriate benchmark methods to the training set and forecast the periods covered by the test set.
- Compute the accuracy of your forecasts. Which method does best?
- Repeat the exercise using the Australian takeaway food turnover data (`aus_retail`) with a test set of four years.