



Time Series Analysis & Forecasting Using R

12. Accuracy evaluation



Outline

- 1 Forecasting recap
- 2 Residual diagnostics
- 3 Lab Session 10
- 4 Forecast accuracy measures
- 5 Lab Session 11

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Tidy time series data

Use `as_tsibble()` to convert a dataset into a tsibble.

Identify which column(s) are:

- The index variable
- Identifying key variable(s)
- Measured variable(s)

Visualising time series

- Time plot: `data |> autoplot(y)`
- Season plot: `data |> gg_season(y)`
- Seasonal subseries plot: `data |> gg_subseries(y)`
- Lag plot: `data |> gg_lag(y)`
- ACF plot: `data |> ACF(y) |> autoplot()`

Transformations and decompositions

Simplify patterns with transformations:

- Population and inflation adjustments
- Mathematical transformations (`log()`, `sqrt()`, `box_cox()`)

Separate trend and seasonal patterns with decomposition:

- `STL()` decomposition (additive, choose windows)
- Extract decomposition with `components()`
- Produce seasonally adjusted data for decision making

Forecasting basics

Estimate a model on data with `model()`

Benchmark forecasting methods:

- Simple average: `MEAN(y)`
- Naive method: `NAIVE(y)`
- Seasonal naive method: `SNAIVE(y)`
- RW w/ drift: `RW(y ~ drift())`

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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

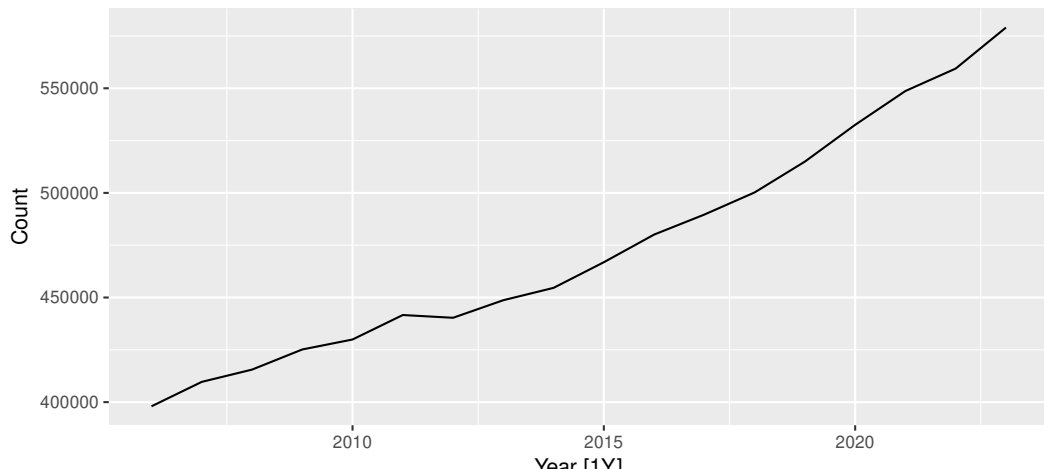
- 1 $\{e_t\}$ uncorrelated. If they aren't, then information left in residuals that should be used in computing forecasts.
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Useful properties (for prediction intervals)

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

Total in-school staff

```
total_staff <- staff |>  
  summarise(Count = sum(`In-School Staff Count`))  
total_staff |> autoplot(Count)
```



Total in-school staff

```
fit <- total_staff |> model(RW(Count ~ drift()))  
augment(fit)
```

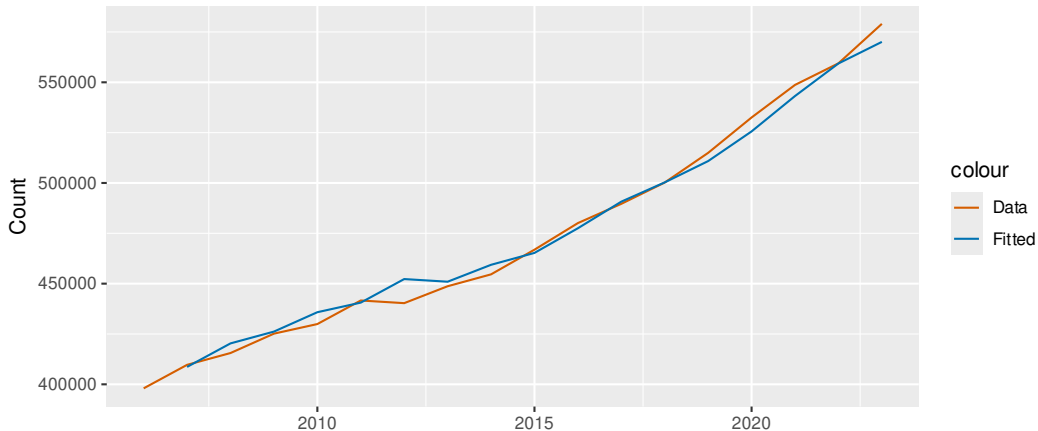
```
# A tsibble: 18 x 6 [1Y]
```

```
# Key:           .model [1]
```

	.model <chr>	Year <dbl>	Count <dbl>	.fitted <dbl>	.resid <dbl>	.innov <dbl>
1	RW(Count ~ drift())	2006	398003	NA	NA	NA
2	RW(Count ~ drift())	2007	409678	408652.	1026.	1026.
3	RW(Count ~ drift())	2008	415541	420327.	-4786.	-4786.
4	RW(Count ~ drift())	2009	425166	426190.	-1024.	-1024.
5	RW(Count ~ drift())	2010	429933	435815.	-5882.	-5882.
6	RW(Count ~ drift())	2011	441631	440582.	1049.	1049.
7	RW(Count ~ drift())	2012	440313	452280.	-11967.	-11967.
8	RW(Count ~ drift())	2013	448711	450962.	-2251.	-2251.
9	RW(Count ~ drift())	2014	454615	459360.	-4745.	-4745.
10	RW(Count ~ drift())	2015	466867	465264.	1603.	1603.
11	RW(Count ~ drift())	2016	480077	477516.	2561.	2561.
12	RW(Count ~ drift())	2017	489645	490726.	-1081.	-1081.

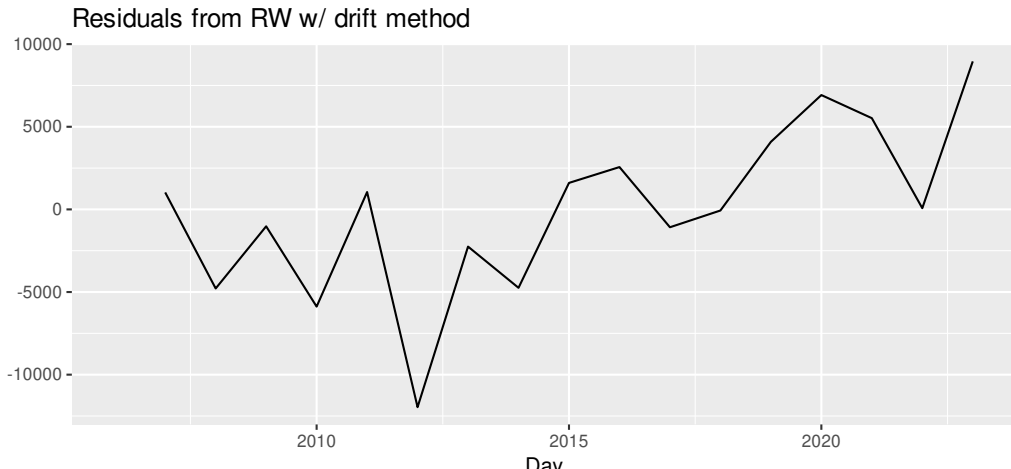
Total in-school staff

```
augment(fit) |>  
  ggplot(aes(x = Year)) +  
  geom_line(aes(y = Count, colour = "Data")) +  
  geom_line(aes(y = .fitted, colour = "Fitted"))
```



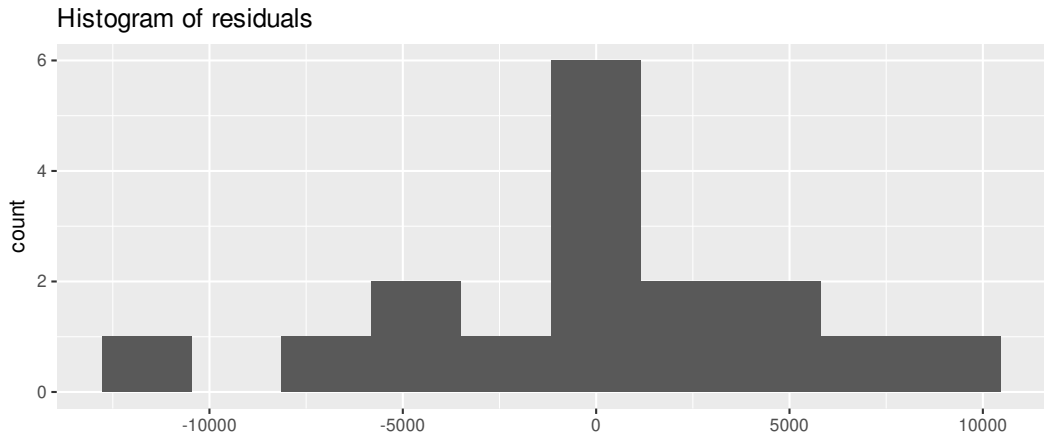
Total in-school staff

```
augment(fit) |>
  autoplot(.resid) +
  labs(x = "Day", y = "", title = "Residuals from RW w/ drift method")
```



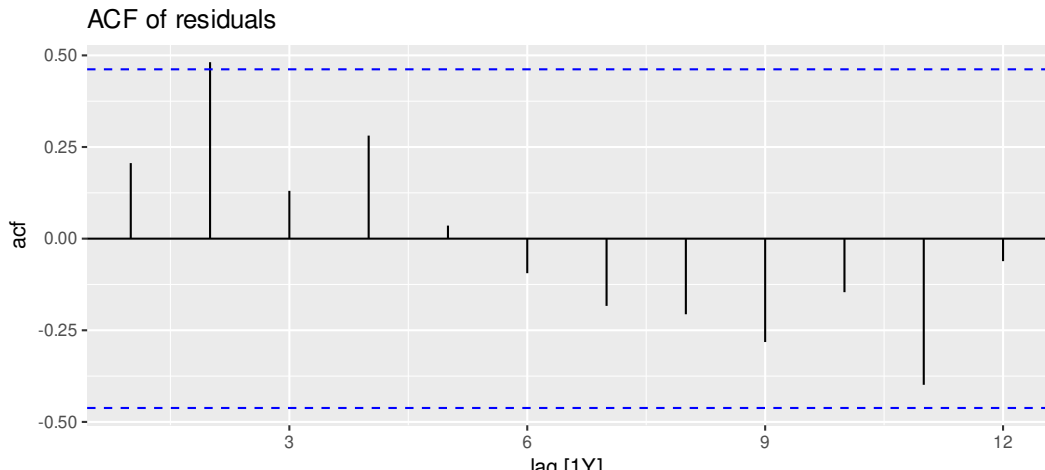
Total in-school staff

```
augment(fit) |>  
  ggplot(aes(x = .resid)) +  
  geom_histogram(bins = 10) +  
  labs(title = "Histogram of residuals")
```



Total in-school staff

```
augment(fit) |>  
  ACF(.resid) |>  
  autoplot() + labs(title = "ACF of residuals")
```

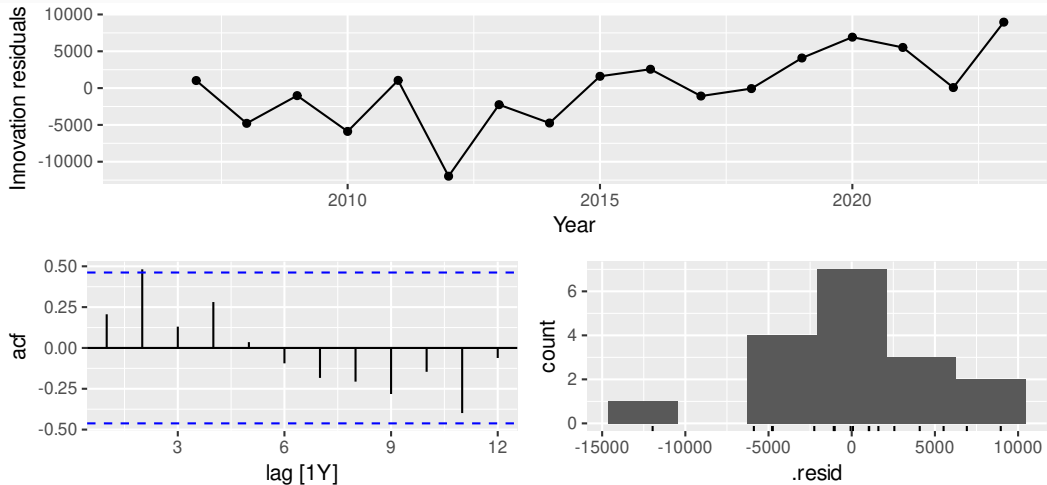


ACF of residuals

- 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

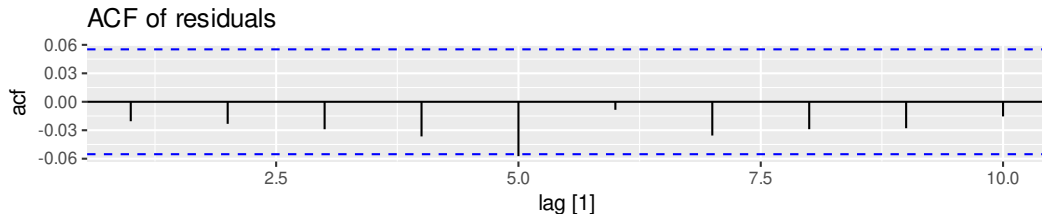
Test whether *whole set* of r_k values is significantly different from zero set.

$$Q = T(T + 2) \sum_{k=1}^{\ell} (T - k)^{-1} r_k^2 \quad \text{where } \ell = \text{max lag and } T = \text{\# observations}$$

- 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 and T large, $Q \sim \chi^2$ with ℓ degrees of freedom.

Ljung-Box test

$$Q = T(T + 2) \sum_{k=1}^{\ell} (T - k)^{-1} r_k^2 \quad \text{where } \ell = \text{max lag and } T = \# \text{ observations.}$$



```
# lag = h  
augment(fit) |> features(.resid, ljung_box, lag = 10)
```

```
# A tibble: 1 x 3  
  .model          lb_stat lb_pvalue  
  <chr>          <dbl>    <dbl>  
1 RW(Count ~ drift()) 15.3      0.121
```

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Lab Session 10

- Compute RW w/ drift forecasts for total student enrolments in Australia (`students`).
- Test if the residuals are white noise. What do you conclude?

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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

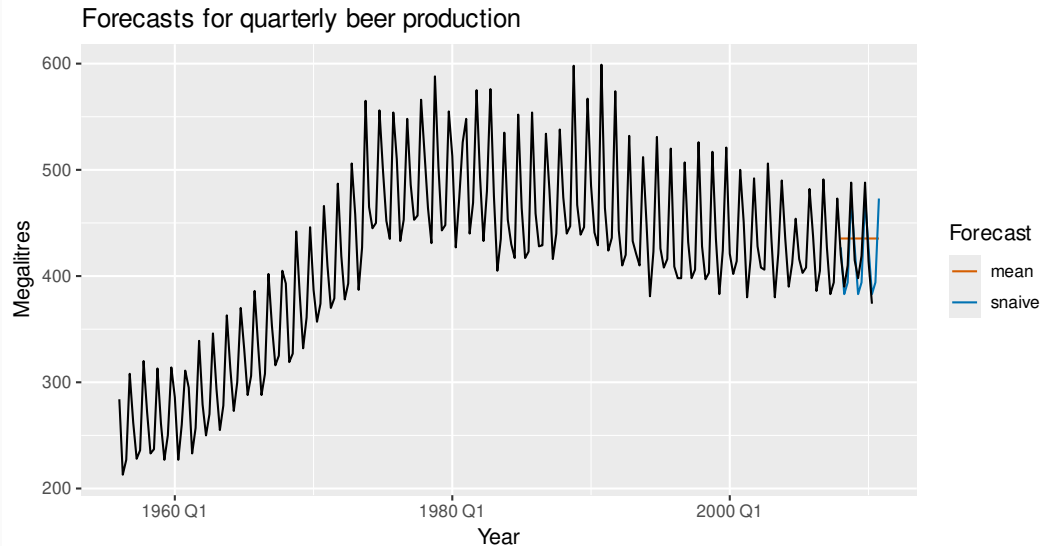
Forecast “error”: the difference between an observed value and its forecast.

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

Measures of forecast accuracy

```
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) +
  labs(title = "Forecasts for quarterly beer production",
       x = "Year", y = "Megalitres") +
  guides(colour = guide_legend(title = "Forecast"))
```

Measures of forecast accuracy



Measures of forecast accuracy

y_{T+h} = $(T + h)$ th observation, $h = 1, \dots, H$

$\hat{y}_{T+h|T}$ = its forecast based on data up to time T .

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

$$\text{MAE} = \text{mean}(|e_{T+h}|)$$

$$\text{MSE} = \text{mean}(e_{T+h}^2)$$

$$\text{MAPE} = 100\text{mean}(|e_{T+h}|/|y_{T+h}|)$$

$$\text{RMSE} = \sqrt{\text{mean}(e_{T+h}^2)}$$

Measures of forecast accuracy

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- 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

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

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- For non-seasonal series, scale uses naïve forecasts:

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

- For seasonal series, scale uses seasonal naïve forecasts:

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

where m is the seasonal frequency

Measures of forecast accuracy

Mean Absolute Scaled Error

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

where m is the seasonal frequency

Proposed by Hyndman and Koehler (IJF, 2006).

Measures of forecast accuracy

Root Mean Squared Scaled Error

$$\text{RMSSE} = \sqrt{\text{mean}(e_{T+h}^2 / Q)}$$

- For non-seasonal series, scale uses naïve forecasts:

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

- For seasonal series, scale uses seasonal naïve forecasts:

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

where m is the seasonal frequency

Proposed by Hyndman and Koehler (IJF, 2006).

Measures of forecast accuracy

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

```
# A tibble: 2 x 10
```

	.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE	ACF1
	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	mean	Test	-13.8	38.4	34.8	-3.97	8.28	2.20	1.96	-0.0691
2	snaive	Test	5.2	14.3	13.4	1.15	3.17	0.847	0.729	0.132

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Lab Session 11

- Create a training set for employed Australian students (`student_labour`) by withholding 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?

i Finished early?

Repeat the exercise using the Australian takeaway food turnover data (`aus_retail`) with a test set of four years.