bit.ly/fable2022

Time Series Analysis & Forecasting Using R

2. Time series graphics

Outline

1 Seasonal plots

2 Lab Session 3

3 Seasonal or cyclic?

4 Lag plots and autocorrelation

5 Lab Session 4

6 White noise

7 Lab Session 5

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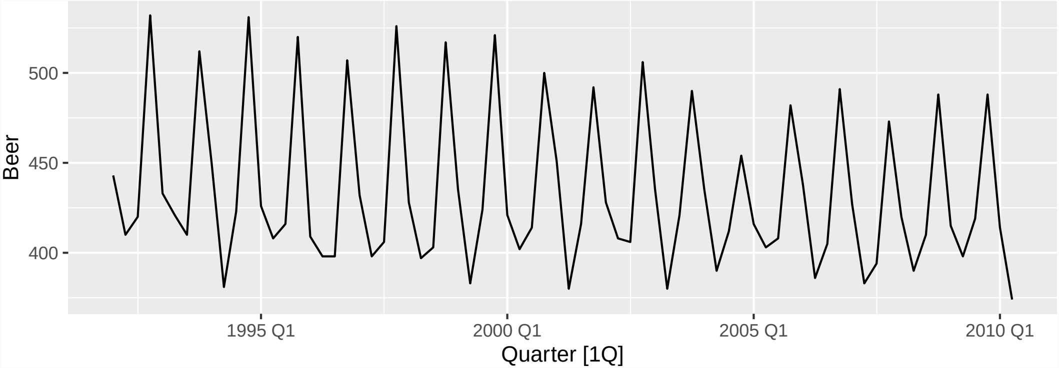
1 Seasonal plots
2 Lab Session 3
3 Seasonal or cyclic?
4 Lag plots and autocorrelation
5 Lab Session 4
6 White noise
7 Lab Session 5

Seasonal plots

- Data plotted against the individual "seasons" in which the data were observed. (In this case a "season" is a month.)
- Something like a time plot except that the data from each season are overlapped.
- Enables the underlying seasonal pattern to be seen more clearly, and also allows any substantial departures from the seasonal pattern to be easily identified.
- In R: `gg_season()`

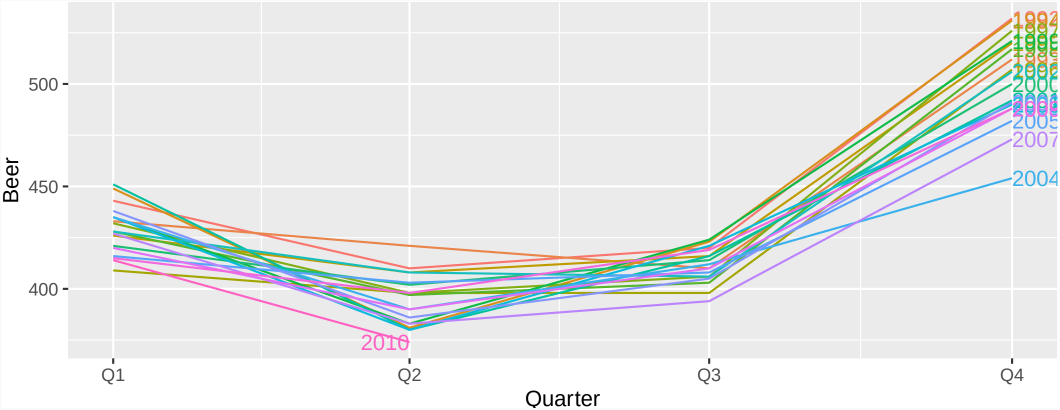
Quarterly Australian Beer Production

```r
beer <- aus_production |>
  select(Quarter, Beer) |>
  filter(year(Quarter) >= 1992)
beer |> autoplot(Beer)
```



Quarterly Australian Beer Production

```
beer ▷ gg_season(Beer, labels = "right")
```



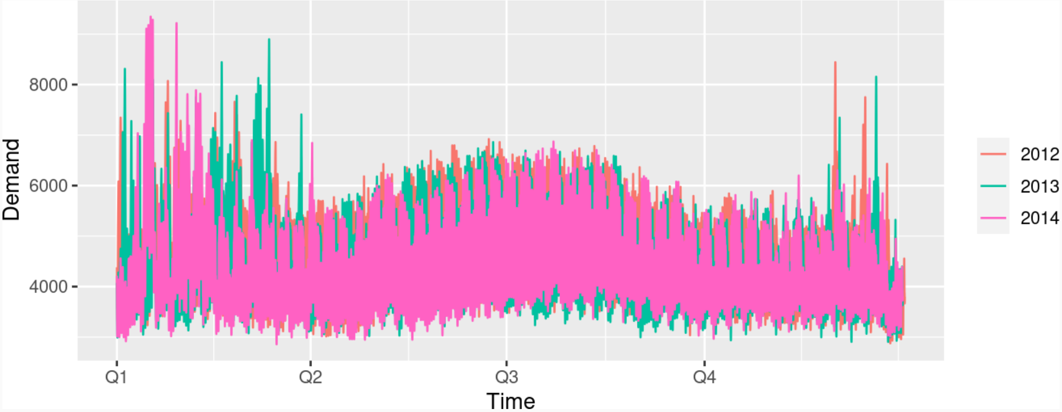
Multiple seasonal periods

```r
vic_elec
```

```
## # A tsibble: 52,608 x 5 [30m] <Australia/Melbourne>
##    Time                Demand Temperature Date       Holiday
##    <dttm>               <dbl>       <dbl> <date>     <lgl>
##  1 2012-01-01 00:00:00  4383.        21.4 2012-01-01 TRUE
##  2 2012-01-01 00:30:00  4263.        21.0 2012-01-01 TRUE
##  3 2012-01-01 01:00:00  4049.        20.7 2012-01-01 TRUE
##  4 2012-01-01 01:30:00  3878.        20.6 2012-01-01 TRUE
##  5 2012-01-01 02:00:00  4036.        20.4 2012-01-01 TRUE
##  6 2012-01-01 02:30:00  3866.        20.2 2012-01-01 TRUE
##  7 2012-01-01 03:00:00  3694.        20.1 2012-01-01 TRUE
##  8 2012-01-01 03:30:00  3562.        19.6 2012-01-01 TRUE
##  9 2012-01-01 04:00:00  3433.        19.1 2012-01-01 TRUE
## 10 2012-01-01 04:30:00  3359.        19.0 2012-01-01 TRUE
## # ... with 52,598 more rows
```

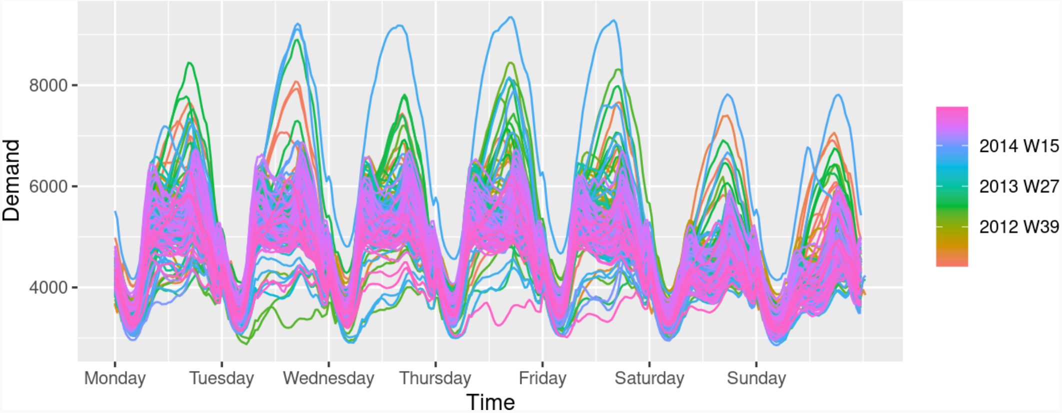
Multiple seasonal periods

```
vic_elec ▷ gg_season(Demand)
```



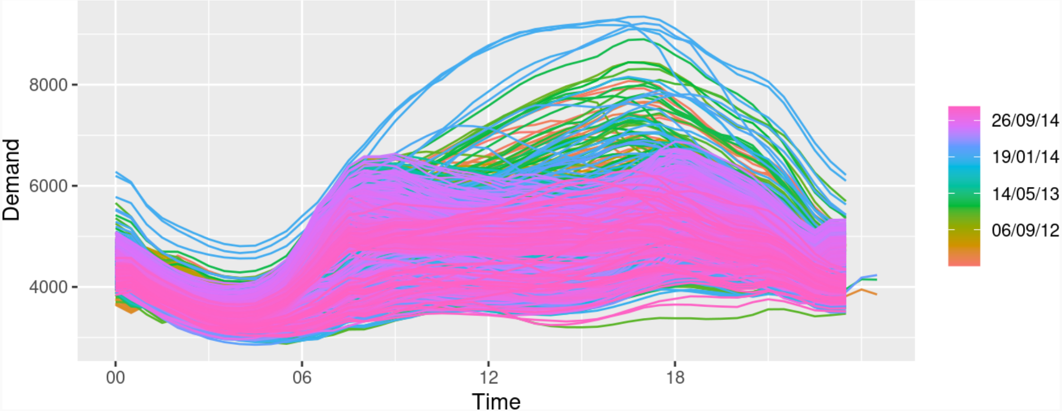
Multiple seasonal periods

```
vic_elec ▷ gg_season(Demand, period = "week")
```



Multiple seasonal periods

```
vic_elec ▷ gg_season(Demand, period = "day")
```

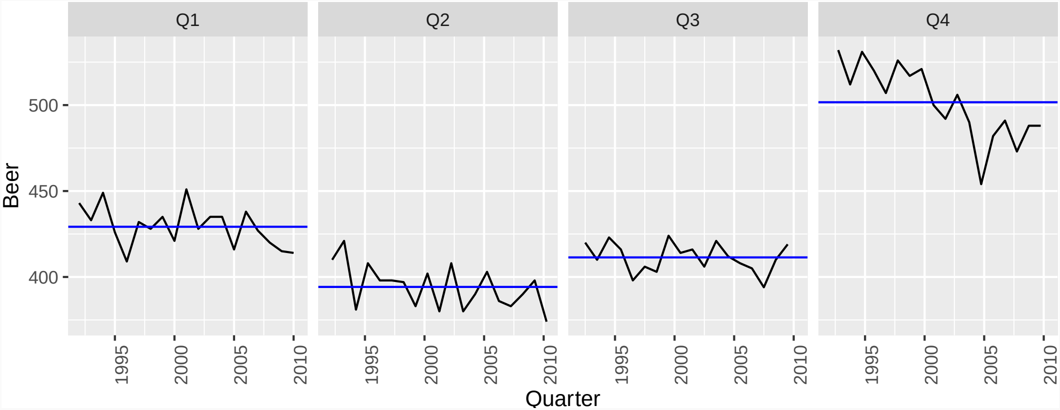


Seasonal subseries plots

- Data for each season collected together in time plot as separate time series.
- Enables the underlying seasonal pattern to be seen clearly, and changes in seasonality over time to be visualized.
- In R: `gg_subseries()`

Quarterly Australian Beer Production

```
beer ▷ gg_subseries(Beer)
```



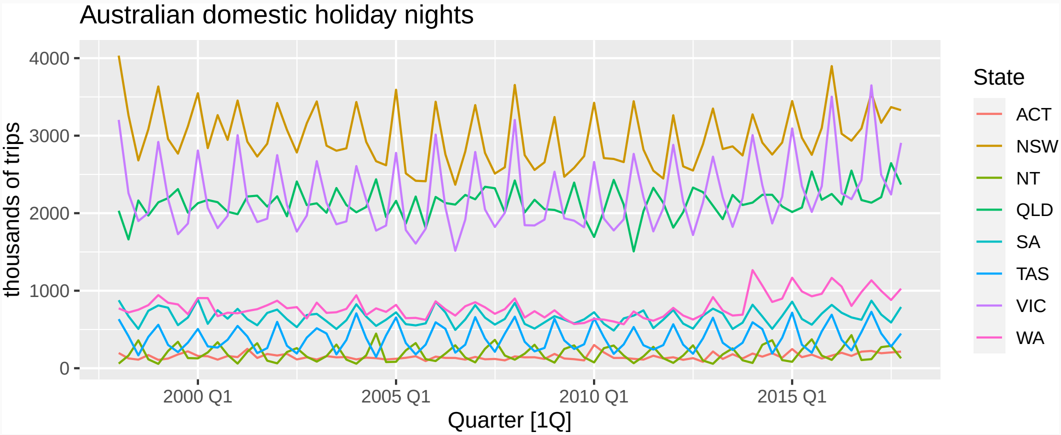
Australian holidays

```r
holidays <- tourism |>
  filter(Purpose == "Holiday") |>
  group_by(State) |>
  summarise(Trips = sum(Trips))
```

```
## # A tsibble: 640 x 3 [1Q]
## # Key:       State [8]
##    State Quarter Trips
##    <chr>   <qtr> <dbl>
##  1 ACT   1998 Q1  196.
##  2 ACT   1998 Q2  127.
##  3 ACT   1998 Q3  111.
##  4 ACT   1998 Q4  170.
##  5 ACT   1999 Q1  108.
##  6 ACT   1999 Q2  125.
##  7 ACT   1999 Q3  178.
##  8 ACT   1999 Q4  218.
##  9 ACT   2000 Q1  158.
```

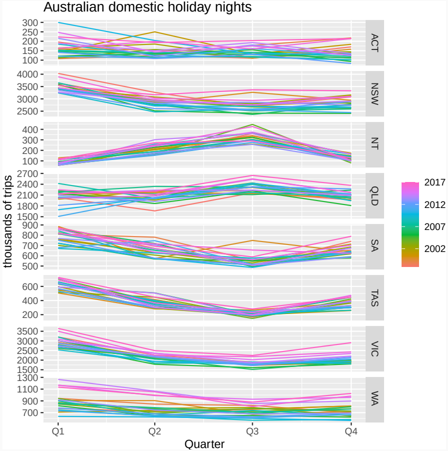
Australian holidays

```r
holidays |> autoplot(Trips) +
  labs(y = "thousands of trips", title = "Australian domestic holiday nights")
```



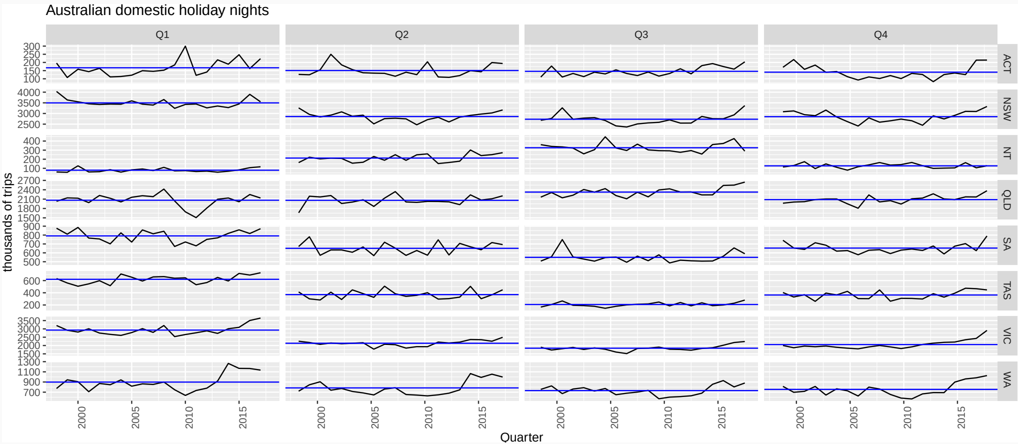
Seasonal plots

```
holidays ▷ gg_season(Trips) +
  labs(y = "thousands of trips", title = "Australian domestic holiday nights")
```



Seasonal subseries plots

```r
holidays |> gg_subseries(Trips) +
  labs(y = "thousands of trips", title = "Australian domestic holiday nights")
```

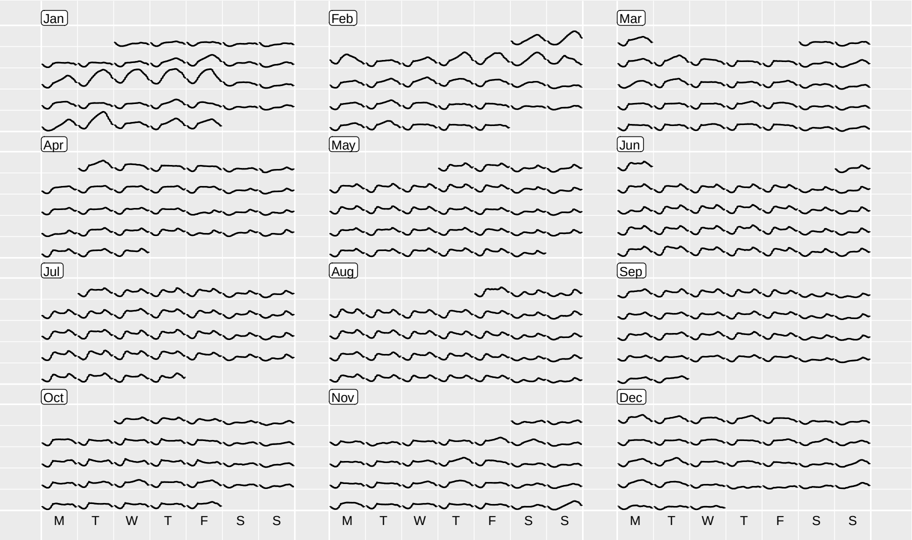


Calendar plots

```r
library(sugrrants)
vic_elec |>
  filter(year(Date) == 2014) |>
  mutate(Hour = hour(Time)) |>
  frame_calendar(x = Hour, y = Demand, date = Date, nrow = 4) |>
  ggplot(aes(x = .Hour, y = .Demand, group = Date)) +
  geom_line() -> p1
prettify(p1,
  size = 3,
  label.padding = unit(0.15, "lines")
)
```

- `frame_calendar()` makes a compact calendar plot
- `facet_calendar()` provides an easier ggplot2 integration.

Calendar plots



Outline

1 Seasonal plots

2 Lab Session 3

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5 Lab Session 4

6 White noise

7 Lab Session 5

Lab Session 3

1. Look at the quarterly tourism data for the Snowy Mountains

```r
snowy <- tourism |>
  filter(Region == "Snowy Mountains")
```

   - Use `autoplot()`, `gg_season()` and `gg_subseries()` to explore the data.
   - What do you learn?

2. Produce a calendar plot for the `pedestrian` data from one location and one year.

Outline

1 Seasonal plots

2 Lab Session 3

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6 White noise

7 Lab Session 5

Time series patterns

Trend pattern exists when there is a long-term increase or decrease in the data.

Seasonal pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).

Cyclic pattern exists when data exhibit rises and falls that are *not of fixed period* (duration usually of at least 2 years).

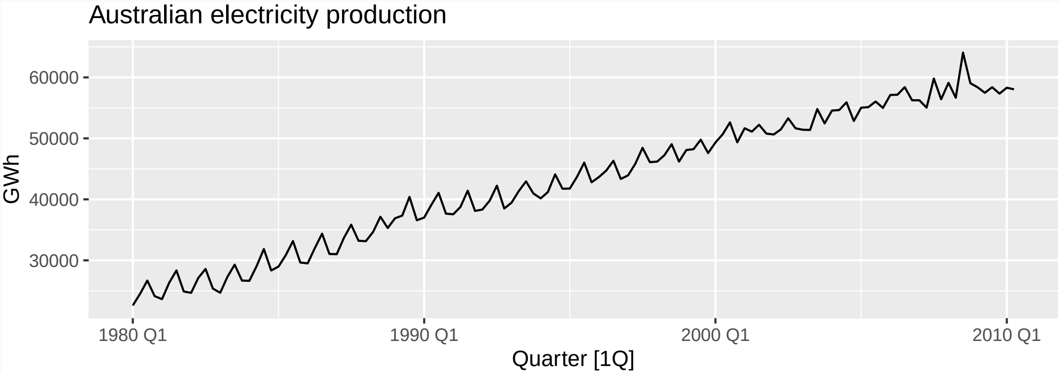
Time series components

Differences between seasonal and cyclic patterns:

- seasonal pattern constant length; cyclic pattern variable length
- average length of cycle longer than length of seasonal pattern
- magnitude of cycle more variable than magnitude of seasonal pattern

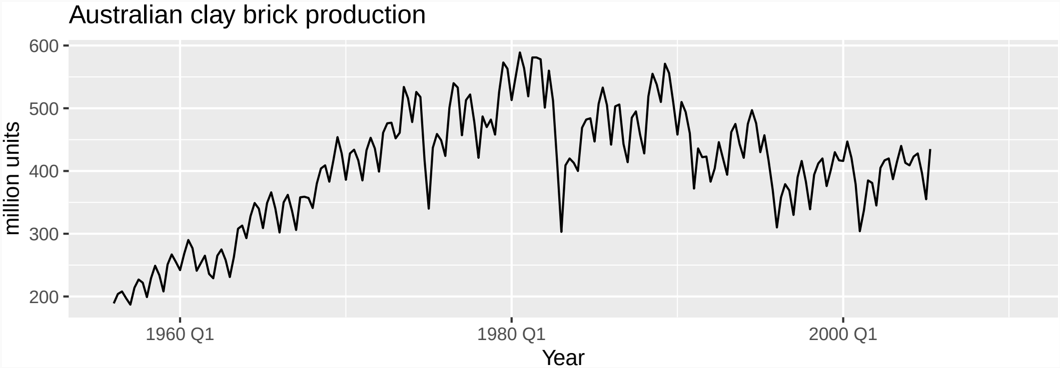
Time series patterns

```
aus_production |>
  filter(year(Quarter) >= 1980) |>
  autoplot(Electricity) +
  labs(y = "GWh", title = "Australian electricity production")
```



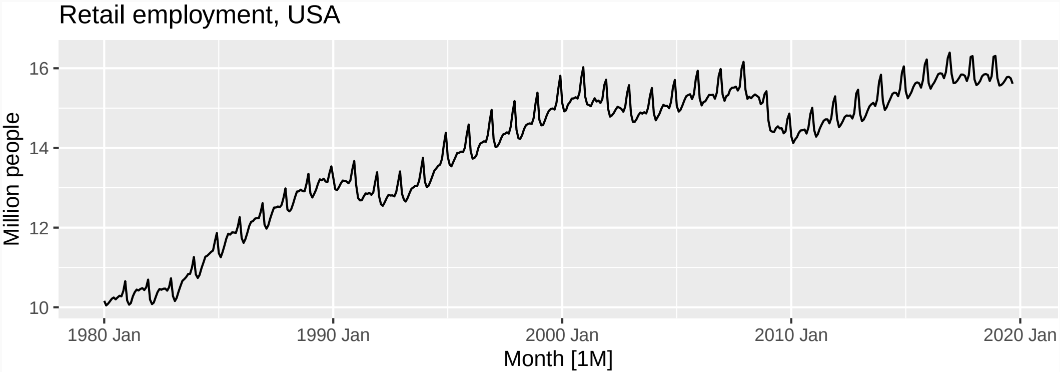
Time series patterns

```r
aus_production |>
  autoplot(Bricks) +
  labs(title = "Australian clay brick production",
       x = "Year", y = "million units")
```



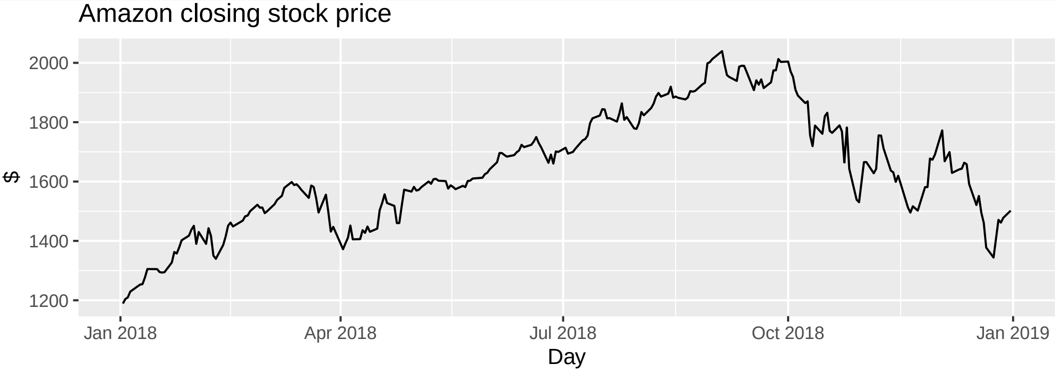
Time series patterns

```
us_employment ▷
  filter(Title == "Retail Trade", year(Month) ⩾ 1980) ▷
  autoplot(Employed / 1e3) +
  labs(title = "Retail employment, USA", y = "Million people")
```



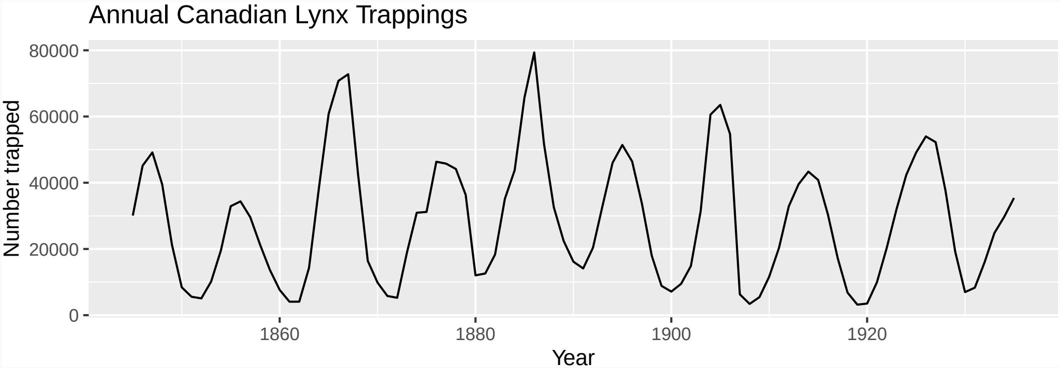
Time series patterns

```
gafa_stock |>
  filter(Symbol == "AMZN", year(Date) >= 2018) |>
  autoplot(Close) +
  labs(title = "Amazon closing stock price", x = "Day", y = "$")
```



Time series patterns

```
pelt |>
  autoplot(Lynx) +
  labs(title = "Annual Canadian Lynx Trappings",
       x = "Year", y = "Number trapped")
```



Seasonal or cyclic?

Differences between seasonal and cyclic patterns:

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Seasonal or cyclic?

Differences between seasonal and cyclic patterns:

- seasonal pattern constant length; cyclic pattern variable length
- average length of cycle longer than length of seasonal pattern
- magnitude of cycle more variable than magnitude of seasonal pattern

The timing of peaks and troughs is predictable with seasonal data, but unpredictable in the long term with cyclic data.

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1 Seasonal plots

2 Lab Session 3

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7 Lab Session 5

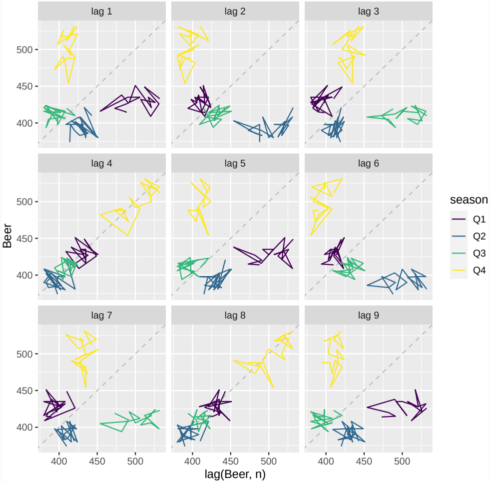
Example: Beer production

```r
new_production <- aus_production |>
  filter(year(Quarter) >= 1992)
new_production
```

```
## # A tsibble: 74 x 7 [1Q]
##     Quarter  Beer Tobacco Bricks Cement Electricity   Gas
##       <qtr> <dbl>   <dbl>  <dbl>  <dbl>       <dbl> <dbl>
##   1 1992 Q1   443    5777    383   1289       38332   117
##   2 1992 Q2   410    5853    404   1501       39774   151
##   3 1992 Q3   420    6416    446   1539       42246   175
##   4 1992 Q4   532    5825    420   1568       38498   129
##   5 1993 Q1   433    5724    394   1450       39460   116
##   6 1993 Q2   421    6036    462   1668       41356   149
##   7 1993 Q3   410    6570    475   1648       42949   163
##   8 1993 Q4   512    5675    443   1863       40974   138
```

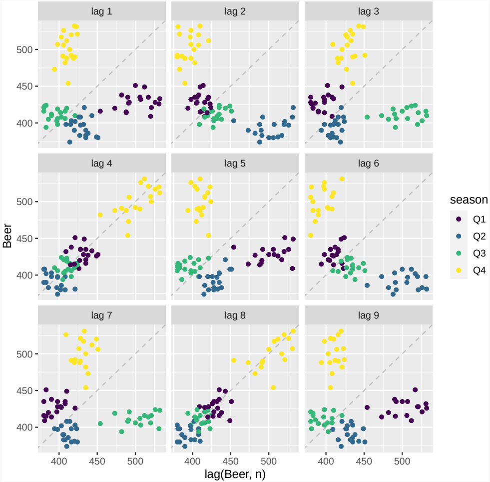
Example: Beer production

```
new_production |> gg_lag(Beer)
```



Example: Beer production

```
new_production |> gg_lag(Beer, geom = "point")
```



Lagged scatterplots

- Each graph shows y_t plotted against y_{t-k} for different values of k.
- The autocorrelations are the correlations associated with these scatterplots.
- ACF (autocorrelation function):
  - $r_1 = \text{Correlation}(y_t, y_{t-1})$
  - $r_2 = \text{Correlation}(y_t, y_{t-2})$
  - $r_3 = \text{Correlation}(y_t, y_{t-3})$
  - etc.
- If there is **seasonality**, the ACF at the seasonal lag (e.g., 12 for monthly data) will be **large and positive**.

Autocorrelation

Results for first 9 lags for beer data:

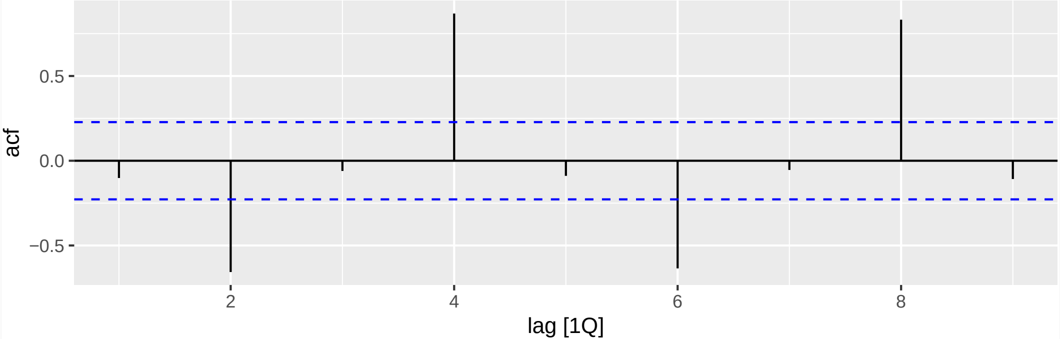
```r
new_production |> ACF(Beer, lag_max = 9)
```

```
## # A tsibble: 9 x 2 [1Q]
##       lag      acf
##     <lag>    <dbl>
## 1      1Q -0.102
## 2      2Q -0.657
## 3      3Q -0.0603
## 4      4Q  0.869
## 5      5Q -0.0892
## 6      6Q -0.635
## 7      7Q -0.0542
```

Autocorrelation

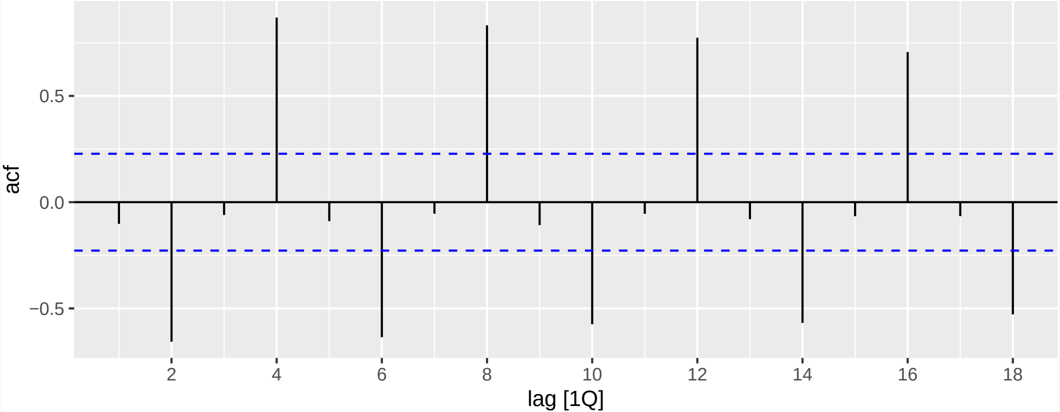
Results for first 9 lags for beer data:

```
new_production ▷
  ACF(Beer, lag_max = 9) ▷
  autoplot()
```



ACF

```
new_production ▷
  ACF(Beer) ▷
  autoplot()
```



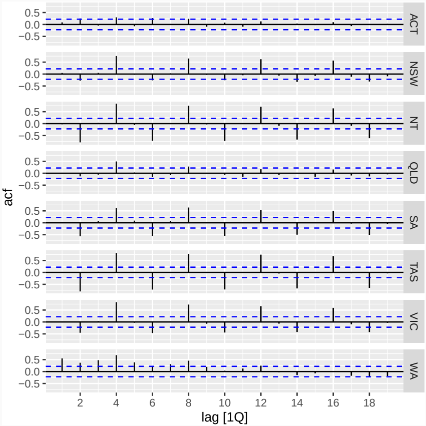
Australian holidays

```
holidays |> ACF(Trips)
```

```
## # A tsibble: 152 x 3 [1Q]
## # Key:       State [8]
##    State   lag      acf
##    <chr> <lag>    <dbl>
##  1 ACT      1Q  0.0877
##  2 ACT      2Q  0.252
##  3 ACT      3Q -0.0496
##  4 ACT      4Q  0.300
##  5 ACT      5Q -0.0741
##  6 ACT      6Q  0.269
##  7 ACT      7Q -0.00504
##  8 ACT      8Q  0.236
##  9 ACT      9Q -0.0953
## 10 ACT     10Q  0.0750
## # ... with 142 more rows
```

Australian holidays

```
holidays |>
  ACF(Trips) |>
  autoplot()
```

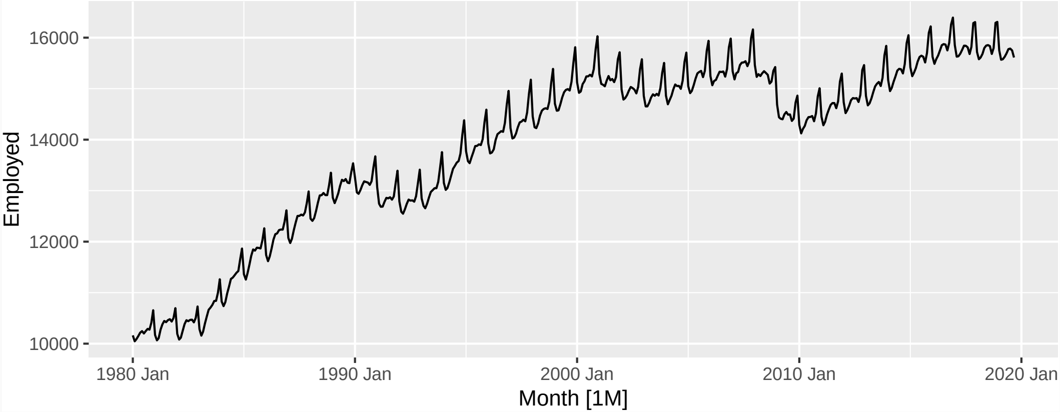


Trend and seasonality in ACF plots

- When data have a trend, the autocorrelations for small lags tend to be large and positive.
- When data are seasonal, the autocorrelations will be larger at the seasonal lags (i.e., at multiples of the seasonal frequency)
- When data are trended and seasonal, you see a combination of these effects.

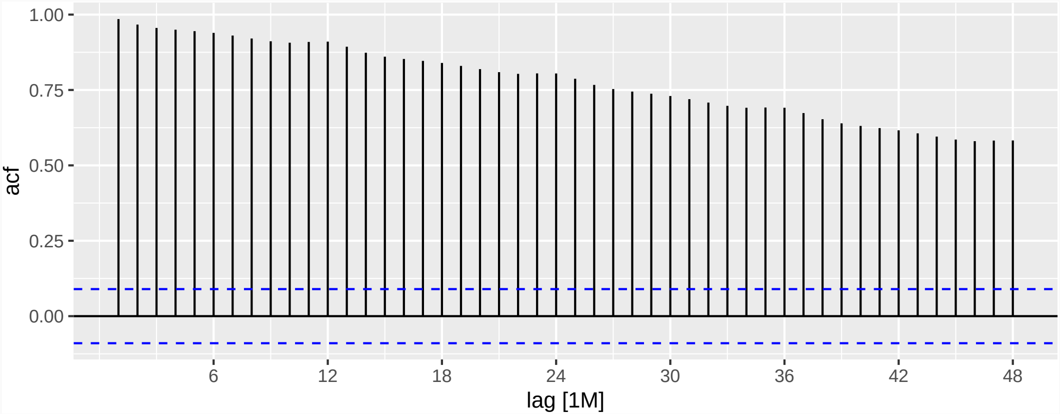
US retail trade employment

```
retail <- us_employment |>
  filter(Title == "Retail Trade", year(Month) >= 1980)
retail |> autoplot(Employed)
```



US retail trade employment

```
retail |>
  ACF(Employed, lag_max = 48) |>
  autoplot()
```



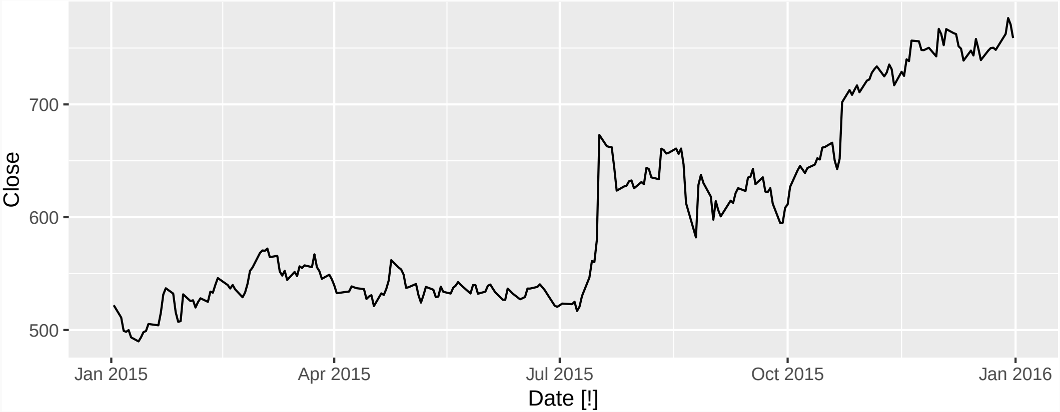
Google stock price

```r
google_2015 <- gafa_stock |>
  filter(Symbol == "GOOG", year(Date) == 2015) |>
  select(Date, Close)
google_2015
```

```
## # A tsibble: 252 x 2 [!]
##    Date       Close
##    <date>     <dbl>
##  1 2015-01-02  522.
##  2 2015-01-05  511.
##  3 2015-01-06  499.
##  4 2015-01-07  498.
##  5 2015-01-08  500.
##  6 2015-01-09  493.
```

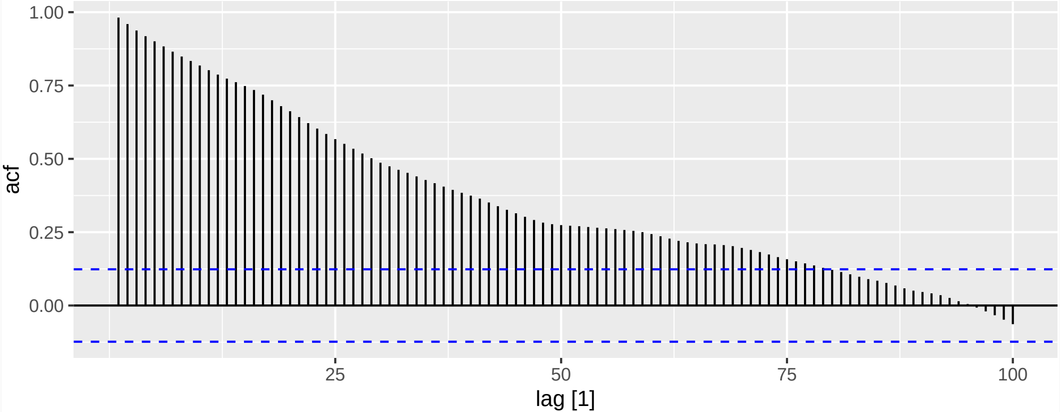
Google stock price

```
google_2015 |> autoplot(Close)
```



Google stock price

```
google_2015 ▷
  ACF(Close, lag_max = 100) ▷
  autoplot()
```



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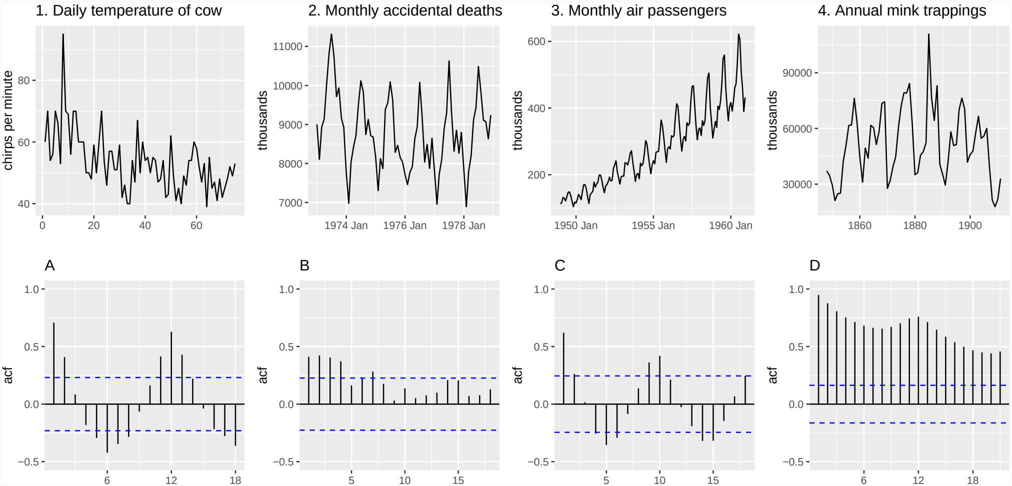
Lab Session 4

We have introduced the following functions: `gg_lag` and `ACF`. Use these functions to explore the four time series: `Bricks` from `aus_production`, `Lynx` from `pelt`, `Close` price of Amazon from `gafa_stock`, `Demand` from `vic_elec`. Can you spot any seasonality, cyclicity and trend? What do you learn about the series?

Which is which?



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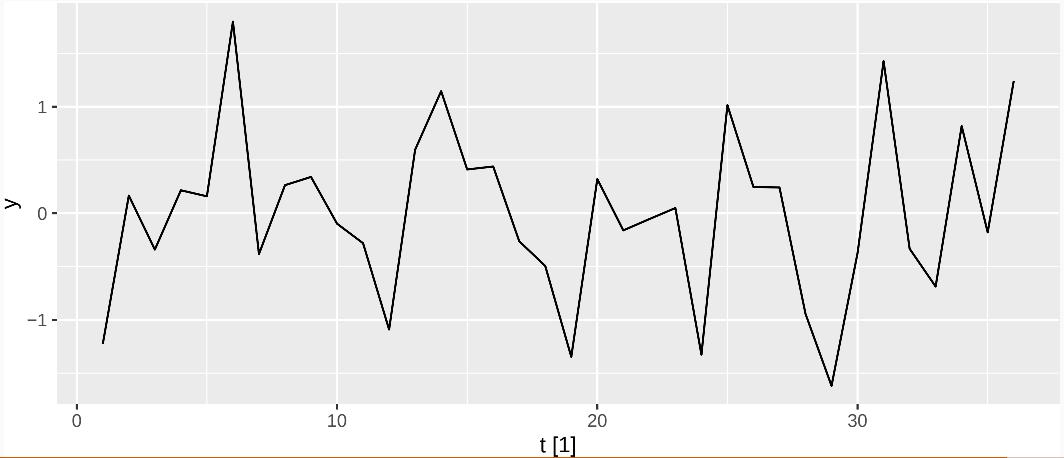
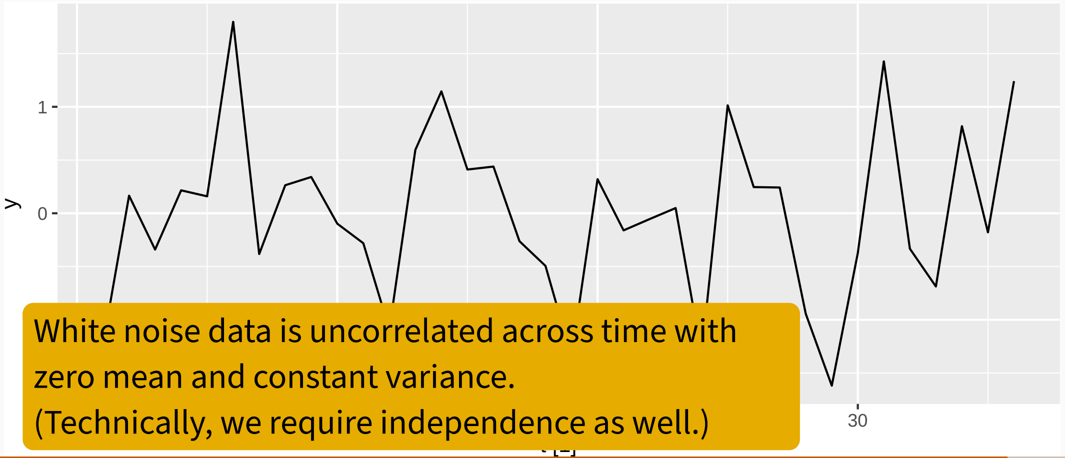
Example: White noise

```
wn <- tsibble(t = seq(36), y = rnorm(36), index = t)
wn ▷ autoplot(y)
```



Example: White noise

```r
wn <- tsibble(t = seq(36), y = rnorm(36), index = t)
wn |> autoplot(y)
```

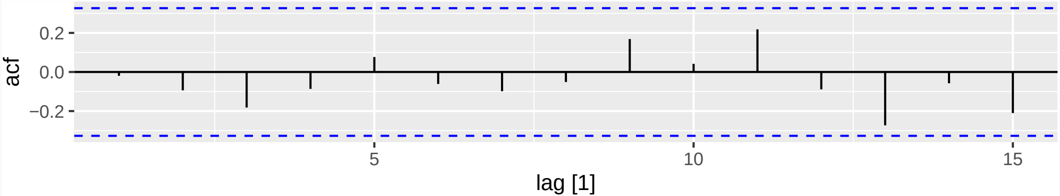


White noise data is uncorrelated across time with zero mean and constant variance.
(Technically, we require independence as well.)

Example: White noise

```
wn ▷ ACF(y)
```

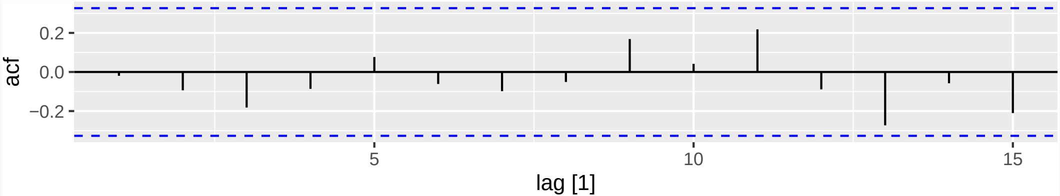
r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}
-0.019	-0.094	-0.182	-0.086	0.077	-0.061	-0.098	-0.051	0.169	0.042



Example: White noise

```
wn ▷ ACF(y)
```

r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}
-0.019	-0.094	-0.182	-0.086	0.077	-0.061	-0.098	-0.051	0.169	0.042



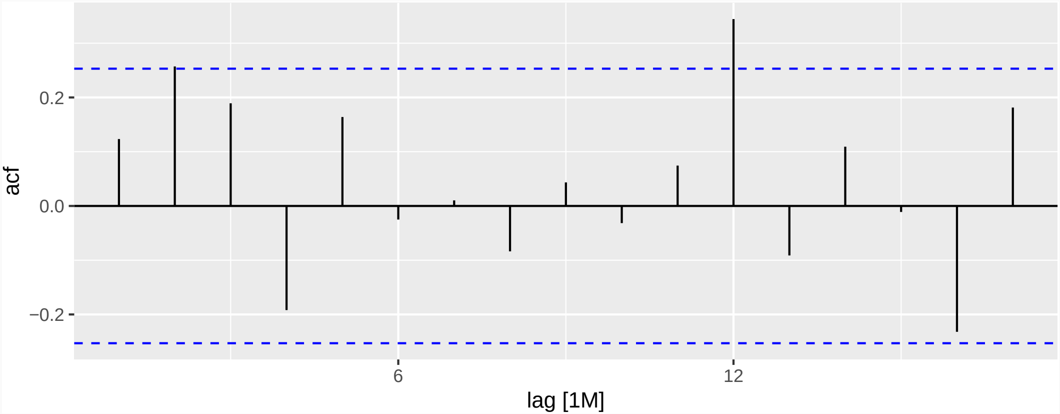
- Sample autocorrelations for white noise series.
- Expect each autocorrelation to be close to zero.
- Blue lines show 95% critical values.

Example: Pigs slaughtered

```r
pigs <- aus_livestock |>
  filter(State == "Victoria", Animal == "Pigs", year(Month) >= 2014)
pigs |> autoplot(Count / 1e3) +
  labs(x = "Year", y = "Thousands",
       title = "Number of pigs slaughtered in Victoria")
```

Example: Pigs slaughtered

```
pigs ▷
  ACF(Count) ▷
  autoplot()
```



Example: Pigs slaughtered

Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 2014 through December 2018 (Source: Australian Bureau of Statistics.)

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Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 2014 through December 2018 (Source: Australian Bureau of Statistics.)

- Difficult to detect pattern in time plot.
- ACF shows significant autocorrelation for lag 2 and 12.
- Indicate some slight seasonality.

Example: Pigs slaughtered

Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 2014 through December 2018 (Source: Australian Bureau of Statistics.)

- Difficult to detect pattern in time plot.
- ACF shows significant autocorrelation for lag 2 and 12.
- Indicate some slight seasonality.

These show the series is **not a white noise series**.

Outline

1 Seasonal plots

2 Lab Session 3

3 Seasonal or cyclic?

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5 Lab Session 4

6 White noise

7 Lab Session 5

Lab Session 5

You can compute the daily changes in the Google stock price in 2018 using

```r
dgoog <- gafa_stock |>
  filter(Symbol == "GOOG", year(Date) >= 2018) |>
  mutate(diff = difference(Close))
```

Does `diff` look like white noise?