workshop.nectric.com.au/tidyfc2024

Time Series Analysis & Forecasting Using R

2. Time series graphics

tsibble feasts fable

Outline

1. Workshop data
2. Time plots
3. Lab Session 3
4. Seasonal plots
5. Lab Session 4
6. Seasonal or cyclic?
7. Lag plots and autocorrelation
8. Lab Session 4
9. White noise
10. Lab Session 5

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Workshop data

https://workshop.nectric.com.au/tidyfc2024/labs.zip

Download this ZIP to access all the tidied data.

Open the project by double-clicking ‘tidyfc-exercises.Rproj’.

> **Alternatively…**
>
> ```
> usethis::use_course("https://workshop.nectric.com.au/tidyfc2024/labs.zip")
> ```

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Time plots

Time plots are the simplest and most common visualisation for time series data (you've certainly seen these before!).

For this we put time on the x-axis and plot the measurements on the y-axis. We can make this plot easily with ggplot2, or with the `data |> autoplot(y)` helper function.

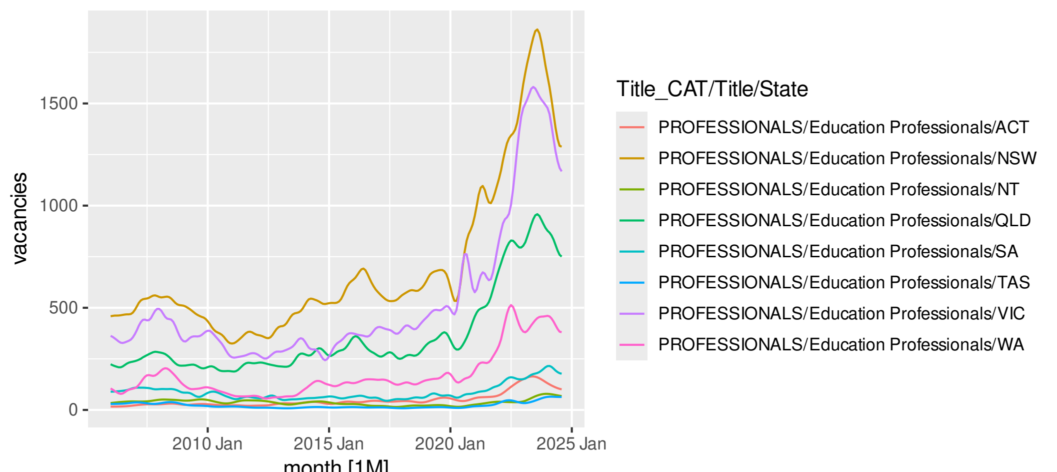
> **Overplotting beware**
>
> When working with many time series it's easy to over plot. Filter or aggregate the data before plotting.

Recall the internet vacancies dataset

```
library(readxl)
anzsco_categories <- read_excel("data/Internet Vacancies, ANZSCO2 Occupations, State
  filter(Level == 2) |>
  distinct(ANZSCO_CODE, Title)
read_excel("data/Internet Vacancies, ANZSCO2 Occupations, States and Territories - A
  # Tidy into a long form
  pivot_longer(matches("\\d{5}"), names_to = "month", values_to = "vacancies") |>
  mutate(month = yearmonth(as.Date(as.integer(month), origin = "1900-01-01"))) |>
  # Remove aggregates
  filter(Level == 3, State != "AUST") |>
  # Add level 2 category information
  mutate(ANZSCO_CODE_CAT = substr(ANZSCO_CODE, 1, 1)) |>
  left_join(anzsco_categories, by = c("ANZSCO_CODE_CAT" = "ANZSCO_CODE"), suffix = c
  select(ANZSCO_CODE, Title_CAT, Title, State, month, vacancies) |>
  # Convert to a tsibble
  as_tsibble(
    key = c(Title_CAT, Title, State),
    index = month
  ) -> internet_vacancies
```

Time plots

```
internet_vacancies |>
  filter(Title == "Education Professionals") |>
  autoplot(vacancies)
```



Time plots

Time plots help show the main changes in the data over time.

Here we can look for:

- Trend
- Seasonality
- Cycles
- Outliers

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Here we can look for:

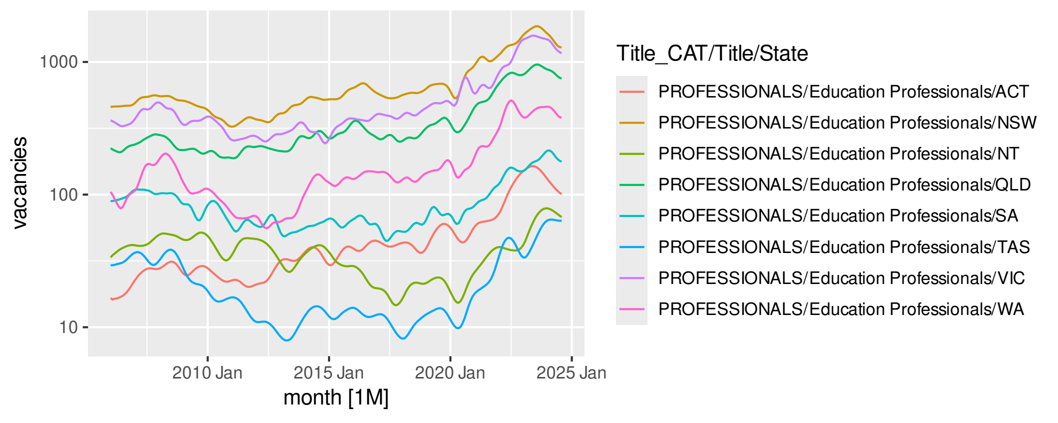
- Trend
- Seasonality
- Cycles
- Outliers

Story of time

Discuss overall patterns across time and highlight specific points in time which are interesting.

Time plots

```r
internet_vacancies |>
  filter(Title == "Education Professionals") |>
  autoplot(vacancies) +
  scale_y_log10()
```



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Lab Session 3

1. Create time plots of the total school students and staff.

   Hint: You'll need to aggregate the data first.

2. Create time plots of the total students and staff by state.
3. Use ggplot2 to create a time plot from scratch, complete with labels.

> **Finished early?**
>
> Try combining the student and staff datasets to create a time plot which directly compares the number of students and staff.

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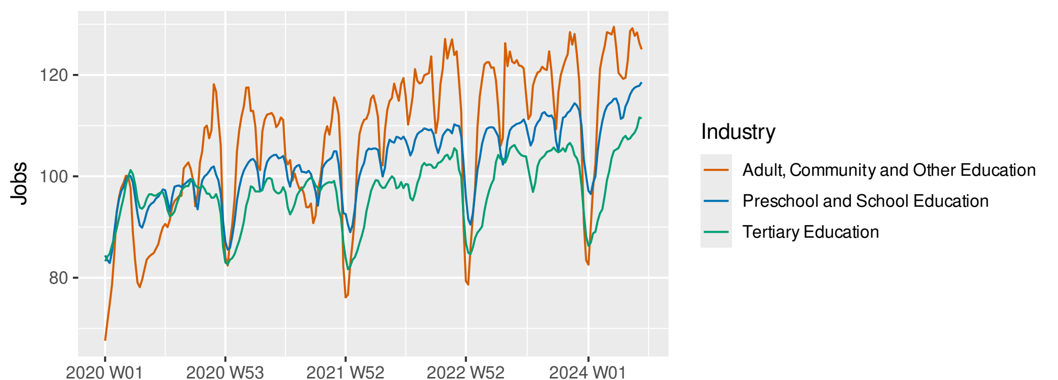
Seasonal plots

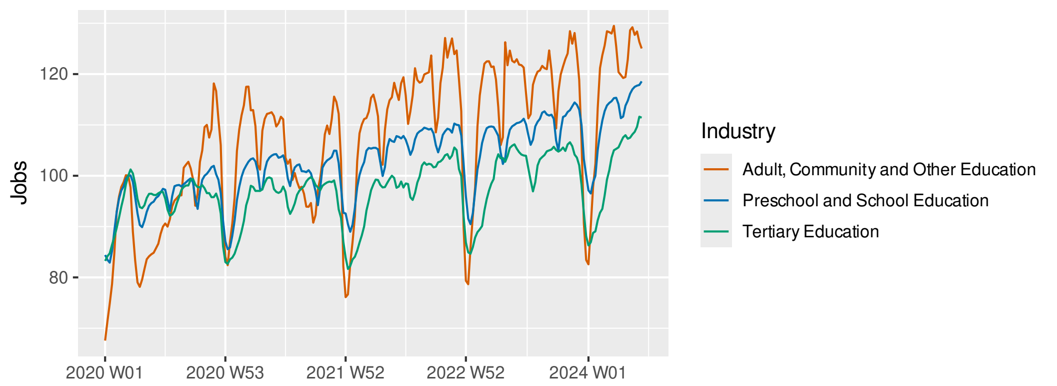
```
payroll_education <- readabs::read_payrolls("subindustry_jobs") |>
  filter(industry_division == "P-Education & training") |>
  transmute(Industry = industry_subdivision, Week = yearweek(date), Jobs = value) |>
  as_tsibble(index = Week, key = Industry)
payroll_education |>
  autoplot(Jobs)
```



Seasonal plots

Ups and downs (peaks and troughs)

When is the seasonal maximum and minimum?

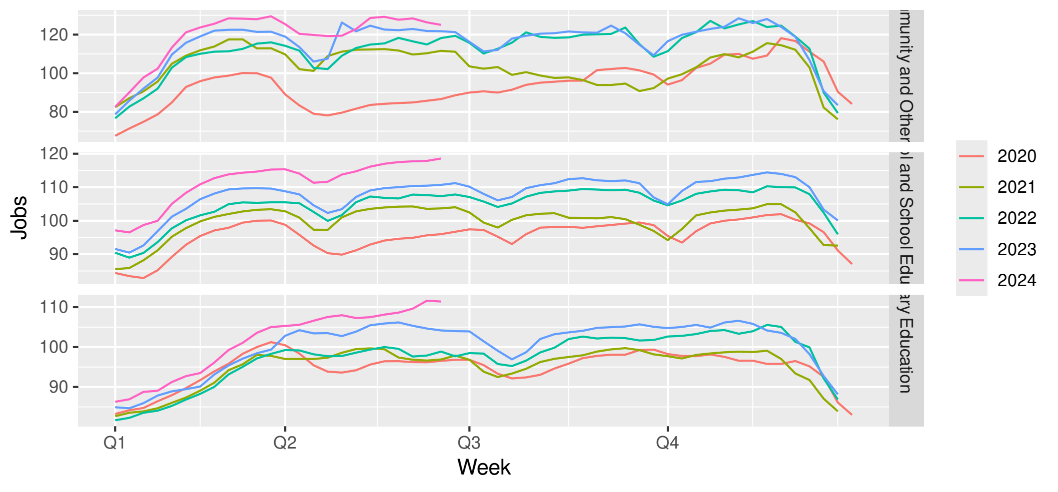


Seasonal plots

- 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()`

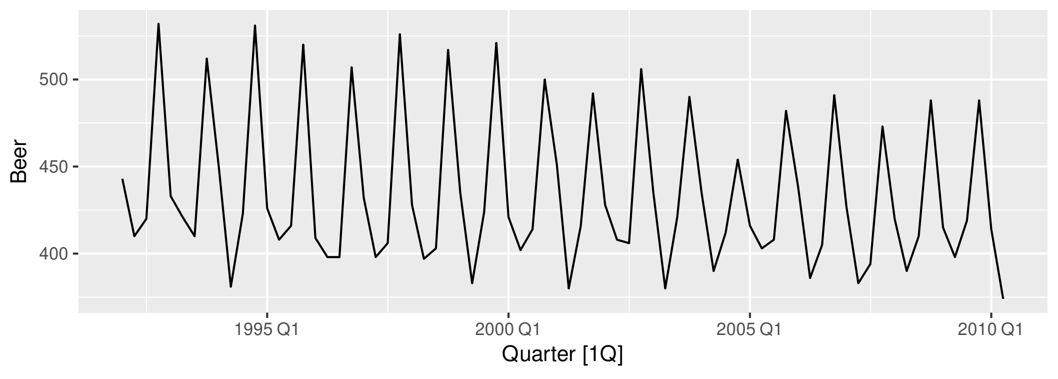
Seasonal plots

```r
payroll_education |>
  gg_season(Jobs)
```



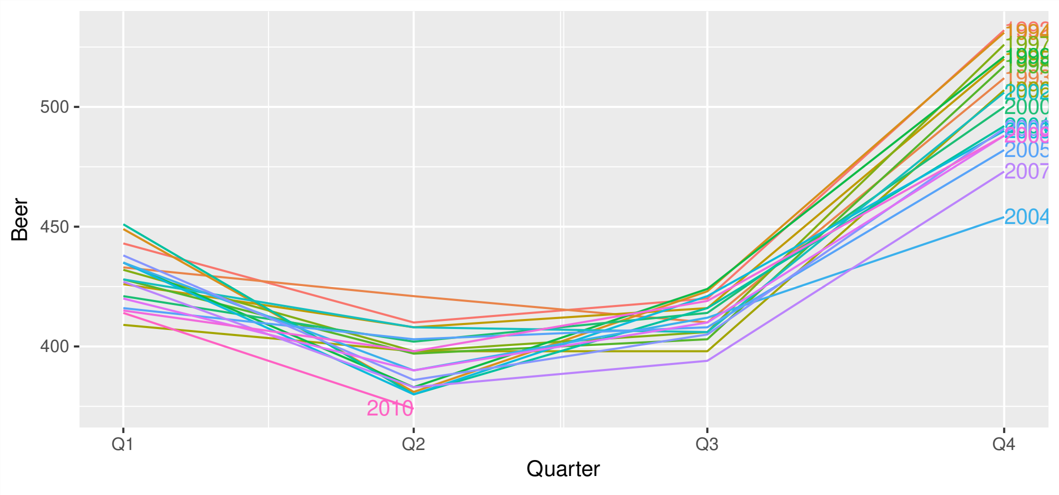
Quarterly Australian Beer Production

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



Quarterly Australian Beer Production

```r
beer |> gg_season(Beer, labels = "right")
```



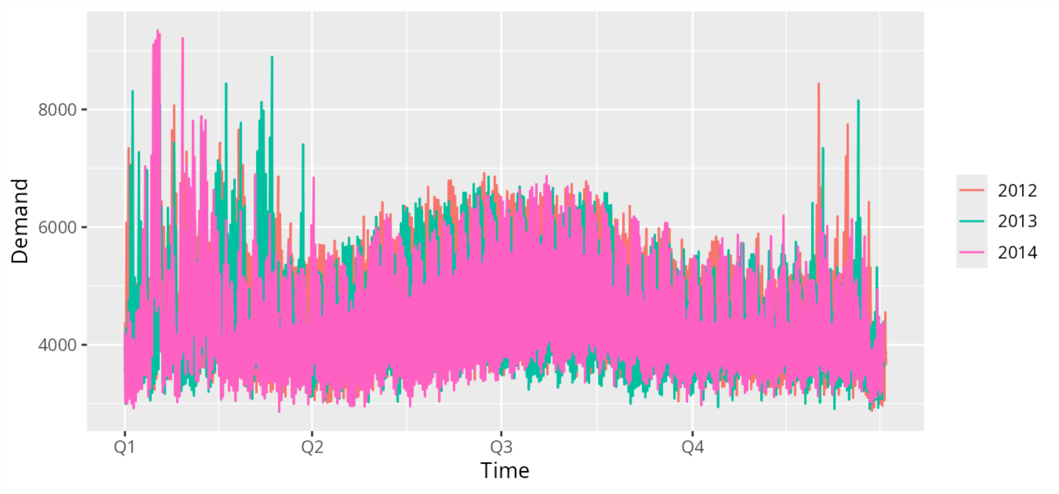
Multiple seasonal periods

```
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
# i 52,598 more rows
```

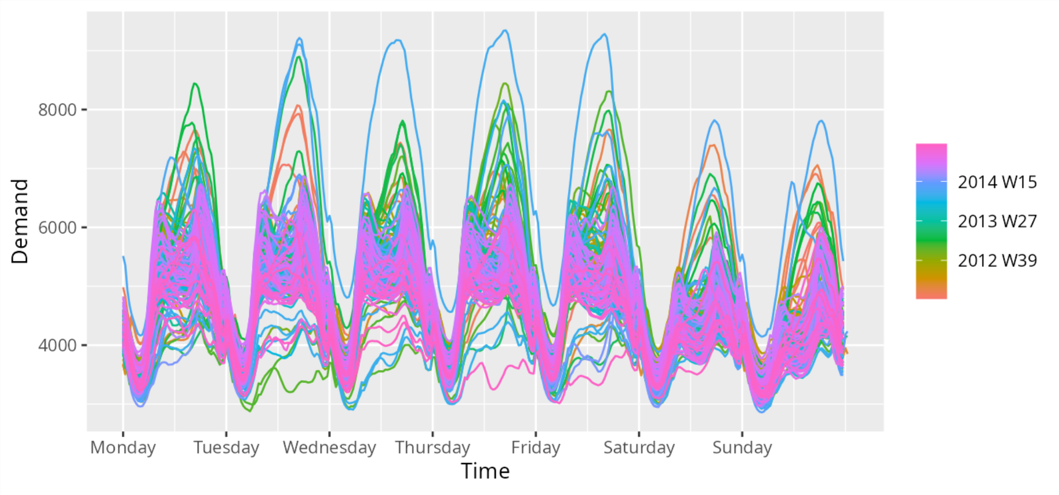
Multiple seasonal periods

```
vic_elec |> gg_season(Demand)
```



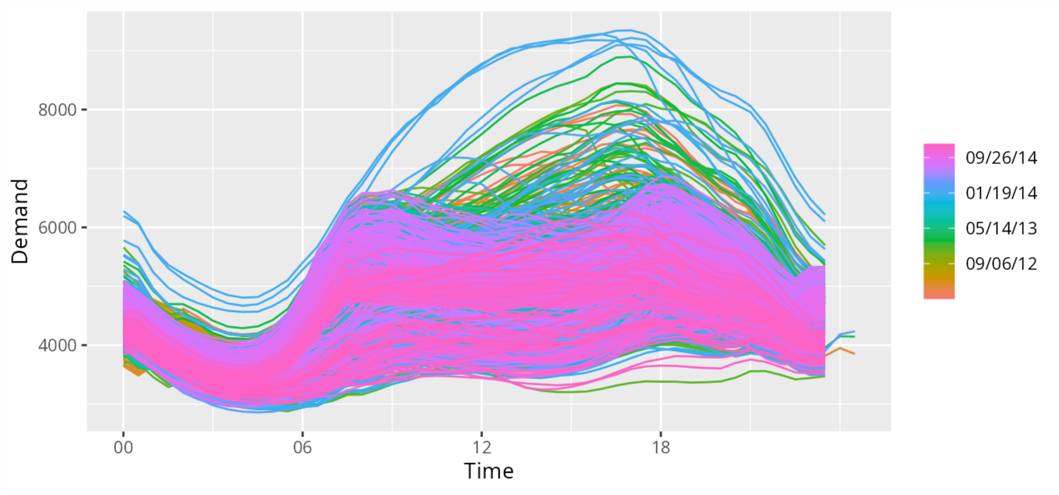
Multiple seasonal periods

```
vic_elec |> gg_season(Demand, period = "week")
```



Multiple seasonal periods

```
vic_elec |> gg_season(Demand, period = "day")
```

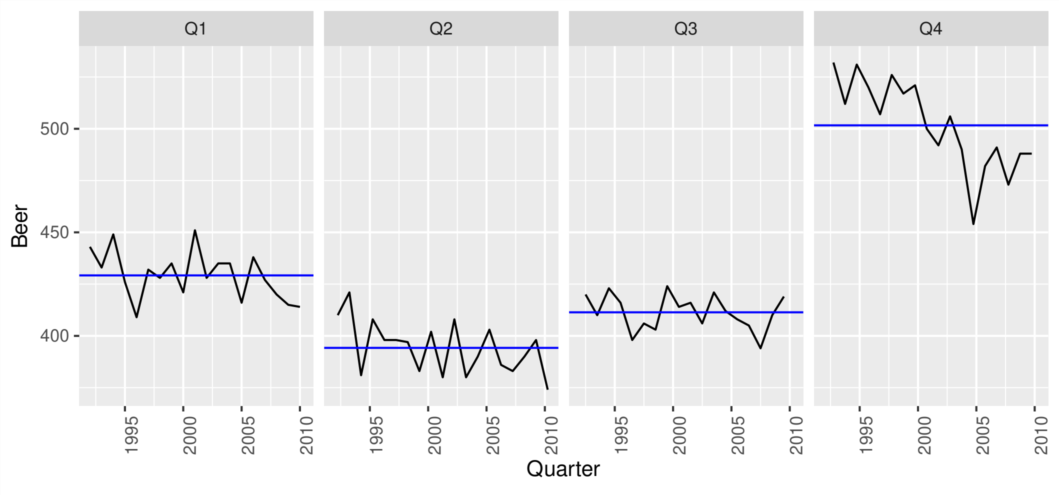


Seasonal subseries plots

- 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)
```

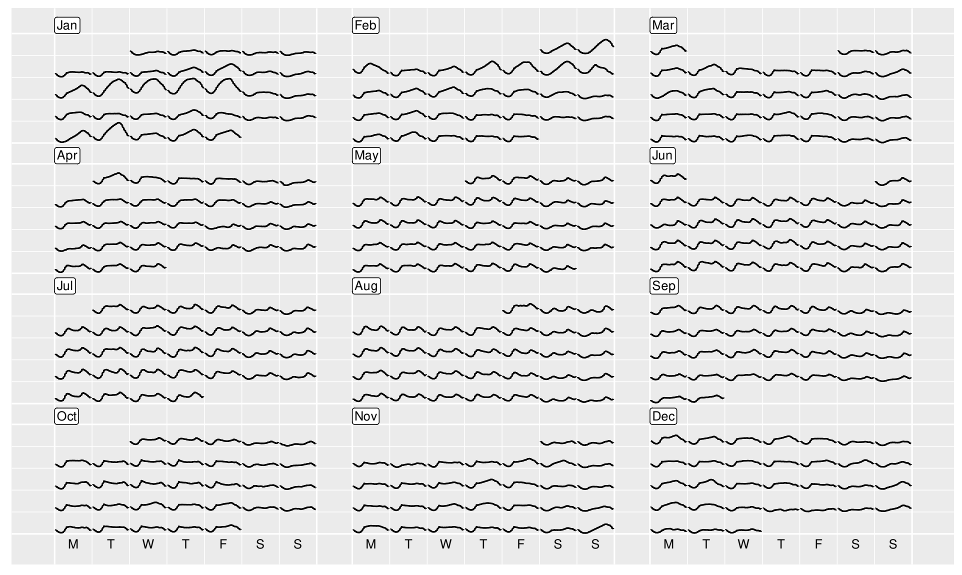


Calendar plots

```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



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Lab Session 4

1. Look at the monthly labour force of 15-24 year olds by State/Territory and educational attendance.

   Data is sourced from the ABS 6202.0 Table 16.

   The code to prepare this data is in `student_labour.R`.

2. Use `autoplot()`, `gg_season()` and `gg_subseries()` to explore the data.

   Look at different aggregations of the data, for example total persons by attendance.

3. What do you learn?

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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).

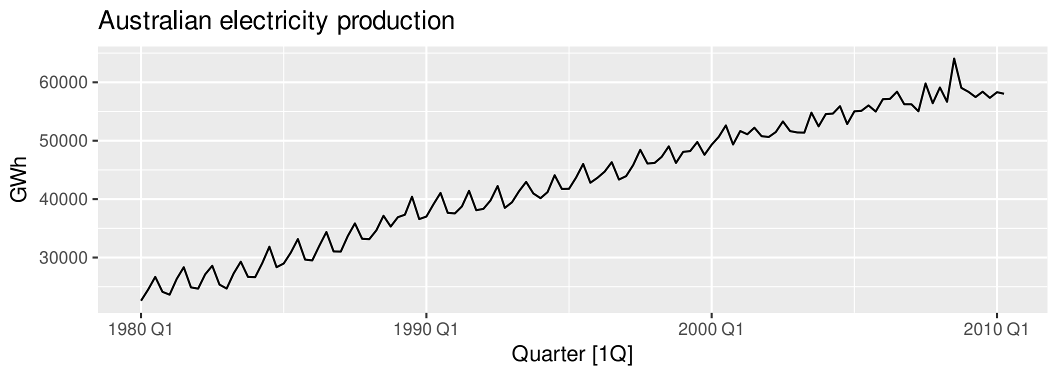
Time series components

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

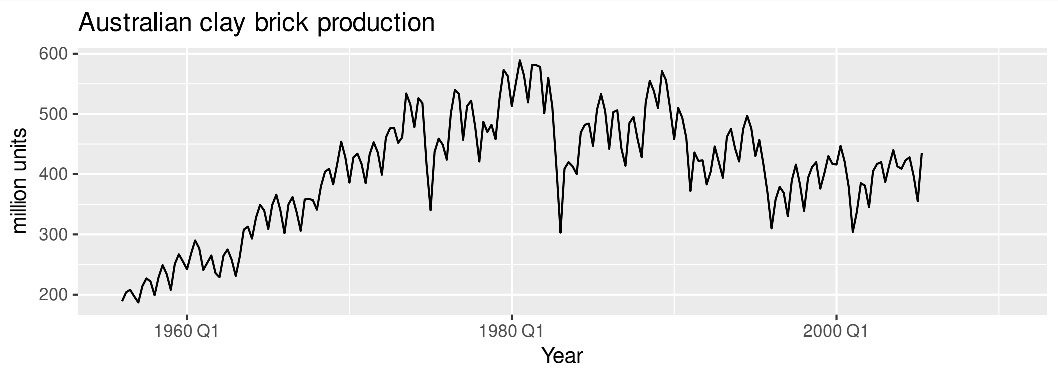
Time series patterns

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



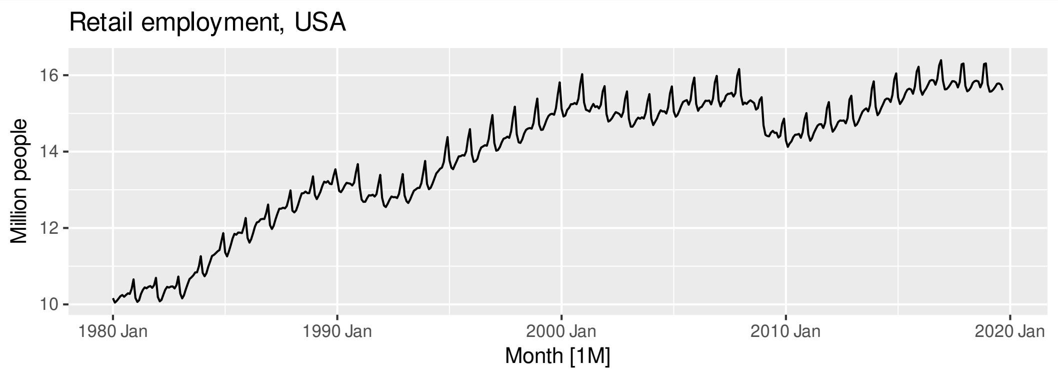
Time series patterns

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



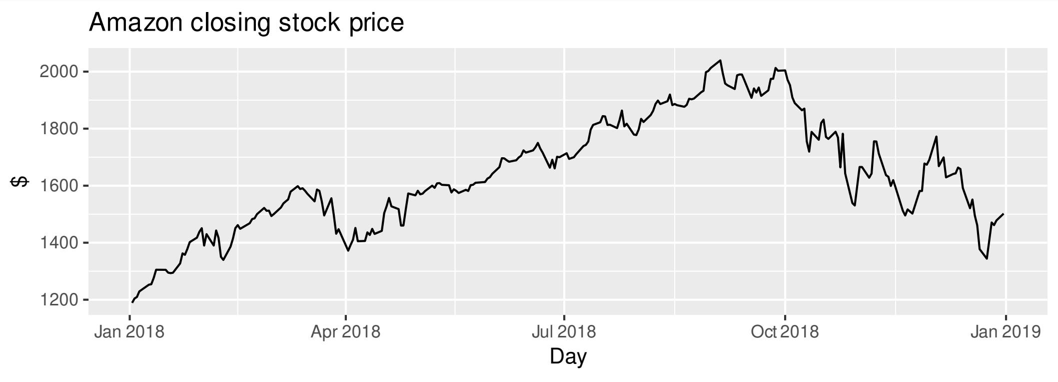
Time series patterns

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



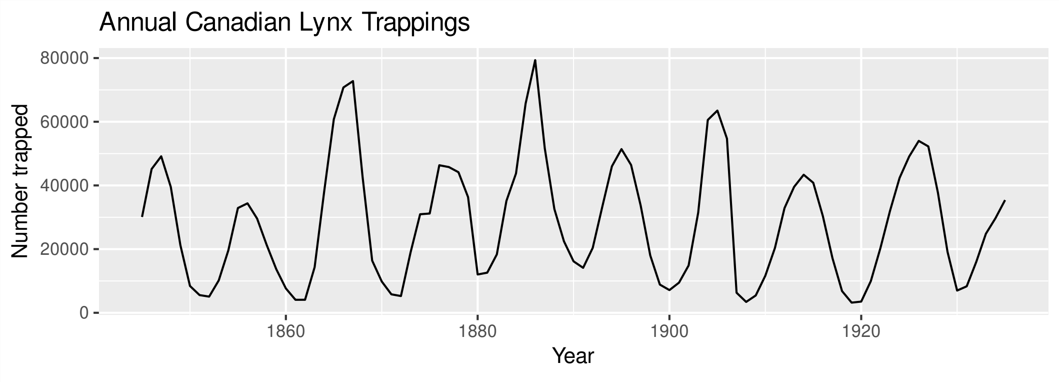
Time series patterns

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



Time series patterns

```r
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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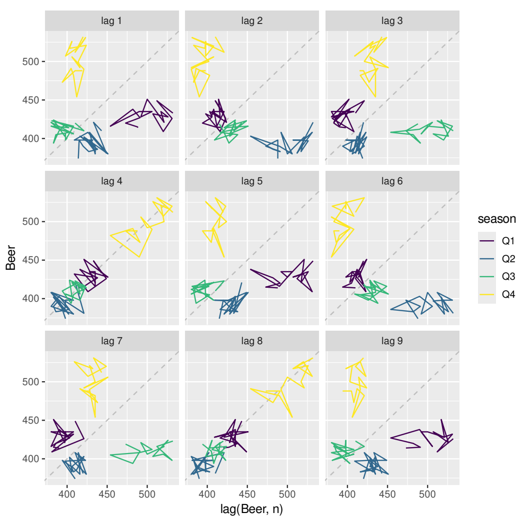
Example: Beer production

```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
 9 1994 Q1   449    5311    421   1468       40162   127
10 1994 Q2   381    5717    475   1755       41199   159
# i 64 more rows
```

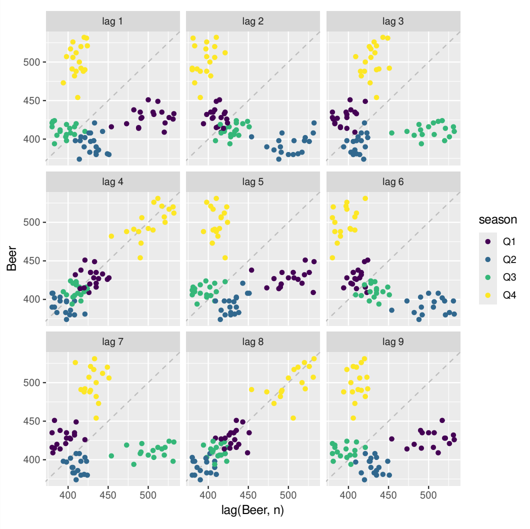
Example: Beer production

```
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:

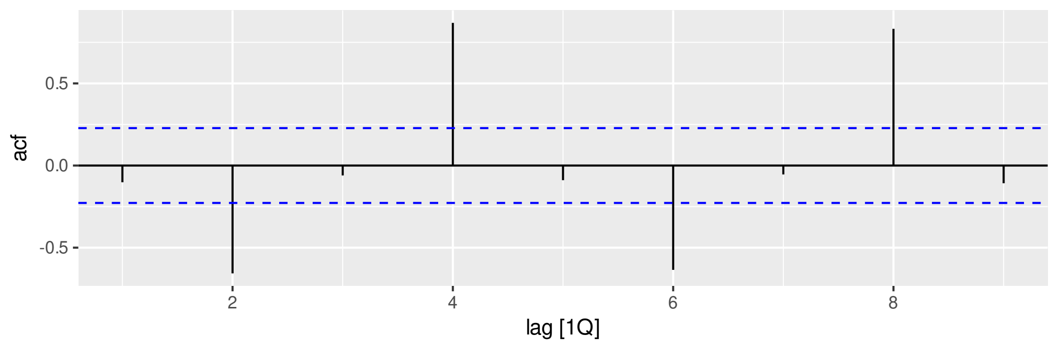
```
new_production |> ACF(Beer, lag_max = 9)
```

```
# A tsibble: 9 x 2 [1Q]
        lag      acf
  <cf_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
8        8Q  0.832
9        9Q -0.108
```

Autocorrelation

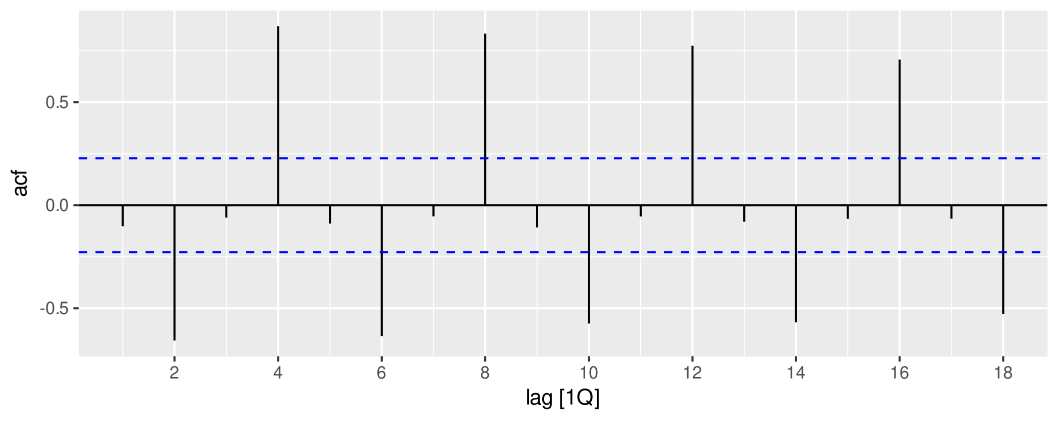
Results for first 9 lags for beer data:

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



ACF

```
new_production |>
  ACF(Beer) |>
  autoplot()
```



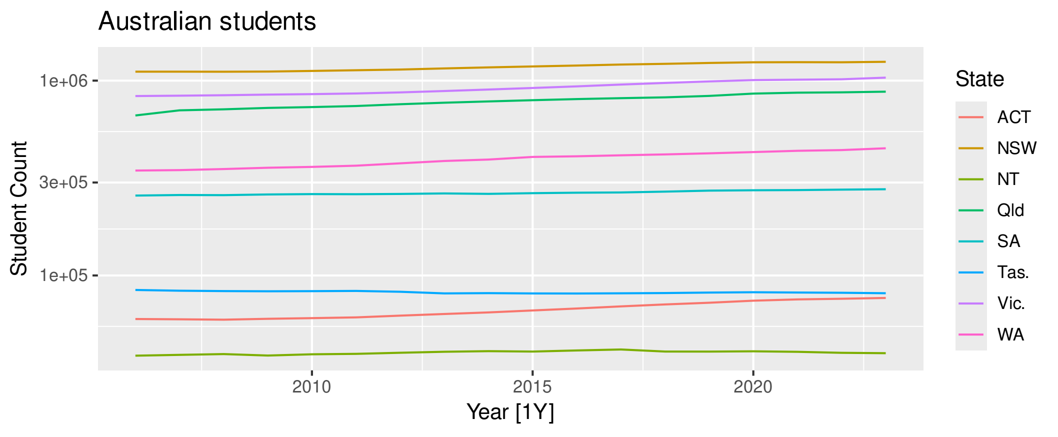
Australian student enrolments

```r
students <- readxl::read_excel("data/schools/Table 42b Number of Full-time and Part-
  # Group by Year and all the character variables
  group_by(Year, across(where(is.character), identity)) |>
  # Add up the duplicate rows
  summarise(across(ends_with("count"), sum), .groups = "drop") |>
  # Convert to a tsibble
  as_tsibble(
    key = where(is.character),
    index = Year
  )
```

```
# A tsibble: 81,307 x 13 [1Y]
# Key:       State/Territory, Affiliation (Gov/Non-gov), Affiliation
#   (Gov/Cath/Ind), Sex, Aboriginal and Torres Strait Islander Status,
#   School Level, National Report on Schooling (ANR) School Level, Year
#   (Grade), Age [6,575]
    Year `State/Territory` Affiliation (Gov/Non-go~1 Affiliation (Gov/Cat~2
   <dbl> <chr>             <chr>                     <chr>
 1  2006 a NSW             a Government              a Government
```

Australian student enrolments

```
students |> autoplot(Count) +
  labs(y = "Student Count", title = "Australian students") +
  scale_y_log10()
```



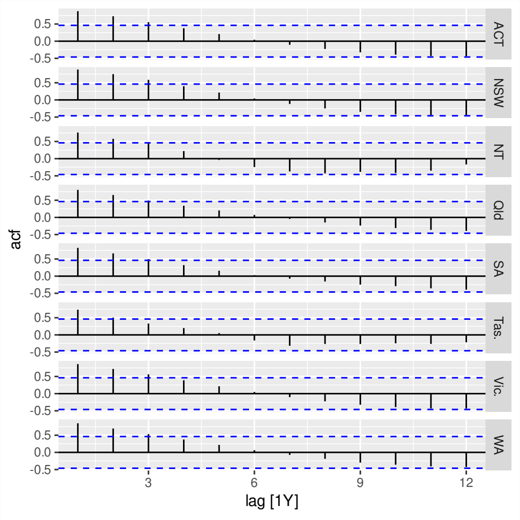
Australian holidays

```
students |> ACF(Count)
```

```
# A tsibble: 96 x 3 [1Y]
# Key:       State [8]
   State      lag     acf
   <chr> <cf_lag>   <dbl>
 1 ACT         1Y  0.875
 2 ACT         2Y  0.727
 3 ACT         3Y  0.555
 4 ACT         4Y  0.377
 5 ACT         5Y  0.207
 6 ACT         6Y  0.0415
 7 ACT         7Y -0.104
 8 ACT         8Y -0.226
 9 ACT         9Y -0.324
10 ACT        10Y -0.392
# i 86 more rows
```

Australian holidays

```
students |> ACF(Count) |> autoplot()
```

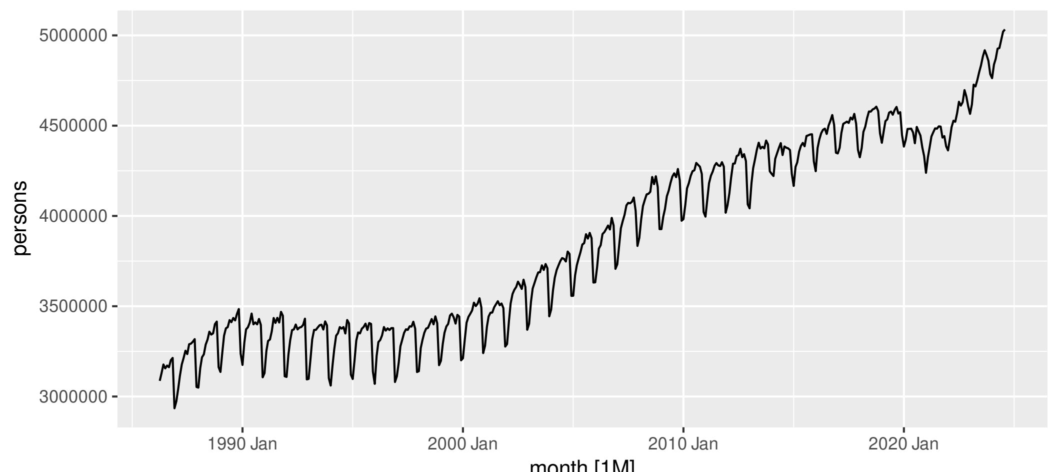


Trend and seasonality in ACF plots

- 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.

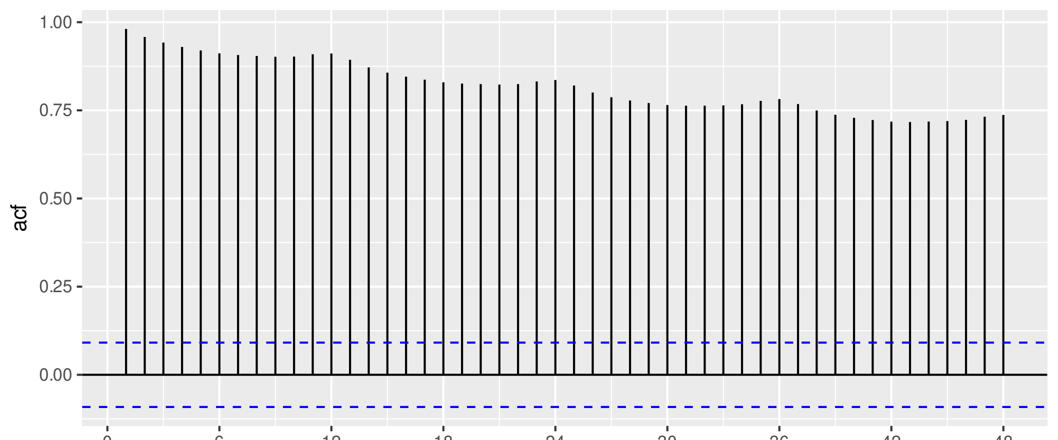
Youth labour force

```
student_labour |>
  summarise(persons = sum(persons)) |>
  autoplot(persons)
```



US retail trade employment

```r
student_labour |>
  summarise(persons = sum(persons)) |>
  ACF(persons, lag_max = 48) |>
  autoplot()
```



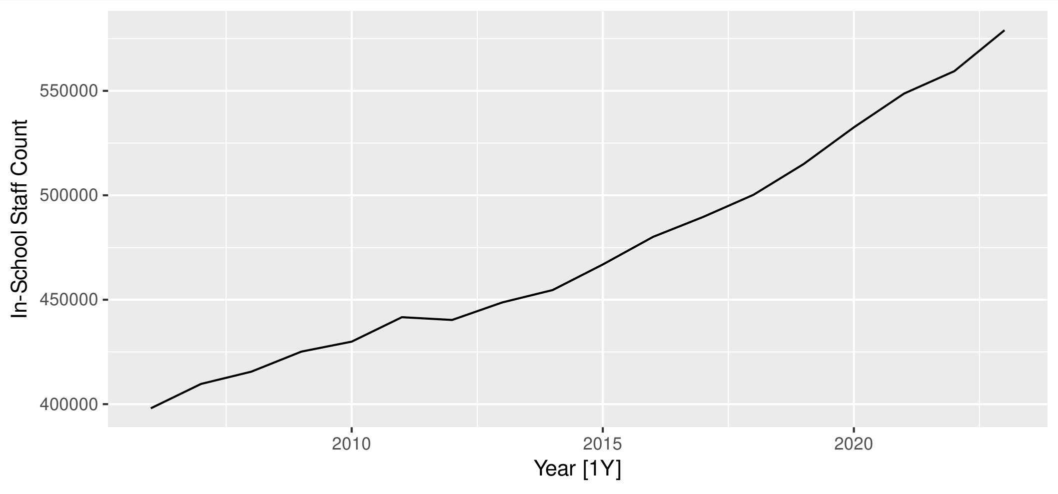
In-school staff

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

```
# A tsibble: 18 x 2 [1Y]
    Year `In-School Staff Count`
   <dbl>                   <dbl>
 1  2006                  398003
 2  2007                  409678
 3  2008                  415541
 4  2009                  425166
 5  2010                  429933
 6  2011                  441631
 7  2012                  440313
 8  2013                  448711
 9  2014                  454615
10  2015                  466867
11  2016                  480077
```

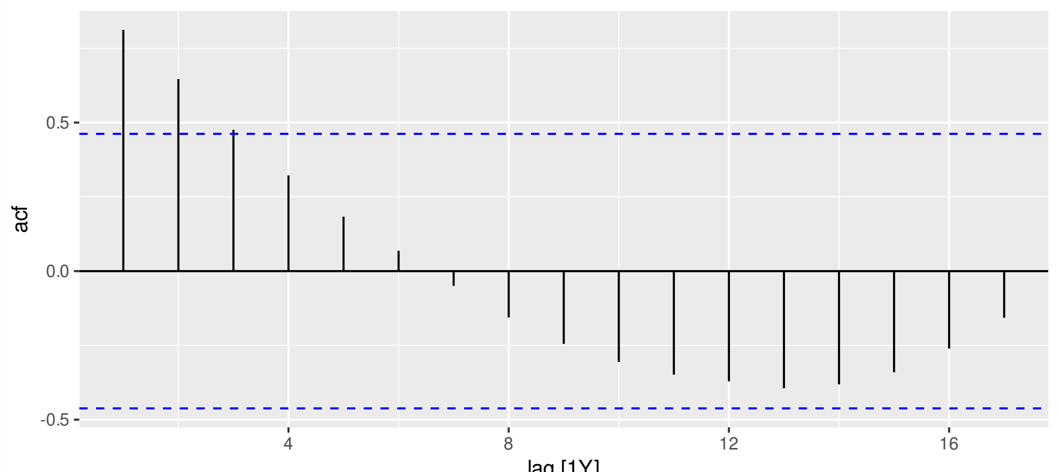
Google stock price

```
staff_total |> autoplot(`In-School Staff Count`)
```



Google stock price

```
staff_total |>
  ACF(`In-School Staff Count`, lag_max = 100) |>
  autoplot()
```



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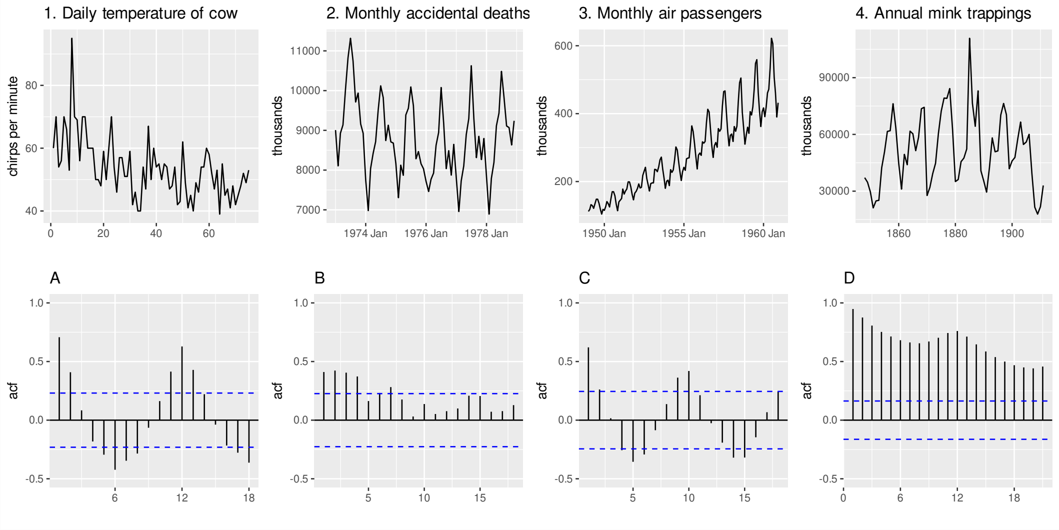
Lab Session 4

Explore the `ACF()` of the following time series:

1. Education payroll (`payroll_education`)
2. Total full-time students (`students`)
3. Total working students aged 15-24 in ACT (`student_labour`)

Can you spot any seasonality, cyclicity and trend? What do you learn about the series?

Which is which?

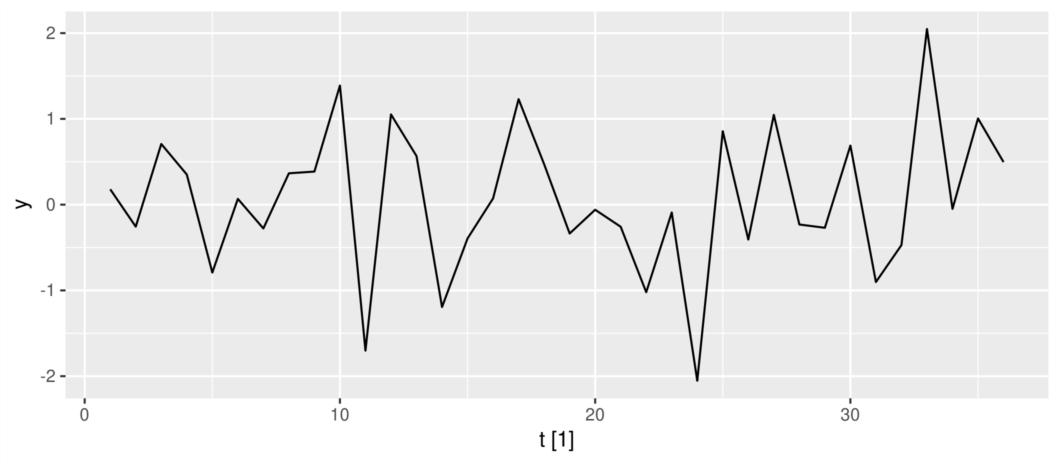


Outline

1. Workshop data
2. Time plots
3. Lab Session 3
4. Seasonal plots
5. Lab Session 4
6. Seasonal or cyclic?
7. Lag plots and autocorrelation
8. Lab Session 4
9. White noise
10. Lab Session 5

Example: White noise

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



Example: White noise

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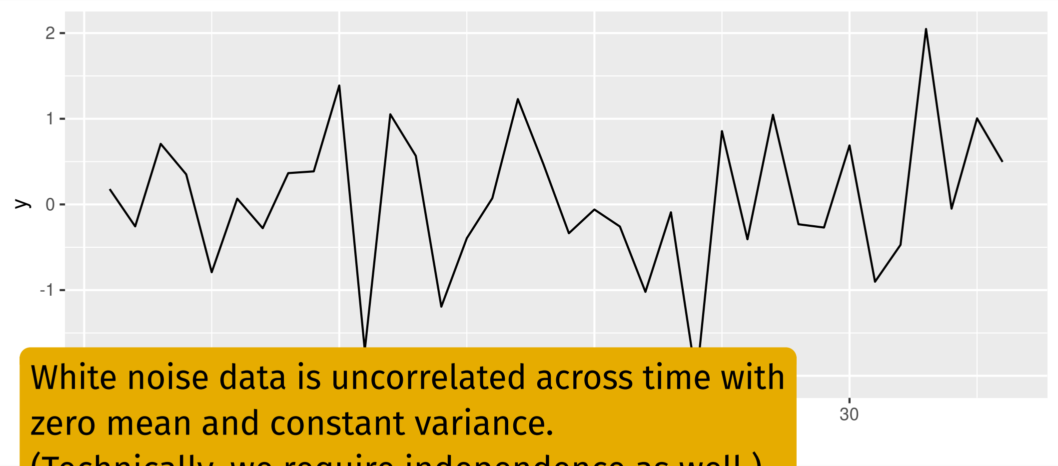
```

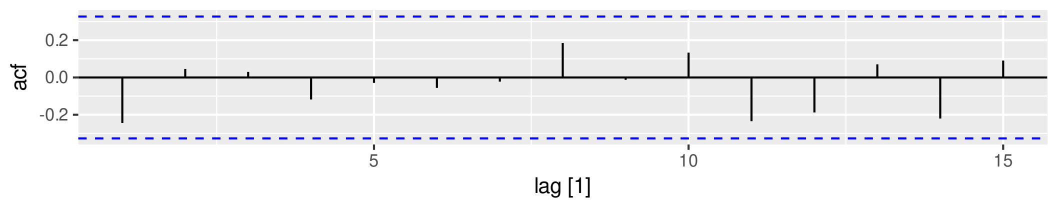


White noise data is uncorrelated across time with zero mean and constant variance.
(Technically, we require independence as well.)

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}
-0.244	0.046	0.030	-0.118	-0.029	-0.056	-0.022	0.185	-0.013	0.133



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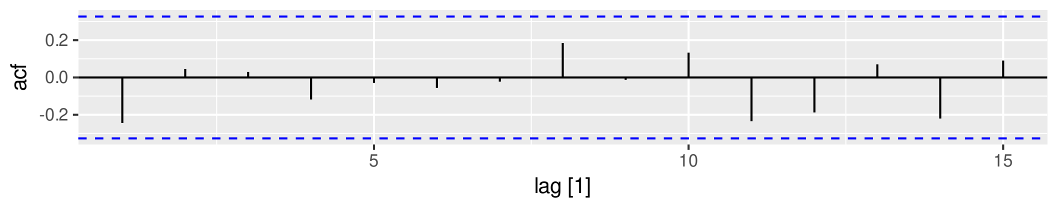
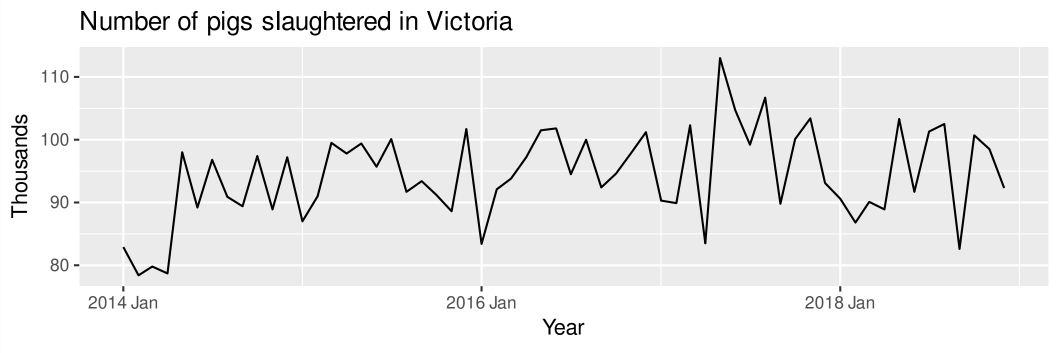


- Sample autocorrelations for white noise series.
- Expect each autocorrelation to be close to zero.
- Blue lines show 95% critical values.

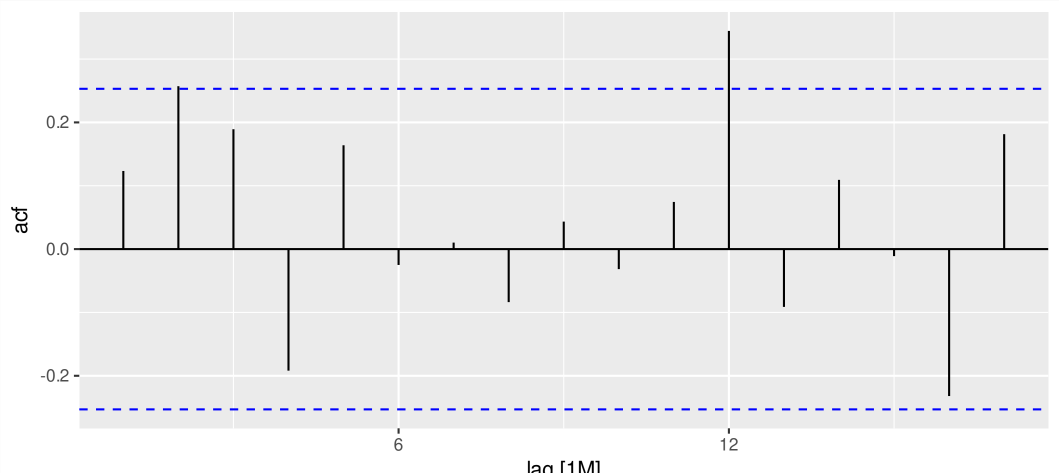
Example: Pigs slaughtered

```
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()
```



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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.)

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

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Lab Session 5

Plot the difference in ACT student enrolments, it can be done as follows:

```
students |>
  filter(`State/Territory` == "ACT") |>
  summarise(total = sum(`All Full-time and Part-time Student count`)) |>
  autoplot(difference(total))
```

Does `diff` look like white noise? Hint: Check the ACF