CARDIFF UNIVERSITY
PRIFYSGOL CAERDYDD

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Forecasting in R

Time series patterns

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Outline

1. Learning outcome
2. Time series Patterns
3. Time plots and lab 2
4. Seasonal plots and lab 3
5. Autocorrelation and lab 4

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Learning outcome

You should be able to:

1. Create time series graphics
2. Identify key feature in time series data

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Key features of time series

- Underlying trend
- Seasonal/cycle pattern
- Autocorrelation
- Unpredictable patterns/Noise

Time series patterns

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

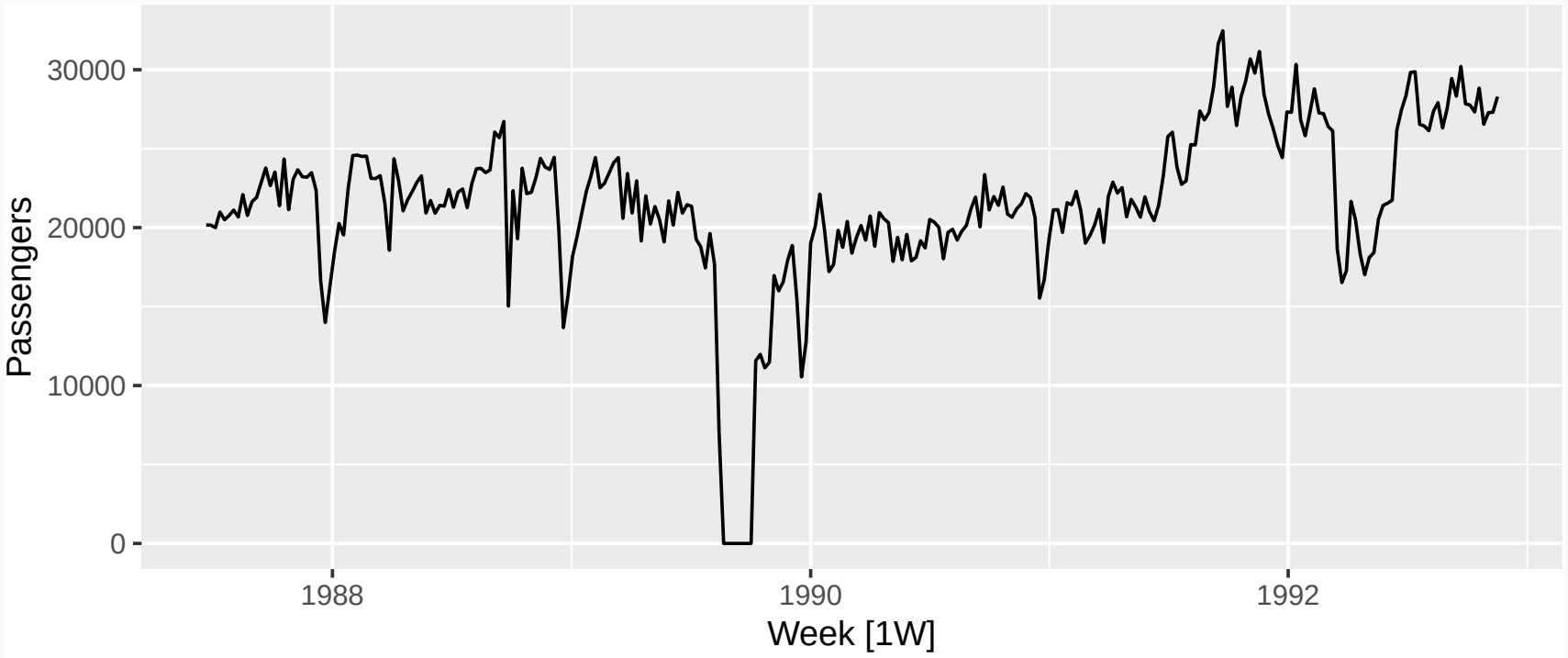
Seasonal pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).

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

Outline

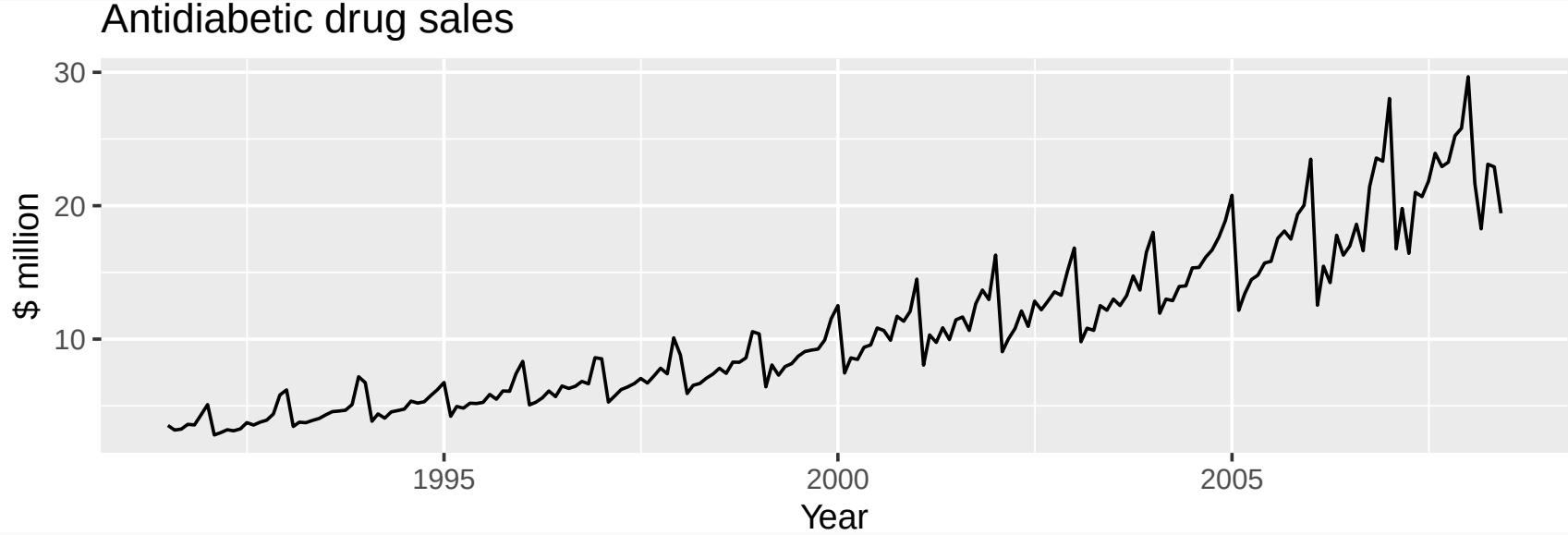
Time plots

```
ansett %>%
  filter(Airports=="MEL-SYD", Class=="Economy") %>%
  autoplot(Passengers)
```



Time plots

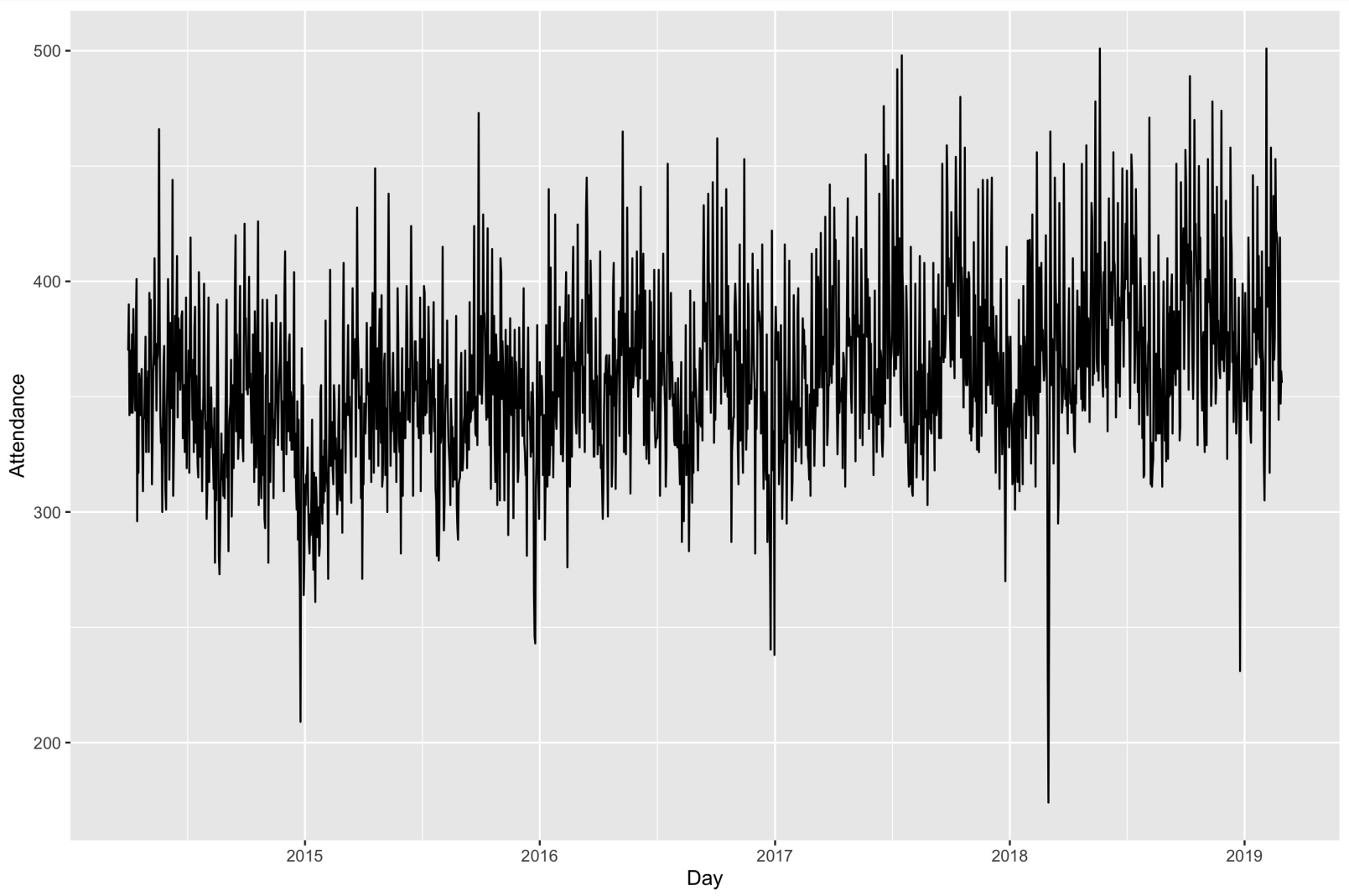
```
PBS %>% filter(ATC2 == "A10") %>%
  summarise(Cost = sum(Cost)/1e6) %>% autoplot(Cost) +
  ylab("$ million") + xlab("Year") +
  ggtitle("Antidiabetic drug sales")
```



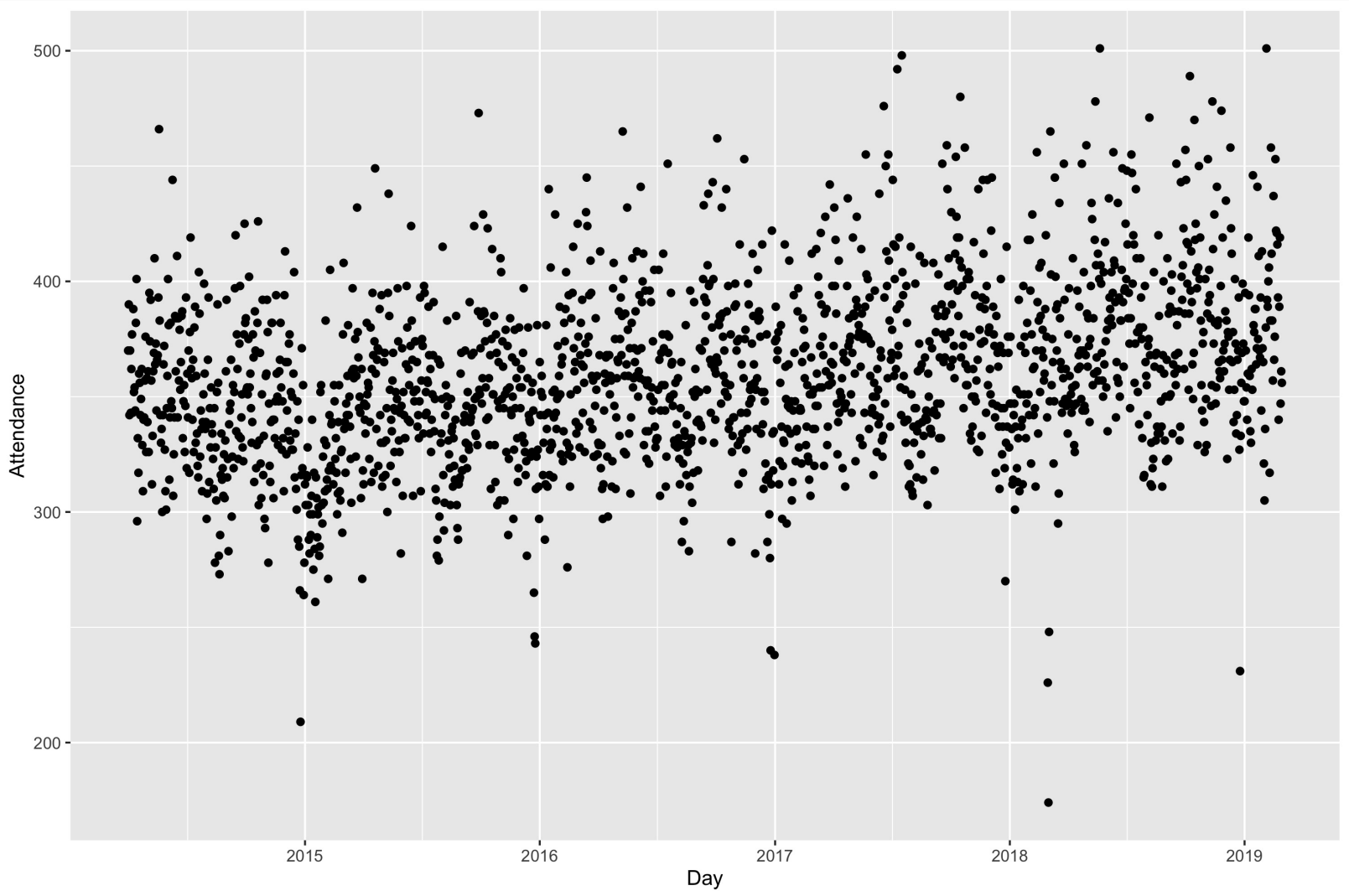
Lab Session 2

- use `autoplot` to crearte a time plot of hourly attendnace
- Create plots of `A&E` total daily attendances
- Create plots of `A&E` total monthly attendances

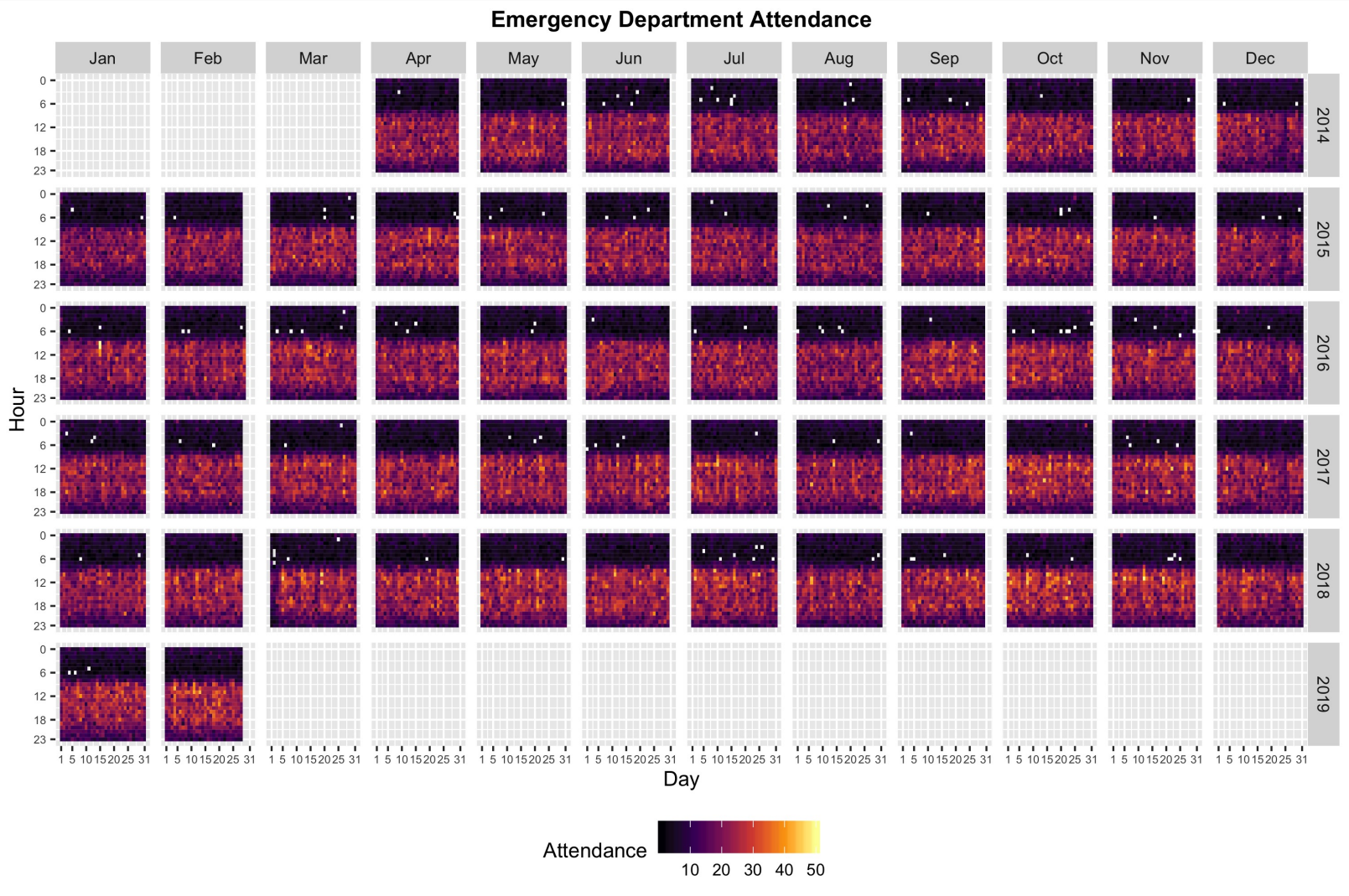
Are time plots best?



Are time plots best?



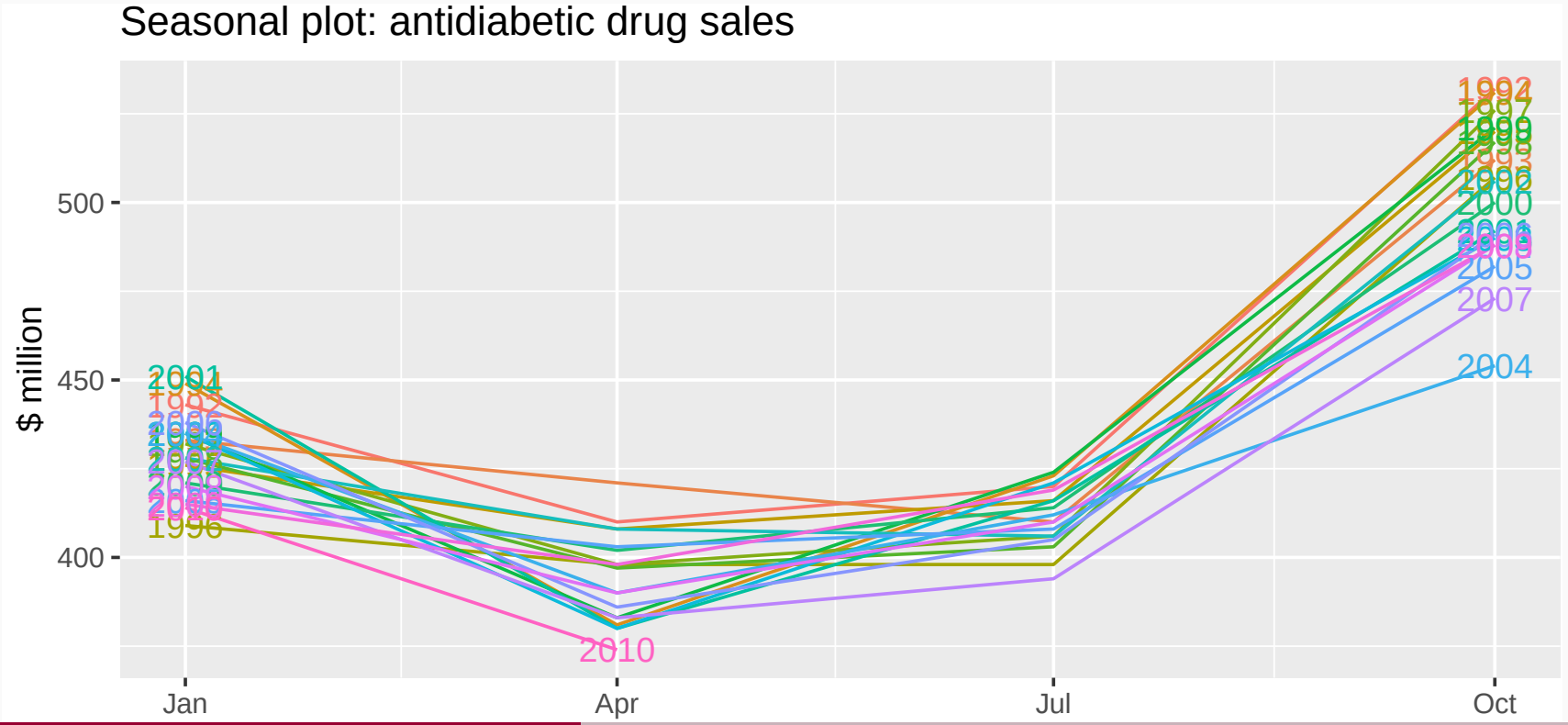
Are time plots best?



Outline

Seasonal plots

```
new_production <- aus_production %>%
  filter(year(Quarter) >= 1992)
new_production %>% gg_season(Beer, labels = "both")+
  ylab("$ million") +
  ggtitle("Seasonal plot: antidiabetic drug sales")
```

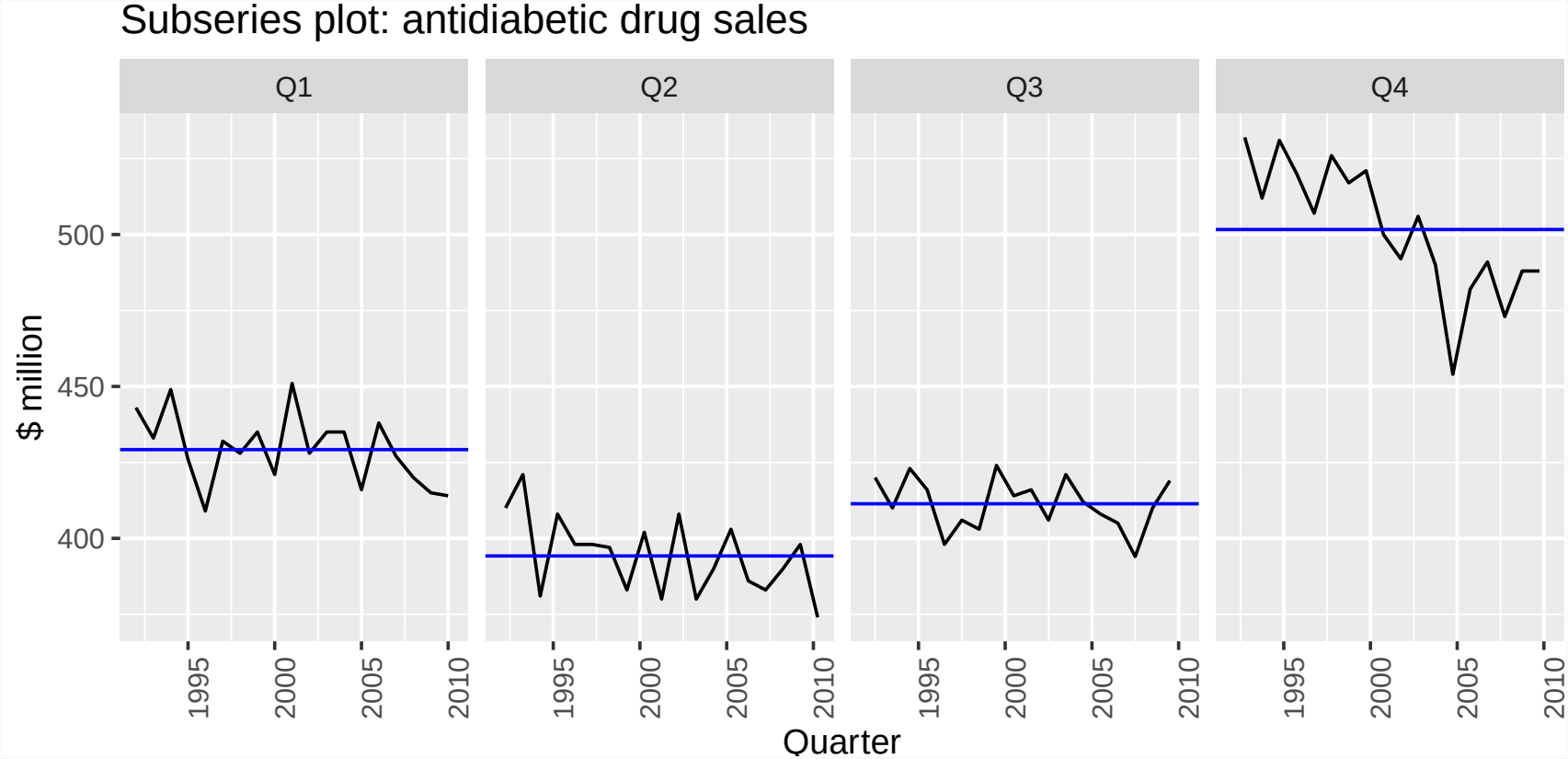


Seasonal plots

- 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 subseries plots

```
new_production %>% gg_subseries(Beer) + ylab("$ million
  ggtitle("Subseries plot: antidiabetic drug sales")
```



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()`

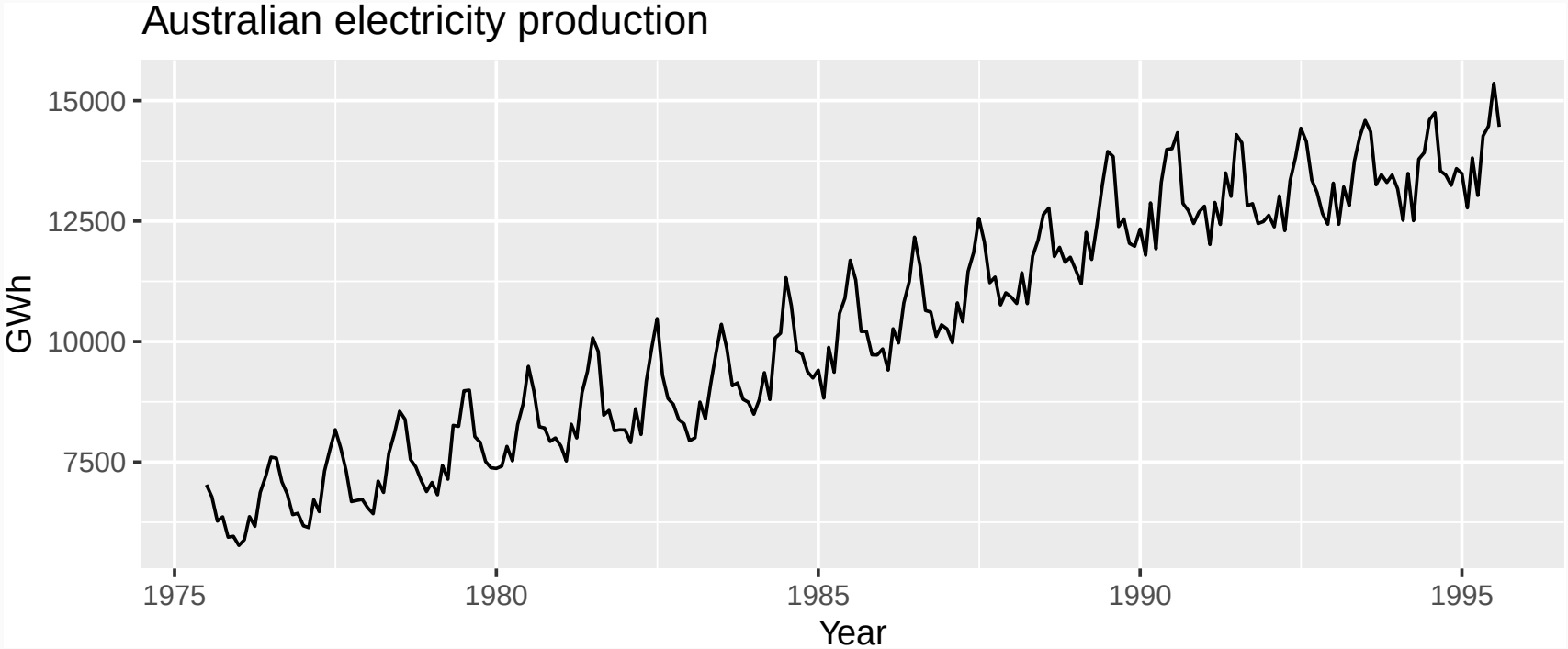
Lab Session 3

Given the hourly A&E attendance you computed:

- Use `gg_season()` and `gg_subseries()` to explore the series
  - use above plots to check hourly, daily patterns
- What do you learn?

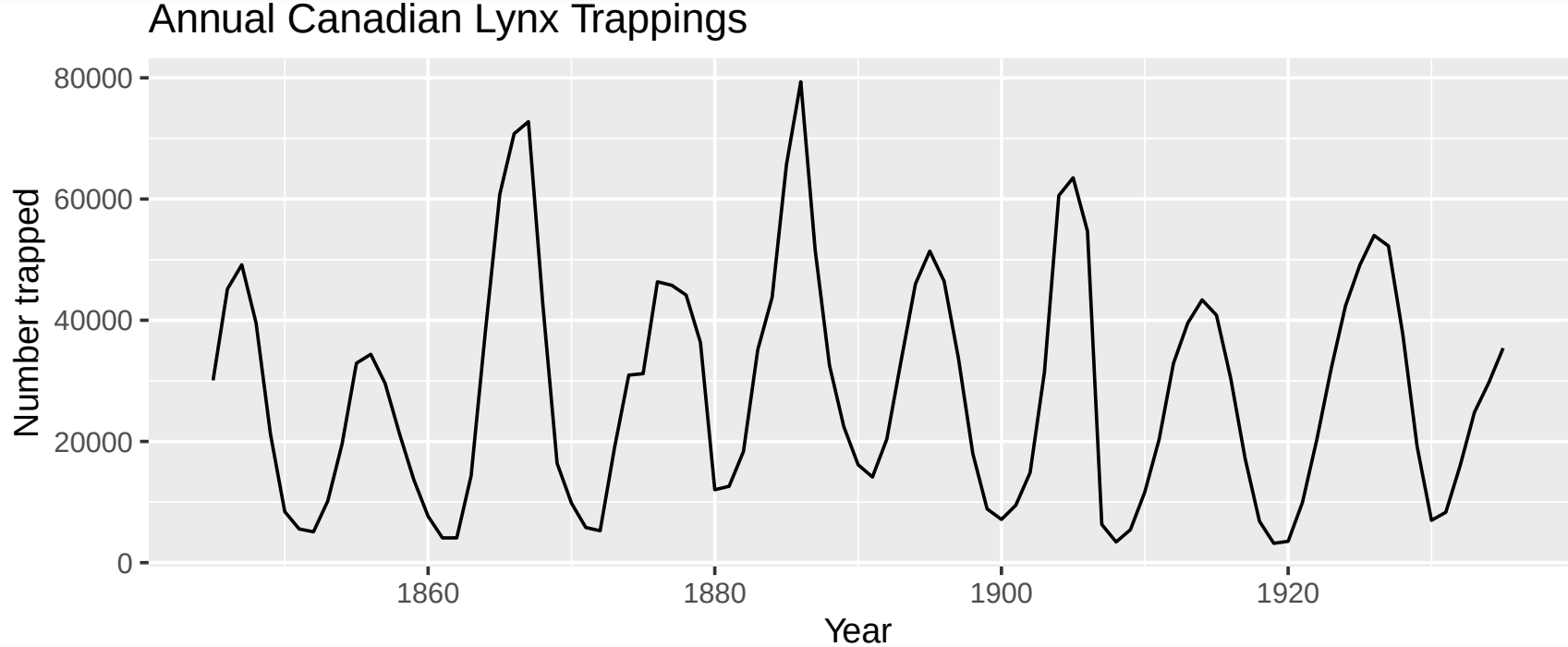
Time series patterns

```
as_tsibble(fma::elec) %>%
  filter(index >= 1980) %>%
  autoplot(value) + xlab("Year") + ylab("GWh") +
  ggtitle("Australian electricity production")
```



Time series patterns

```
pelt %>%
  autoplot(Lynx) +
  ggtitle("Annual Canadian Lynx Trappings") +
  xlab("Year") + ylab("Number trapped")
```



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

Seasonal or cyclic?

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- 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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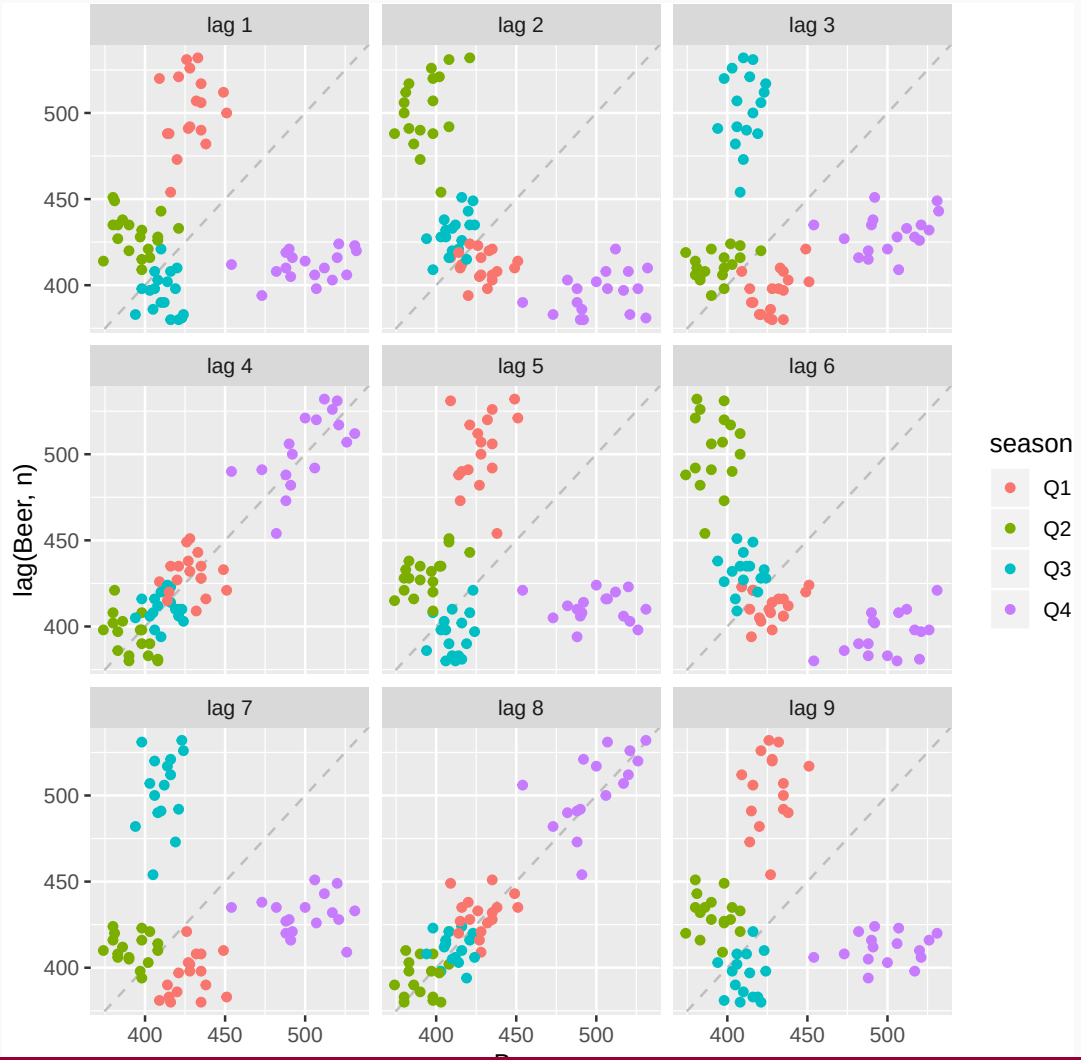
Example: Beer production

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

```
## # A tsibble: 74 x 7 [1Q]
##       Quarter  Beer Tobacco Bricks Cement
##         <qtr> <dbl>   <dbl>  <dbl>  <dbl>
##  1    1992 Q1   443    5777    383   1289
##  2    1992 Q2   410    5853    404   1501
##  3    1992 Q3   420    6416    446   1539
##  4    1992 Q4   532    5825    420   1568
##  5    1993 Q1   433    5724    394   1450
##  6    1993 Q2   421    6036    462   1668
```

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.

Autocorrelation

Covariance and **correlation**: measure extent of **linear relationship** between two variables (y and X).

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Autocovariance and **autocorrelation**: measure linear relationship between **lagged values** of a time series *y*.

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Covariance and **correlation**: measure extent of **linear relationship** between two variables (y and X).

Autocovariance and **autocorrelation**: measure linear relationship between **lagged values** of a time series y.

We measure the relationship between:

- y_t and y_{t-1}
- y_t and y_{t-2}
- y_t and y_{t-3}
- etc.

Autocorrelation

We denote the sample autocovariance at lag k by c_k and the sample autocorrelation at lag k by r_k. Then define

$$c_k = \frac{1}{T}\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})$$

and $$r_k = c_k/c_0$$

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and $$r_k = c_k/c_0$$

- r_1 indicates how successive values of y relate to each other
- r_2 indicates how y values two periods apart relate to each other
- r_k is *almost* the same as the sample correlation between y_t and y_{t-k}.

Autocorrelation

Results for first 9 lags for beer data:

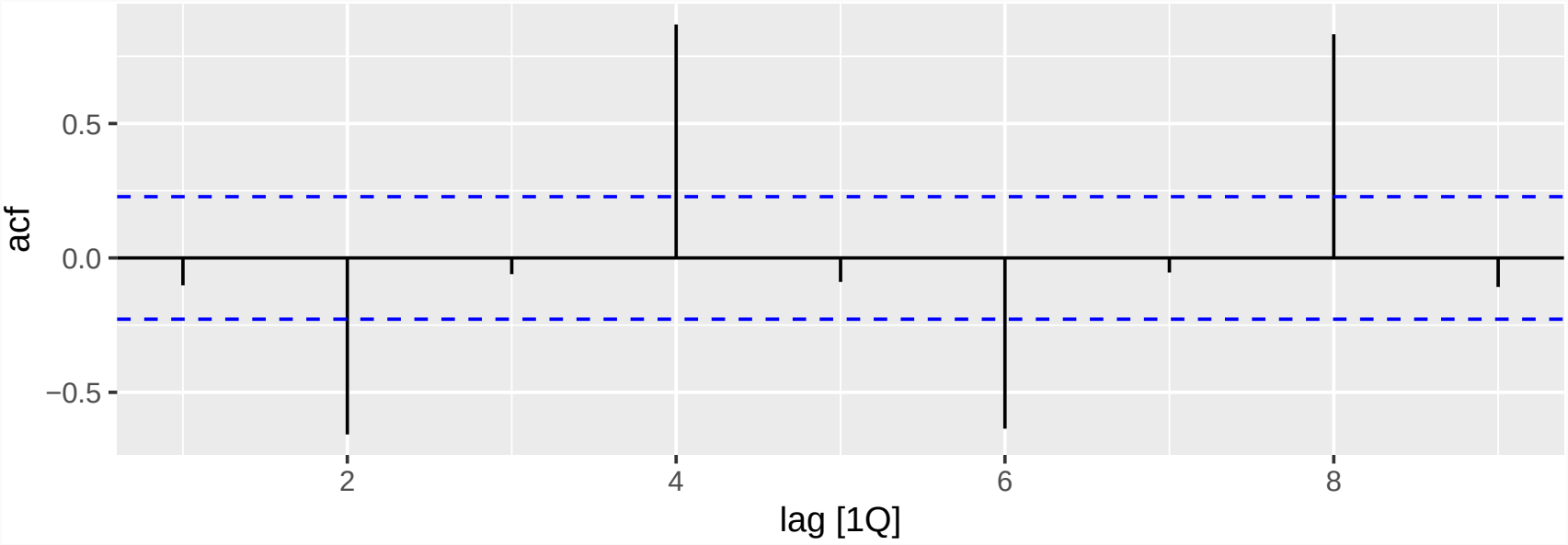
```
new_production %>% ACF(Beer, lag_max = 9)
```

```
## # 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
## 8    8Q  0.832
```

Autocorrelation

Results for first 9 lags for beer data:

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



Autocorrelation

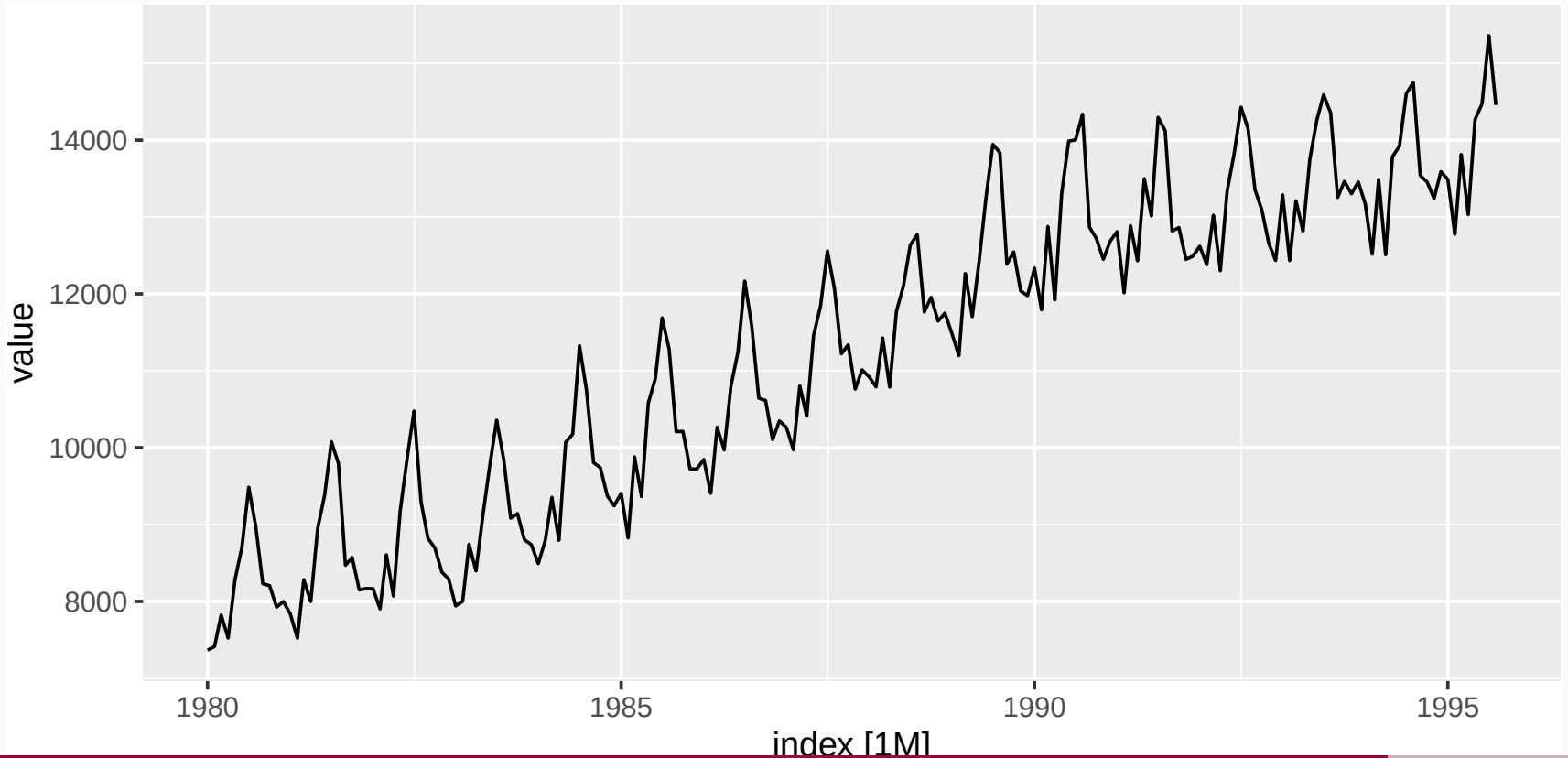
- r_4 higher than for the other lags. This is due to **the seasonal pattern in the data**: the peaks tend to be **4 quarters** apart and the troughs tend to be **2 quarters** apart.
- r_2 is more negative than for the other lags because troughs tend to be 2 quarters behind peaks.
- Together, the autocorrelations at lags 1, 2, . . . , make up the *autocorrelation* or ACF.
- The plot is known as a **correlogram**

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.

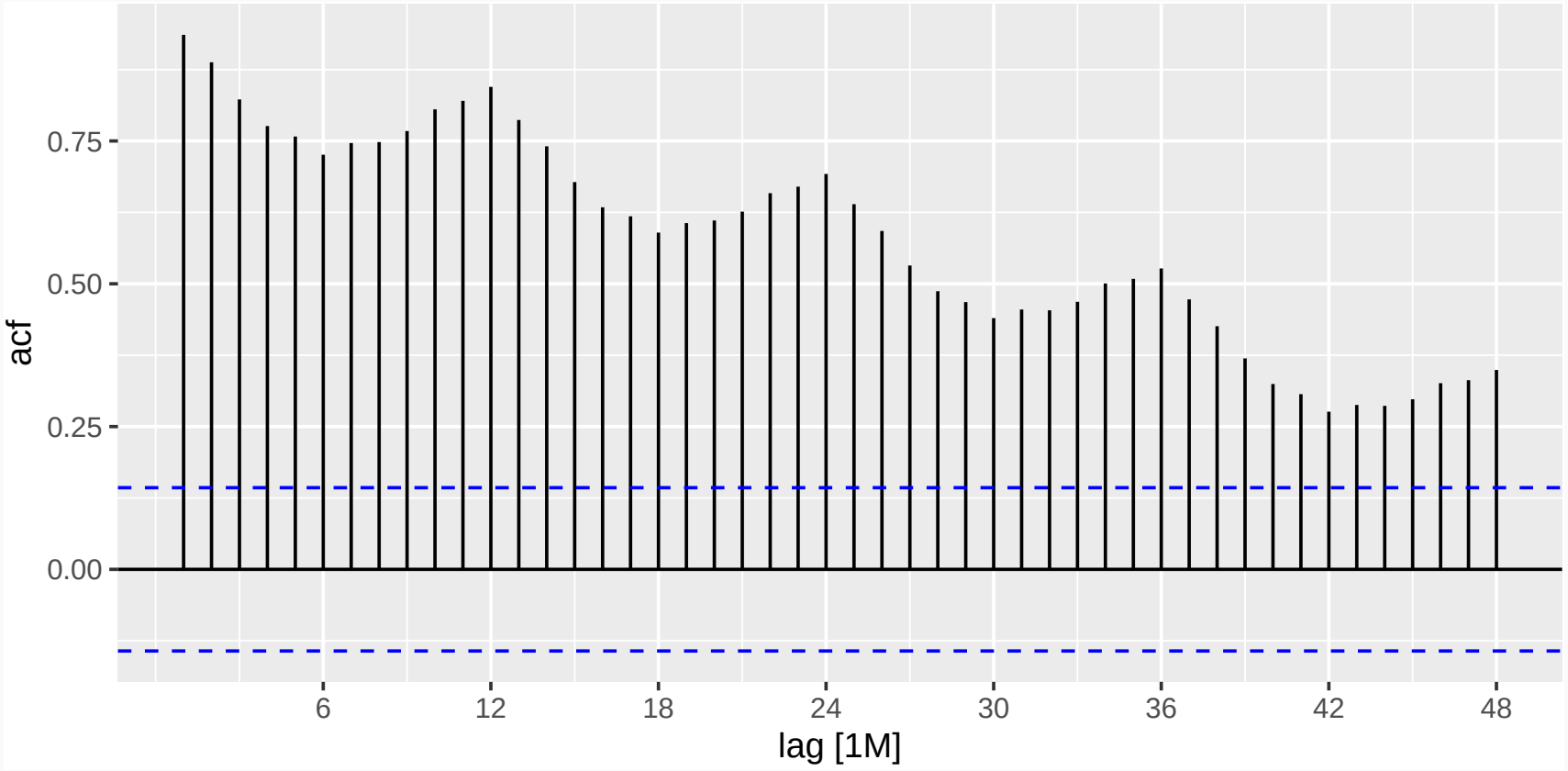
Aus monthly electricity production

```
elec2 <- as_tsibble(fma::elec) %>%
  filter(year(index) >= 1980)
elec2 %>% autoplot(value)
```



Aus monthly electricity production

```
elec2 %>% ACF(value, lag_max=48) %>%
  autoplot()
```



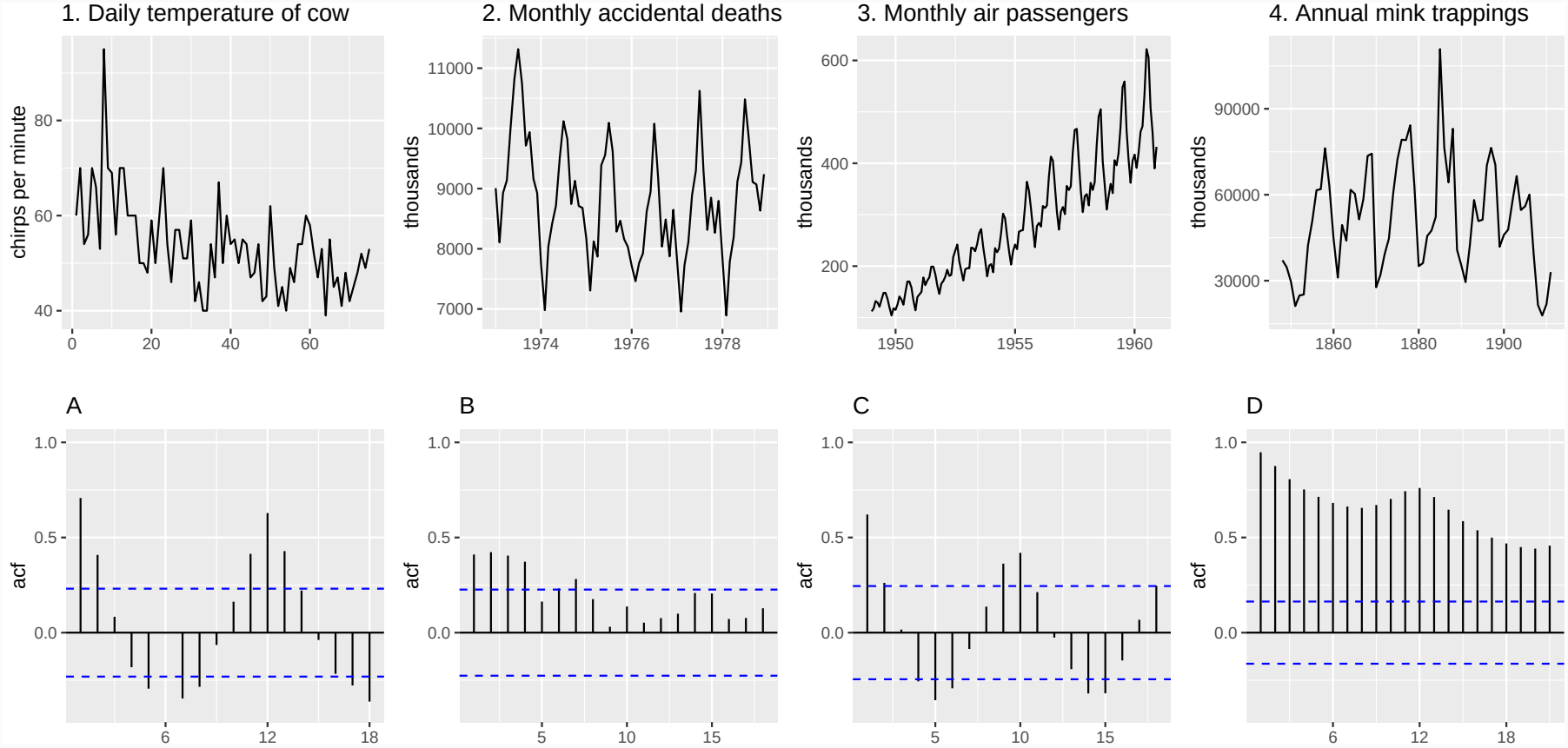
Aus monthly electricity production

Time plot shows clear trend and seasonality.

The same features are reflected in the ACF.

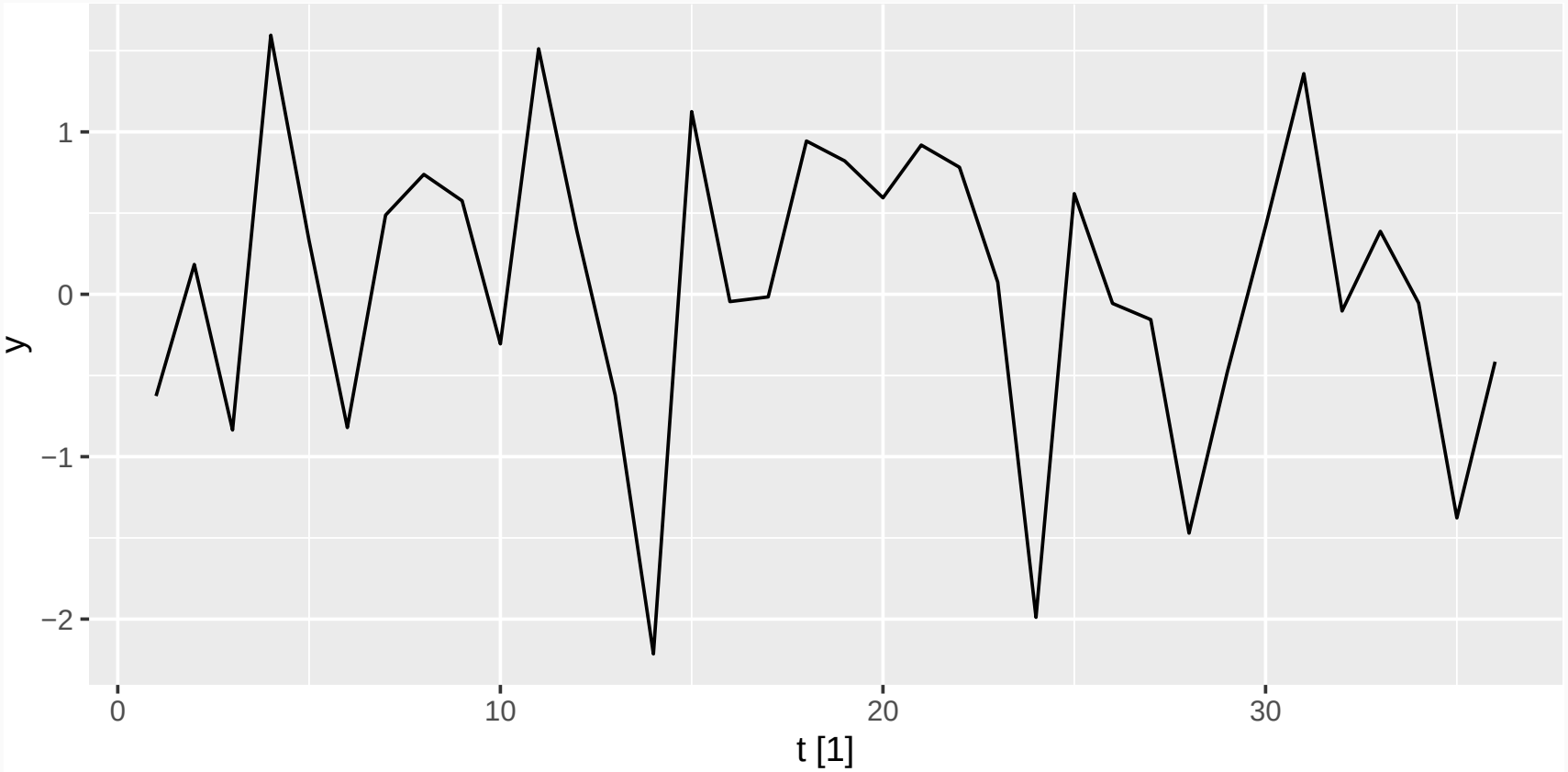
- The slowly decaying ACF indicates trend.
- The ACF peaks at lags 12, 24, 36, …, indicate seasonality of length 12.

Which is which?



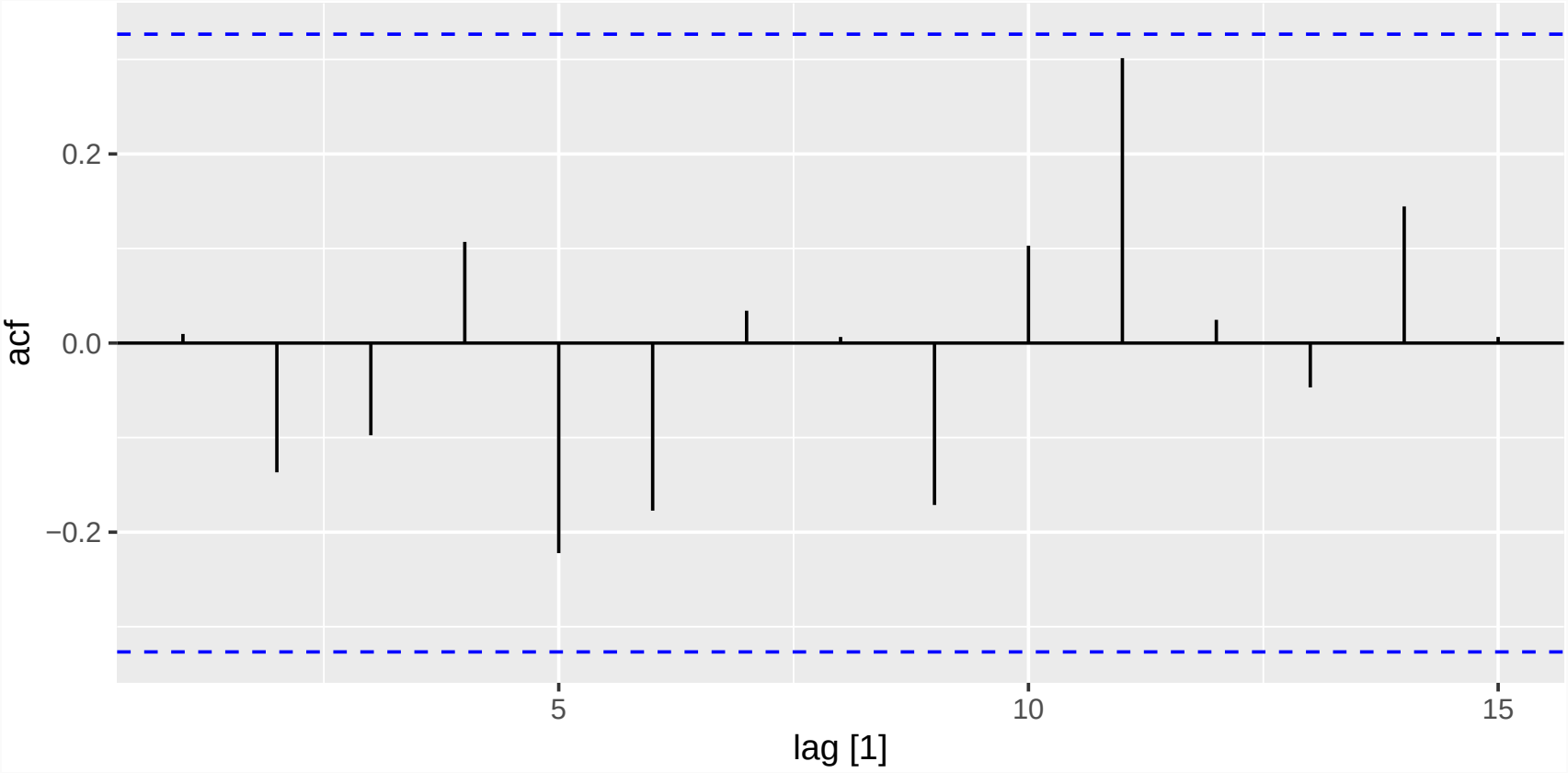
Example: White noise

```
set.seed(1)
wn <- tsibble(t = seq_len(36), y = rnorm(36),
              index = t)
wn %>% autoplot(y)
```



Example: White noise

r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}
0.010	-0.137	-0.098	0.107	-0.222	-0.177	0.034	0.006	-0.171	0.103



Sampling distribution of autocorrelations

Sampling distribution of r_k for white noise data is asymptotically $\mathrm{N}(0,1/T)$.

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Sampling distribution of r_k for white noise data is asymptotically N(0,1/T).

- 95% of all r_k for white noise must lie within $\pm 1.96/\sqrt{T}$.
- If this is not the case, the series is probably not WN.
- Common to plot lines at $\pm 1.96/\sqrt{T}$ when plotting ACF. These are the **critical values**.

Lab Session 4

You can compute the daily attendances in the A&E using

```
ae_daily <- ae_hourly %>%
  index_by(year_day=as_date(arrival_1h)) %>%
  summarise(n_attendance=sum(n_attendance))
```

Explore the series using `gg_lag` and `ACF` functions. Can you spot any seasonality, cyclicity and trend? What do you learn about the series? Plot only 14 lags.

Does daily series look like white noise?