

Time series visualization techniques II

EC 361–001

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Materials

Required readings:

- Hyndman & Athanasopoulos, ch. 2

Motivation

Motivation

So far, we have studied *three* types of time-series **visualization** techniques:

- *Time* plots;
- *Seasonal* plots;
- *Scatter* plots.

There is *more* to explore, and we will study further techniques that can give important **insights** about the relevant **features** of our time series.

Autocorrelation

Autocorrelation

Before the next plots, we must clarify what a **lag** means:

In time series jargon, the number of **time steps** between a series' observations is known as a **lag**.

In terms of **notation**, we will use the subscript t to denote a **time index**.

- For instance, given a time series called y , its value at time t can be denoted by y_t .

In case we want to denote the value of time series y **one step in the past**, we will write this as y_{t-1} .

Similarly, for any step k in the past, we can denote such value by y_{t-k} .

Such steps must be consistent with the **frequency** of the time series (e.g., monthly, quarterly, daily, yearly, etc.)

Autocorrelation

One key feature of time-series data is that **past** values usually help to explain **present** and/or **future** values.

Therefore, values of a time series in the *past* may be **correlated** with more *recent* observations.

More formally, for a given k value, y_{t-k} and y_t may share a *nonzero* correlation coefficient.

Just as **correlation** measures the extent of a *linear* relationship between two variables, **autocorrelation** measures the linear relationship between *lagged values of a time series*.

Autocorrelation

The sample **autocovariance** at lag k of a time series y is given by

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

The **variance** of y is given by

$$\text{Var}(y) = \frac{\sum_{t=1}^T (y_t - \bar{y})(y_t - \bar{y})}{T}$$

And the **autocorrelation coefficient** at lag k is given by

$$r_k = \frac{c_k}{\text{Var}(y)}$$

Lag plots

Lag plots

Lag plots display the data plotted against its different **lags** in a scatter plot.

Different **colors** correspond to each period (*vertical axis*) against lagged values (*horizontal axis*).

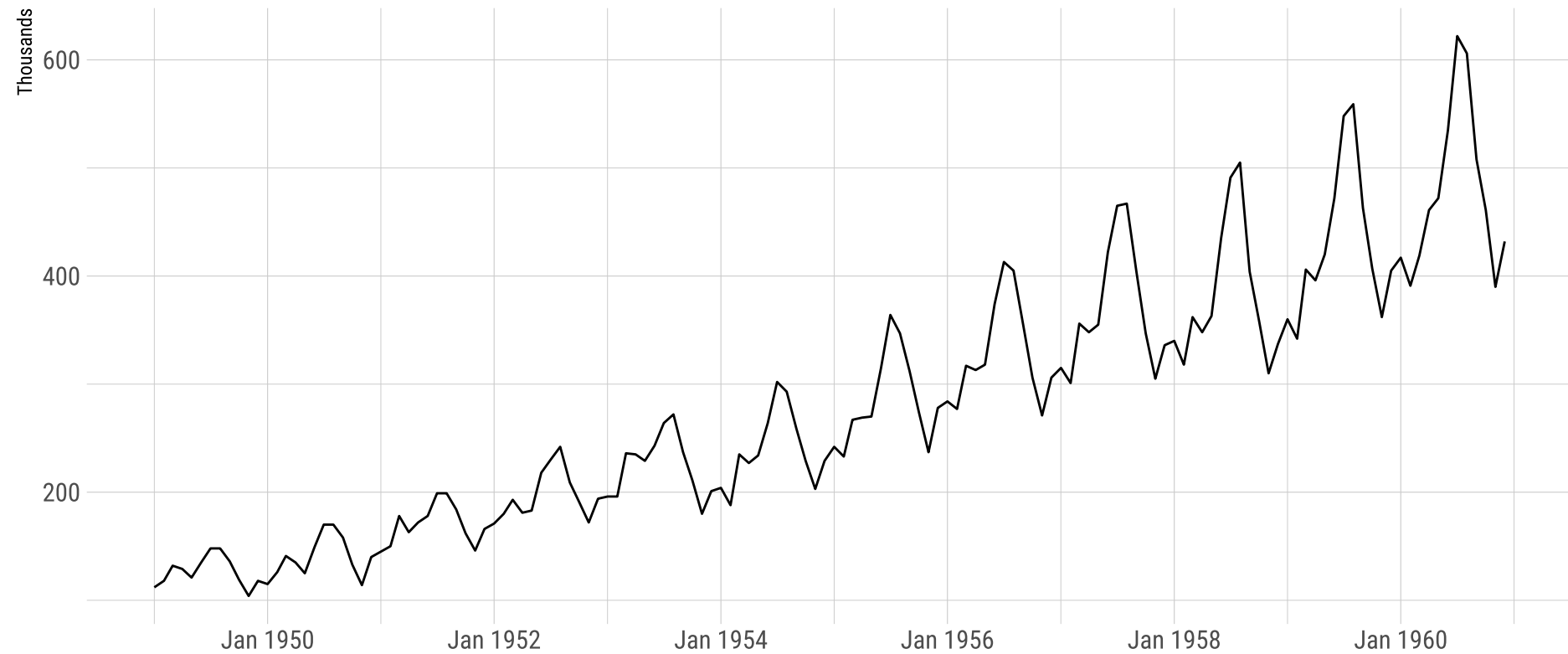
In case the time series shows **seasonality**, the autocorrelation coefficient will be **large** and **positive** at the **multiples** of the seasonal period.

- e.g., 12 lags for *monthly* data; 4 lags for *quarterly* data, and so on.

Lag plots

International airline passengers

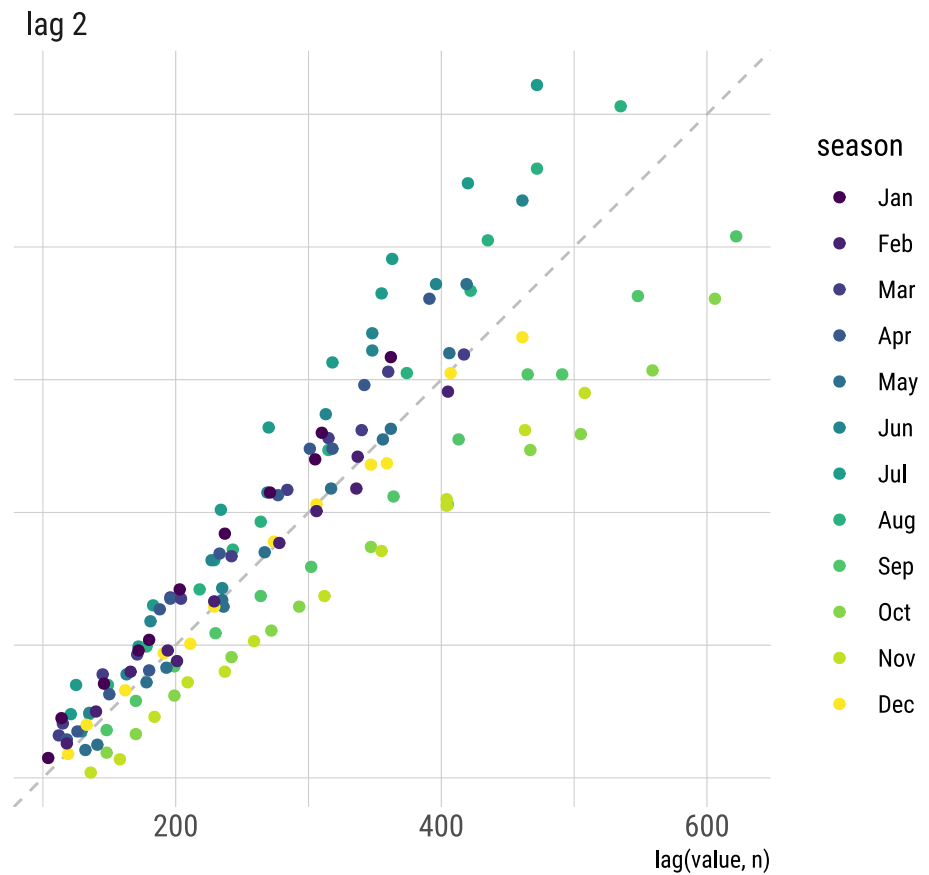
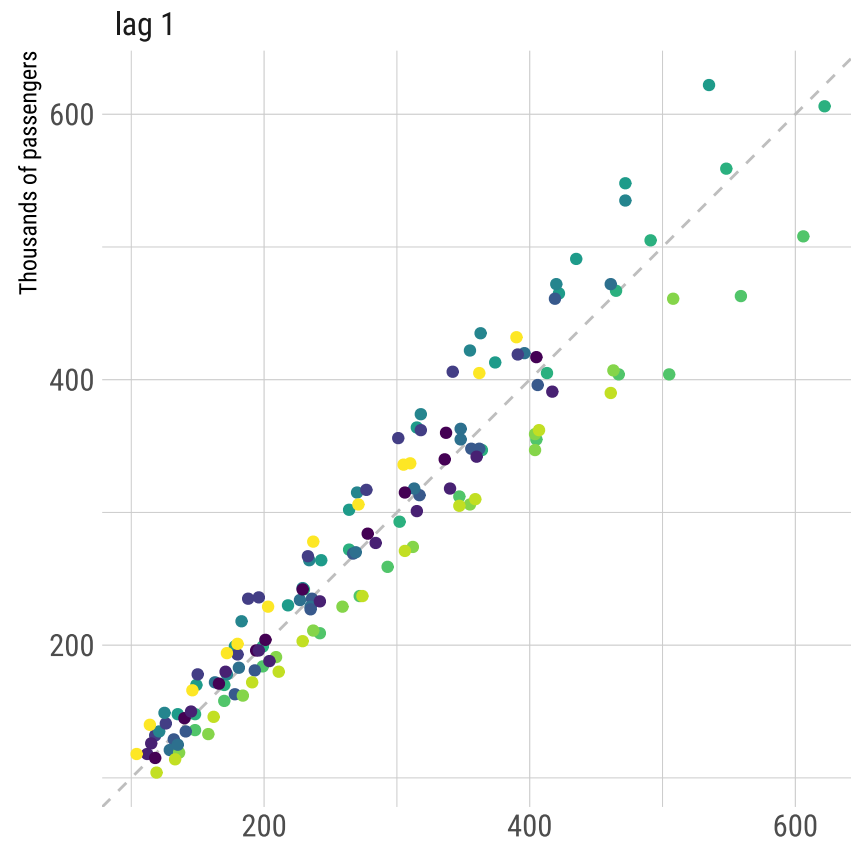
Jan 1949 – Dec 1960



Source: Brown (1962).

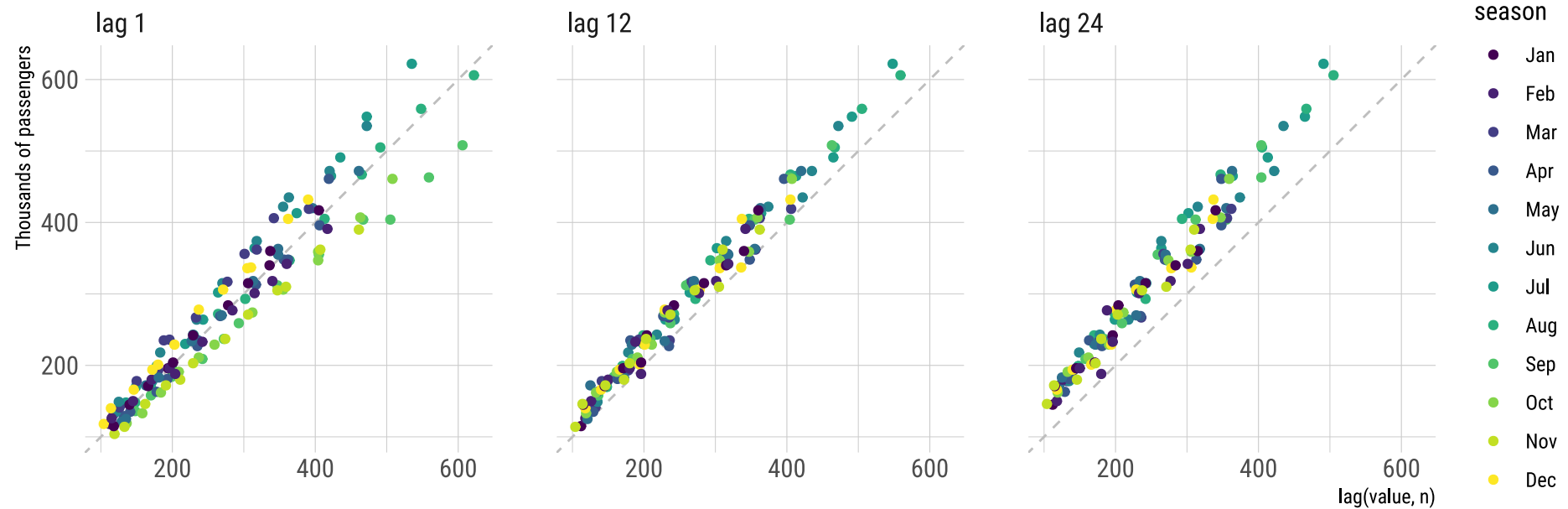
Lag plots

Lag plot: Airline passengers



Lag plots

Lag plot: Airline passengers



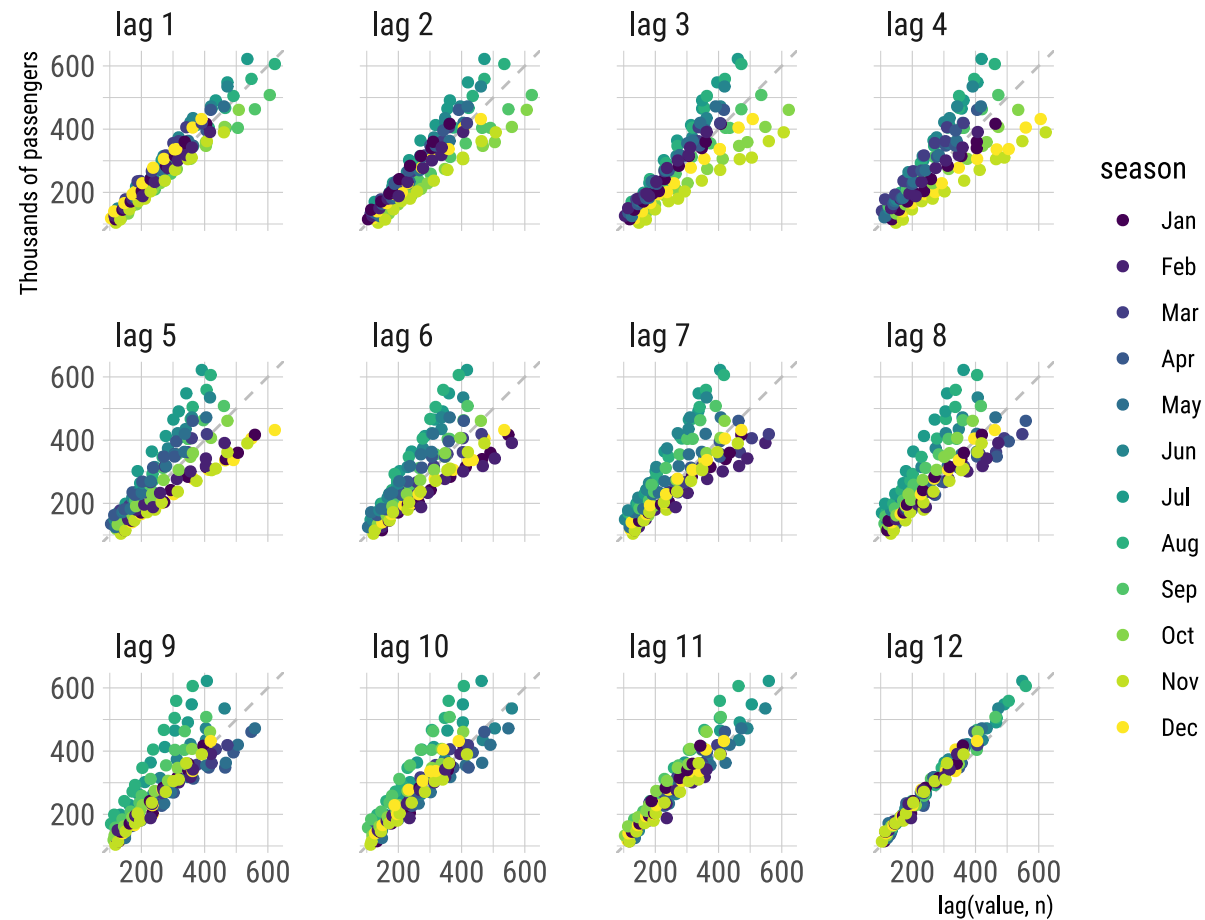
Lag plots

```
air_passengers ▷  
  ACF(lag_max = 12)
```

```
#> # A tsibble: 12 x 2 [1M]  
#>       lag  acf  
#>   <cf_lag> <dbl>  
#> 1      1M 0.948  
#> 2      2M 0.876  
#> 3      3M 0.807  
#> 4      4M 0.753  
#> 5      5M 0.714  
#> 6      6M 0.682  
#> 7      7M 0.663  
#> 8      8M 0.656  
#> 9      9M 0.671  
#> 10     10M 0.703  
#> 11     11M 0.743  
#> 12     12M 0.760
```

Lag plots

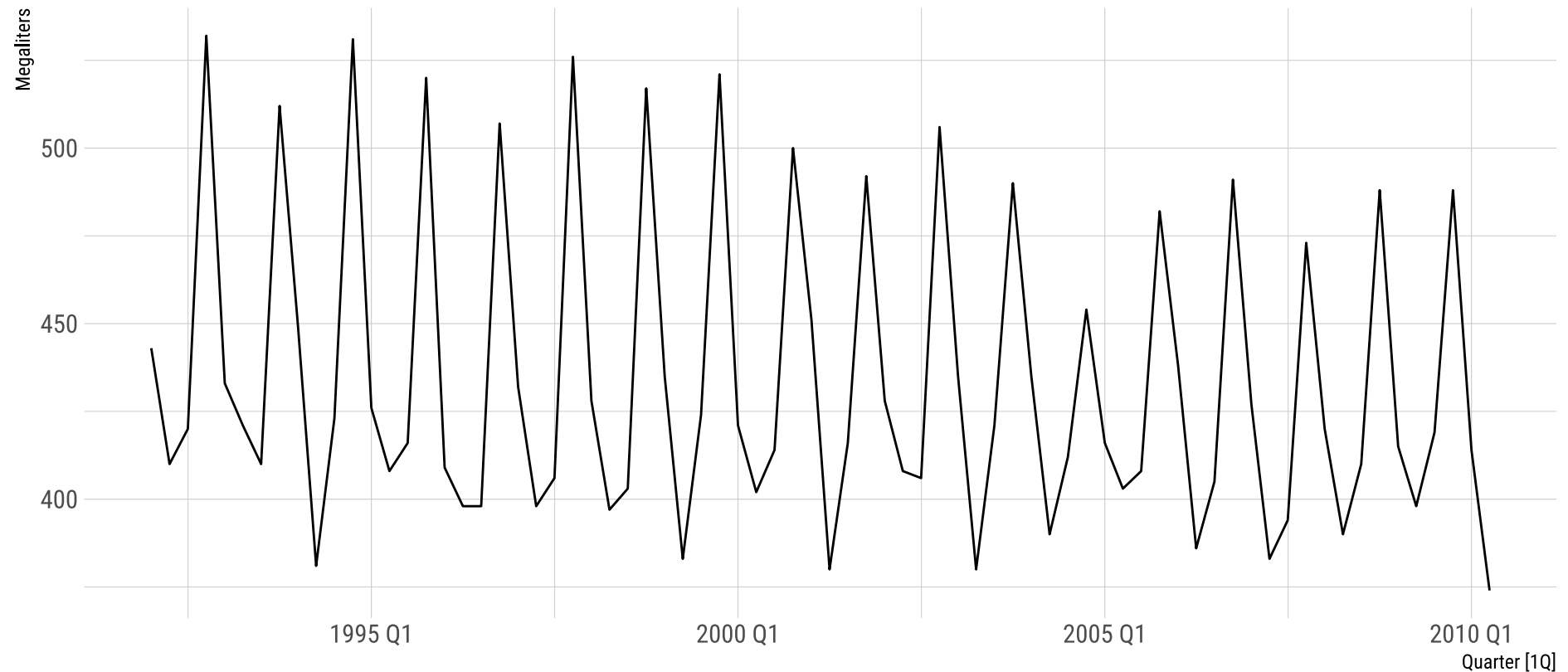
Lag plot: Airline passengers



Lag plots

Australian beer production

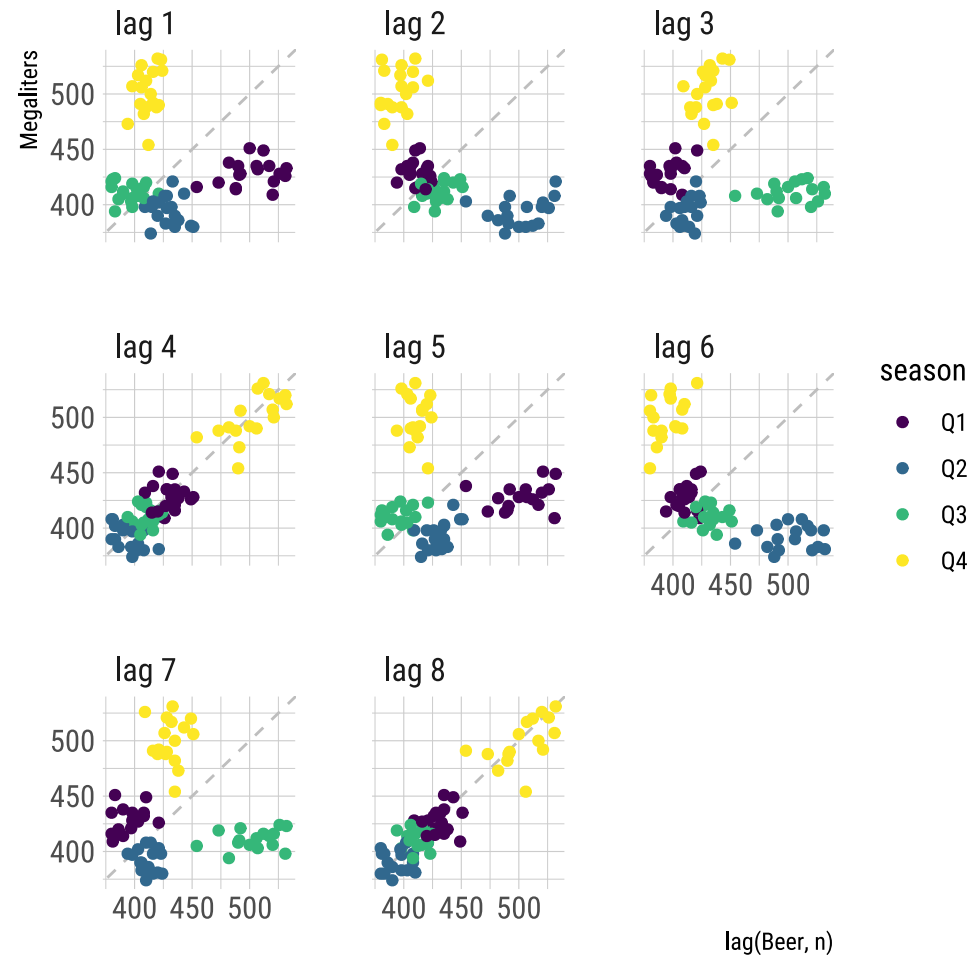
1992Q1–2010Q2



Source: Hyndman and Athanasopoulos (2021).

Lag plot: Australian beer production

1992Q1–2010Q2



Source: Hyndman and Athanasopoulos (2021).

Lag plots

```
beer ▷  
  ACF(lag_max = 8)
```

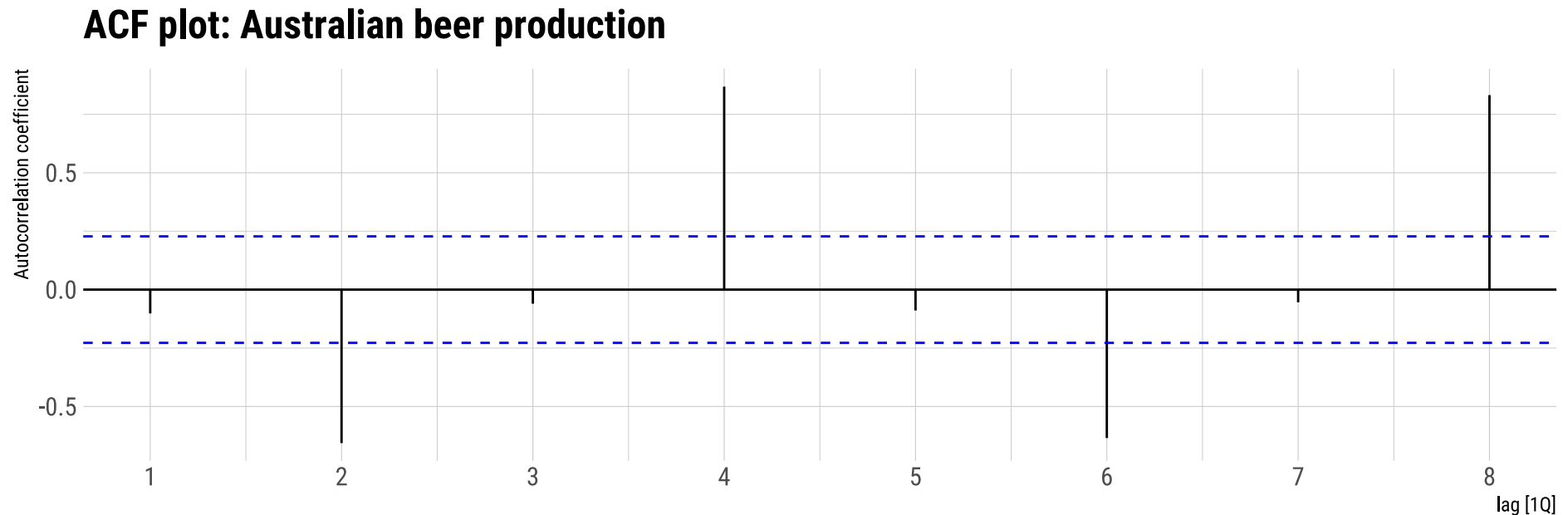
```
#> # A tsibble: 8 x 2 [1Q]  
#>       lag      acf  
#>   <cf_lag>   <dbl>  
#> 1         1Q -0.102  
#> 2         2Q -0.657  
#> 3         3Q -0.0603  
#> 4         4Q  0.869  
#> 5         5Q -0.0892  
#> 6         6Q -0.635  
#> 7         7Q -0.0542  
#> 8         8Q  0.832
```

The autocorrelation function

The autocorrelation function

A more **insightful** way to observe the autocorrelation coefficient is through the **Autocorrelation Function (ACF) plot**.

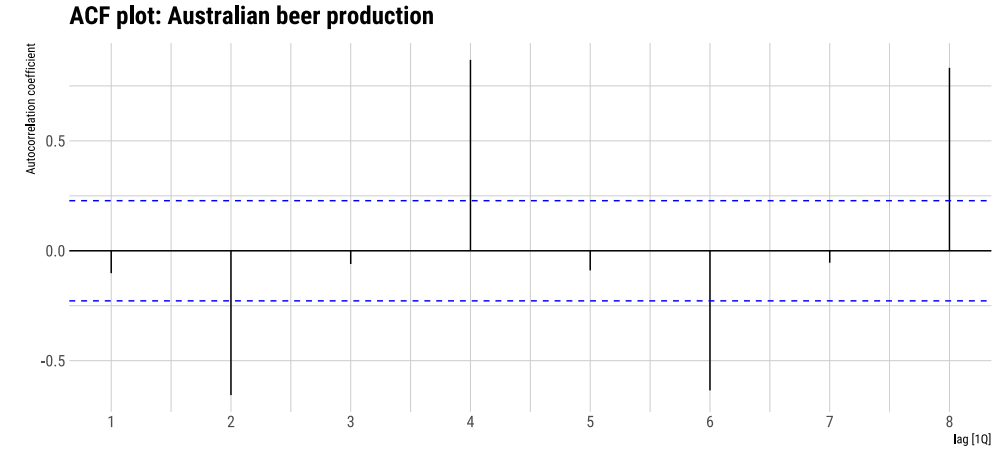
It simply plots together the *values* of the **autocorrelation coefficient** against different *lags*.



The autocorrelation function

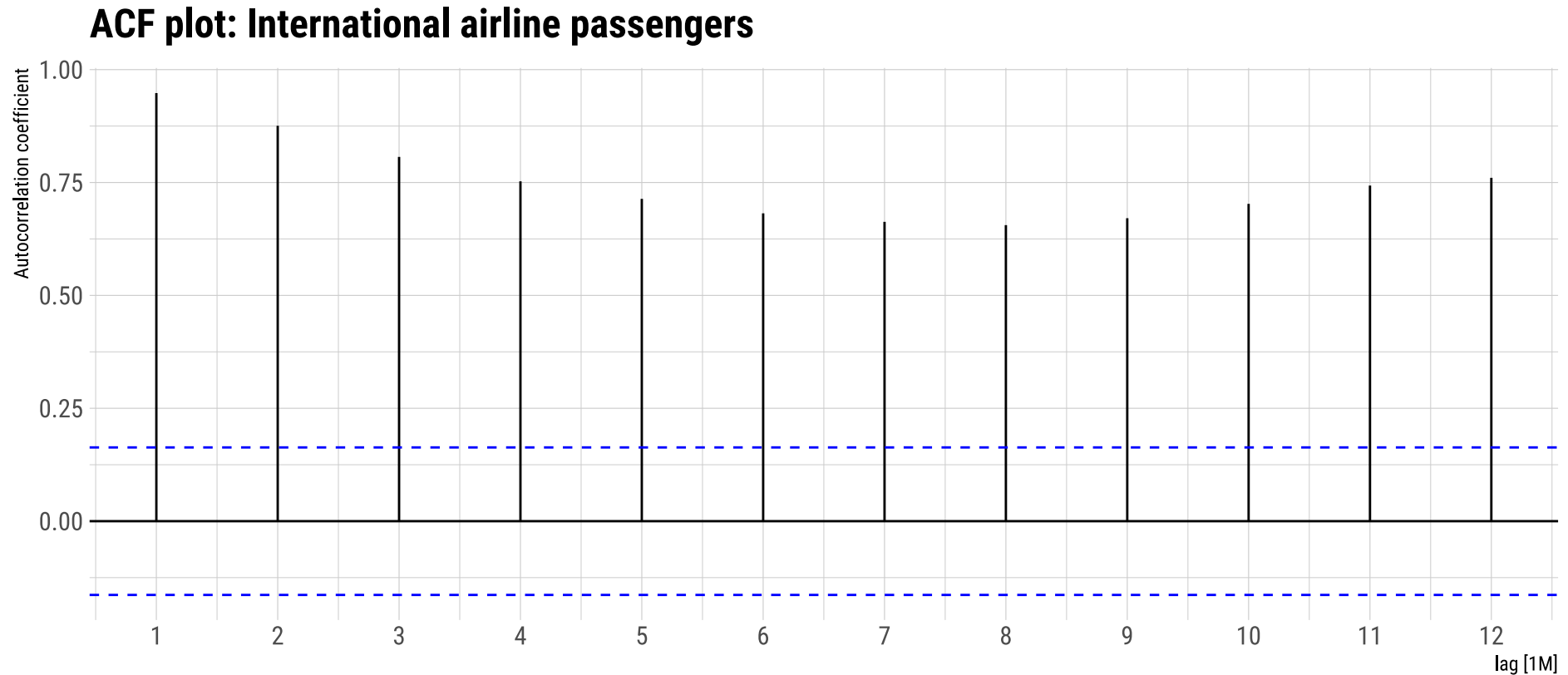
```
beer ▷  
  ACF(lag_max = 8)
```

```
#> # A tsibble: 8 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
```



The autocorrelation function

An autocorrelation function plot is also known as **correlogram**.



The autocorrelation function

```
air_passengers ▷  
  ACF(lag_max = 12)
```

```
#> # A tsibble: 12 x 2 [1M]  
#>       lag  acf  
#>   <cf_lag> <dbl>  
#> 1      1M 0.948  
#> 2      2M 0.876  
#> 3      3M 0.807  
#> 4      4M 0.753  
#> 5      5M 0.714  
#> 6      6M 0.682  
#> 7      7M 0.663  
#> 8      8M 0.656  
#> 9      9M 0.671  
#> 10     10M 0.703  
#> 11     11M 0.743  
#> 12     12M 0.760
```

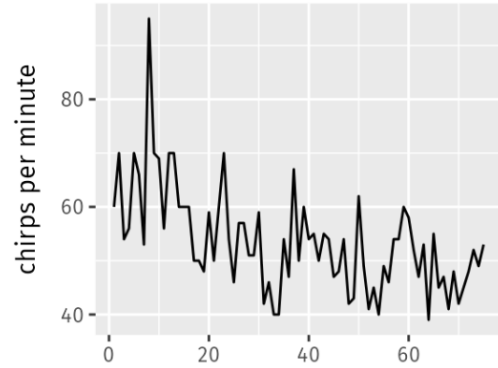
The autocorrelation function

The ACF plot may show interesting patterns, depending on the **features** of the time series.

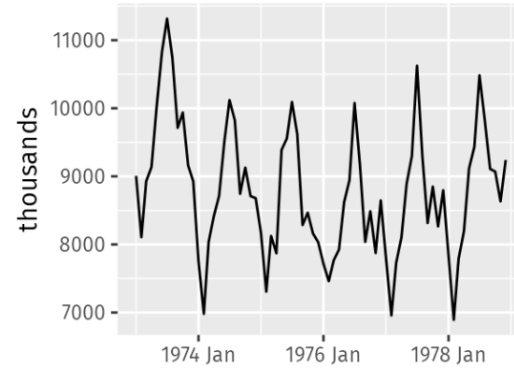
- When data have a **trend**, the autocorrelations for *small* lags tend to be **large** and **positive**.
 - Observations nearby in time are *also* nearby in value!
- When data are **seasonal**, the autocorrelations will be *larger* for the *seasonal* lags (at multiples of the seasonal period) than for other lags.
- When data are both **trended** and **seasonal**, the ACF plot usually shows a **combination** of the above effects.

The autocorrelation function

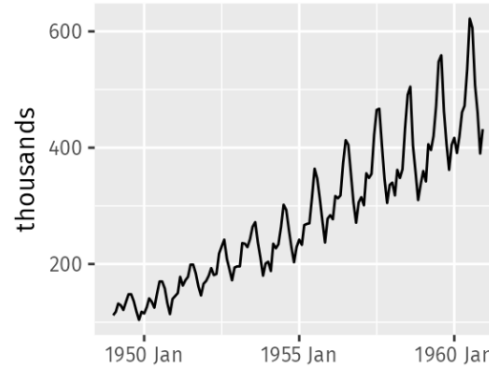
1. Daily temperature of cow



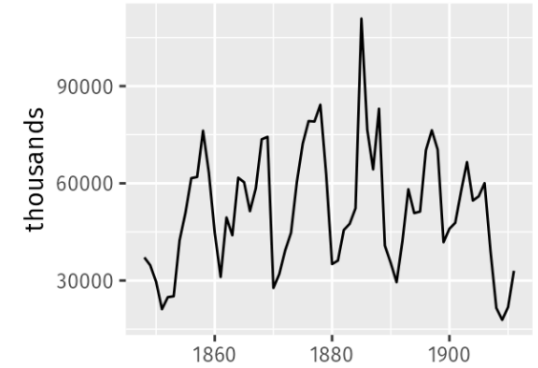
2. Monthly accidental deaths



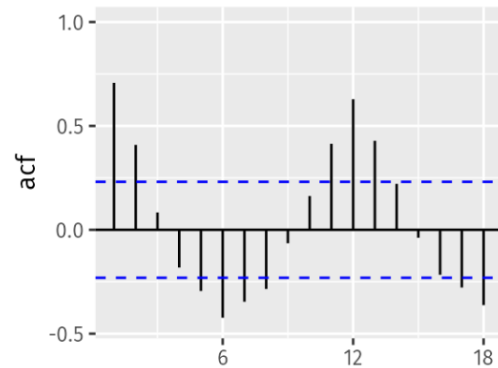
3. Monthly air passengers



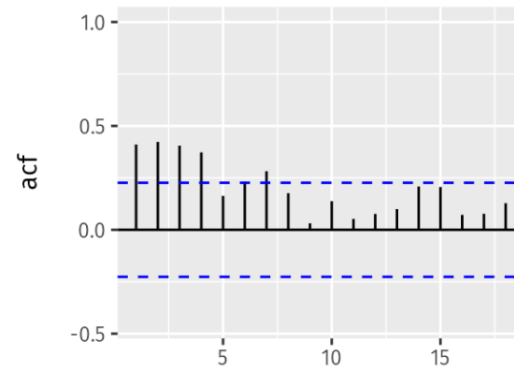
4. Annual mink trappings



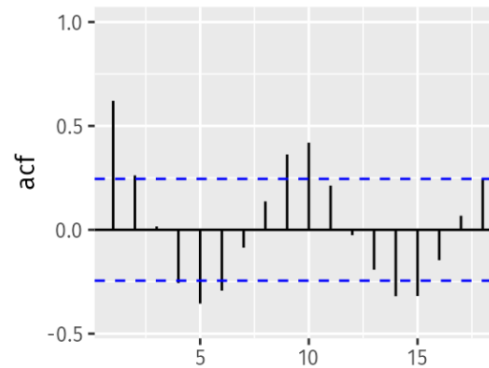
A



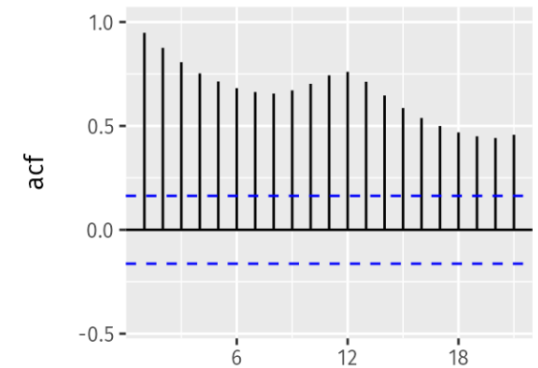
B



C



D



The autocorrelation function

A different look at the autocorrelation function, by Alison Horst

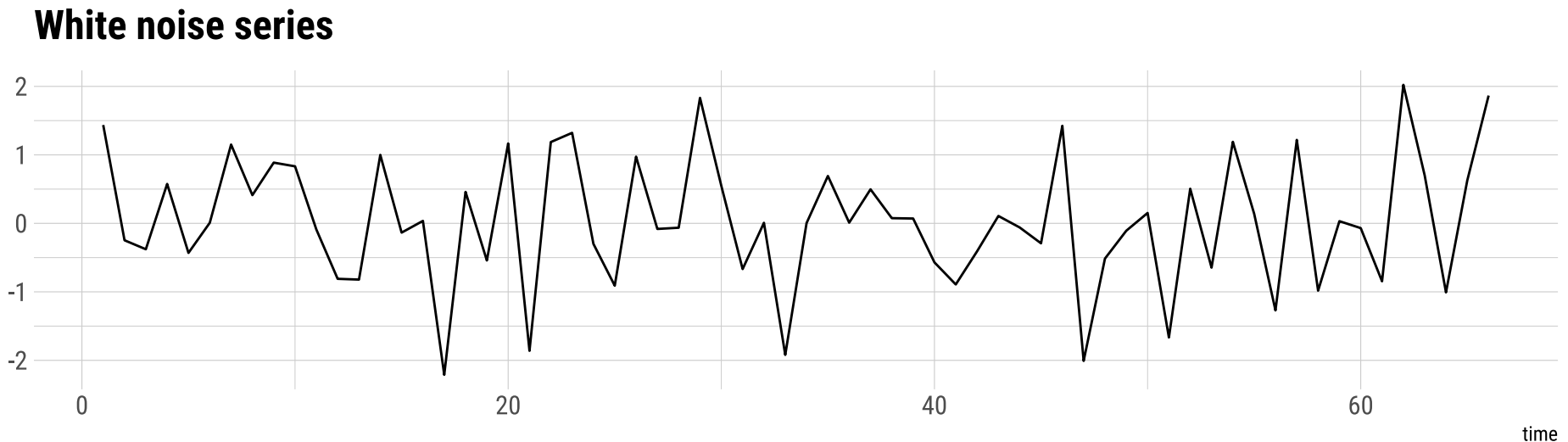
White noise

White noise

Some time series may *not* show autocorrelation **at all**.

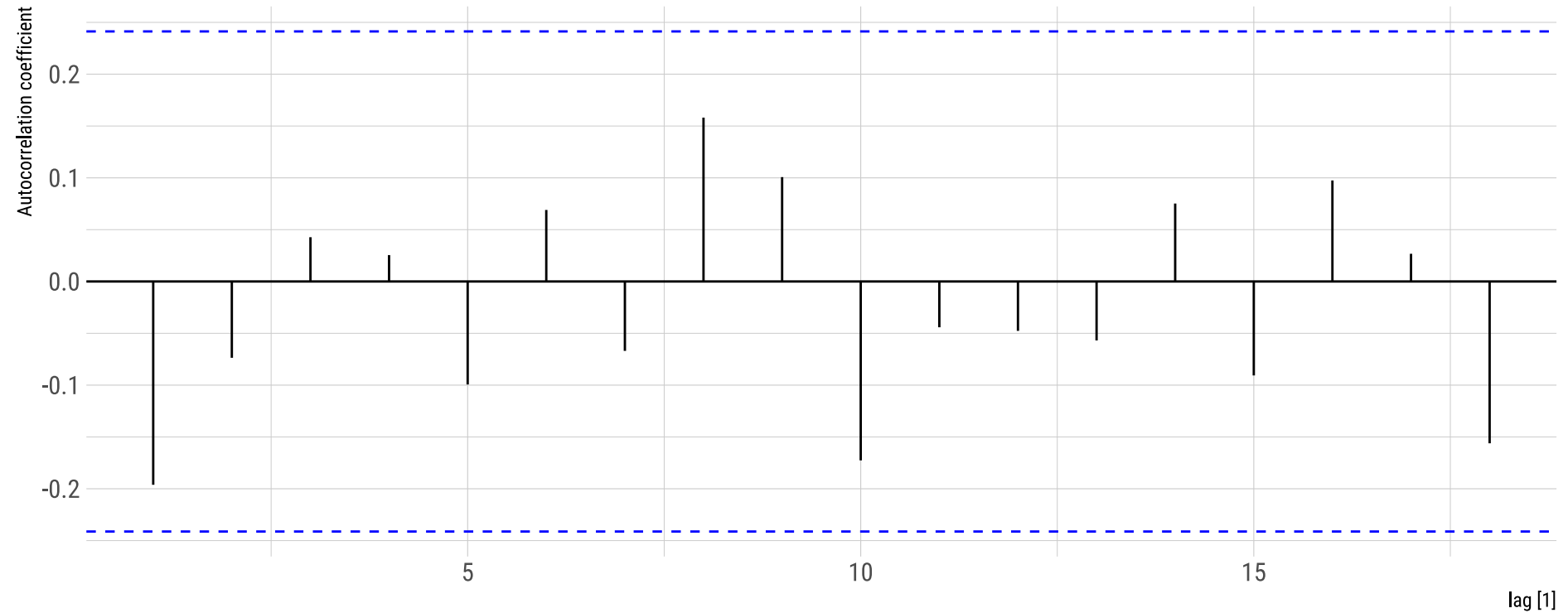
When this is the case, they are called **white noise**.

A time series w_t is defined to be **white noise** if its observations are *identically and independently distributed* (i.i.d.) with a *mean* of zero and constant *variance*.



White noise

ACF plot of white noise data



Next time: Time series decomposition