MONASH University

MONASH BUSINESS SCHOOL

Forecasting using R

Rob J Hyndman

1.1 Time series graphics

Outline

Time series in R

- Time series consist of sequences of observations collected over time.
- We will assume the time periods are equally spaced.

Time series examples

- Daily IBM stock prices
- Monthly rainfall
- Annual Google profits
- Quarterly Australian beer production

Time series in R

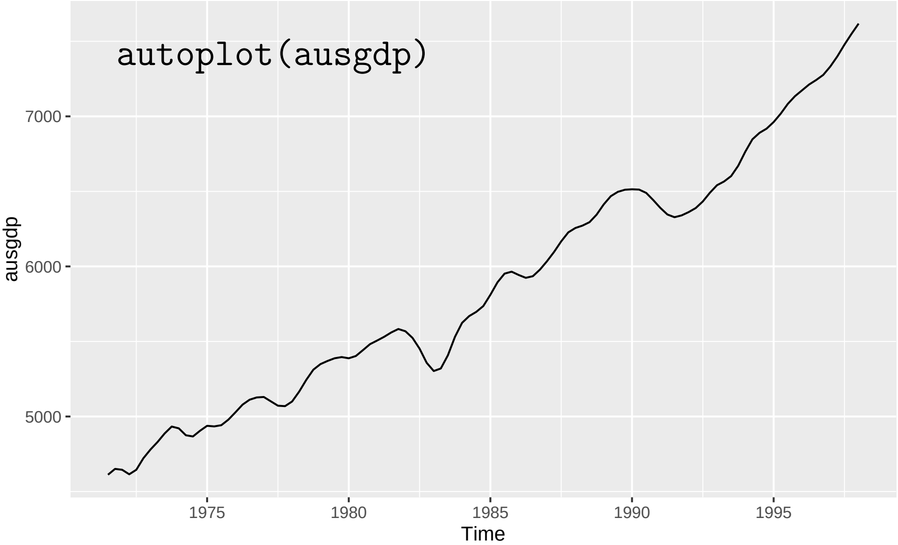
```
ausgdp <- ts(scan("gdp.dat"),frequency=4,
                              start=1971+2/4)
```

- Class: "ts"
- Print and plotting methods available.

```
ausgdp
```

```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 1971           4612 4651
## 1972 4645 4615 4645 4722
## 1973 4780 4830 4887 4933
## 1974 4921 4875 4867 4905
```

Time series in R



Time series in R

Residential electricity sales

```
elecsales
```

```
## Time Series:
## Start = 1989
## End = 2008
## Frequency = 1
##  [1] 2354.34 2379.71 2318.52 2468.99 2386.09
##  [9] 2844.50 3000.70 3108.10 3357.50 3075.70
## [17] 3430.60 3527.48 3637.89 3655.00
```

Time series in R

Main package used in this course

```
> library(fpp)
```

This loads:

- some data for use in examples and exercises
- **forecast** package (for forecasting functions)
- **tseries** package (for a few time series functions)
- **fma** package (for lots of time series data)
- **expsmooth** package (for more time series data)
- **lmtest** package (for some regression functions)

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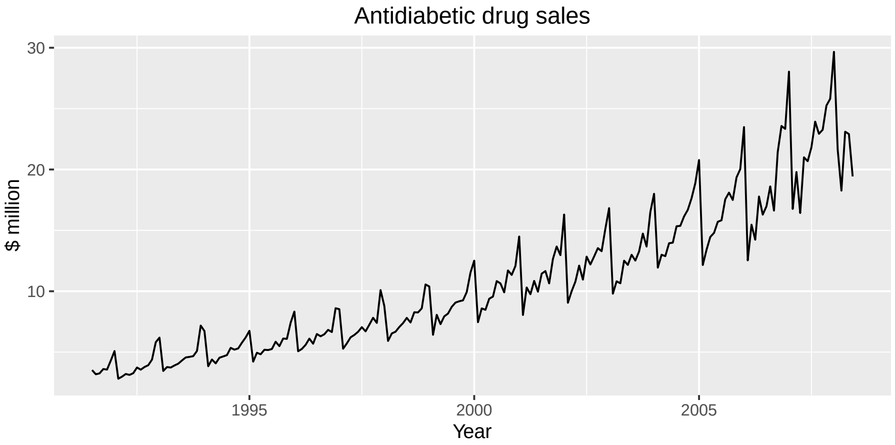
Outline

Time plots

```r
autoplot(melsyd[,"Economy.Class"])
```

Time plots

```r
autoplot(a10, ylab="$ million", xlab="Year",
        main="Antidiabetic drug sales")
```



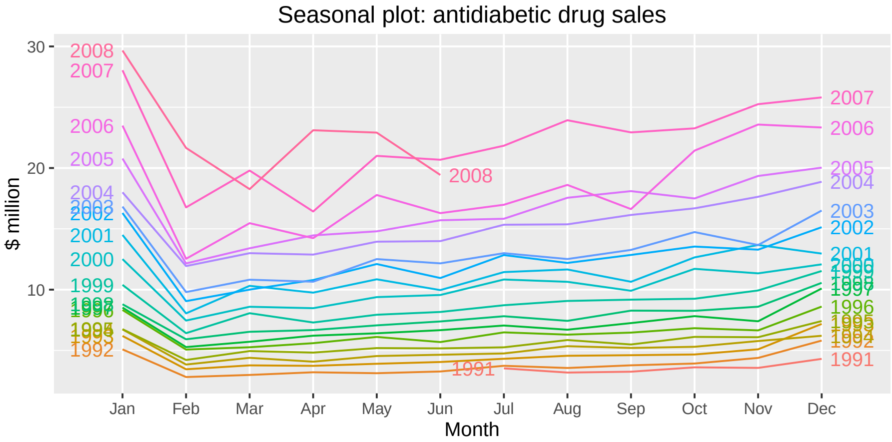
Outline

Lab Session 1

Outline

Seasonal plots

```r
ggseasonplot(a10, ylab="$ million",
  year.labels=TRUE, year.labels.left=TRUE) +
  ggtitle("Seasonal plot: antidiabetic drug sales")
```

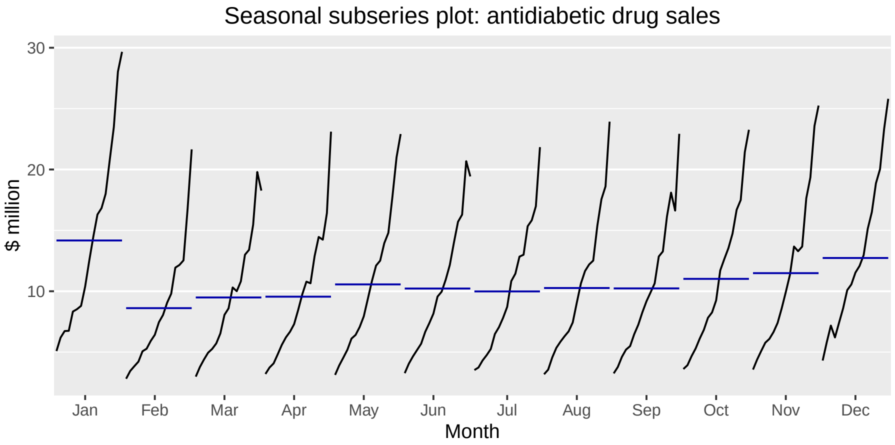


Seasonal plots

- 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: `ggseasonplot` or `seasonplot`.

Seasonal subseries plots

```
ggmonthplot(a10) + ylab("$ million") +
  ggtitle("Seasonal subseries plot: antidiabetic drug sal
```



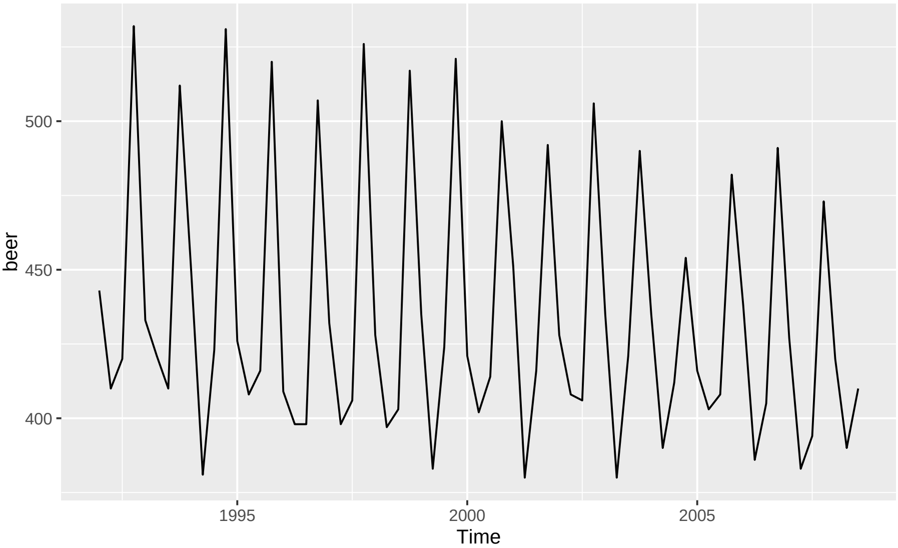
Seasonal subseries plots

- 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: `ggmonthplot` or `monthplot`

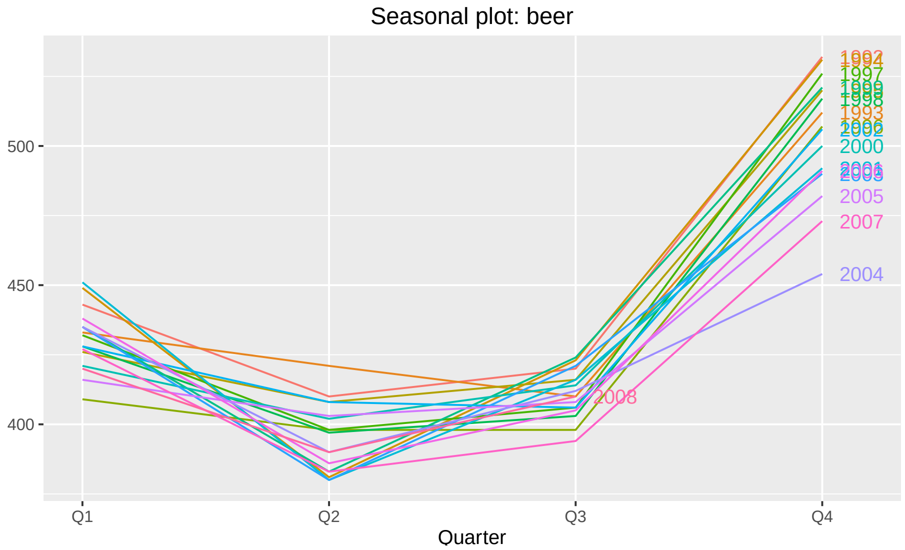
Quarterly Australian Beer Production

```
beer <- window(ausbeer,start=1992)

autoplot(beer)

ggseasonplot(beer,year.labels=TRUE)

ggmonthplot(beer)
```

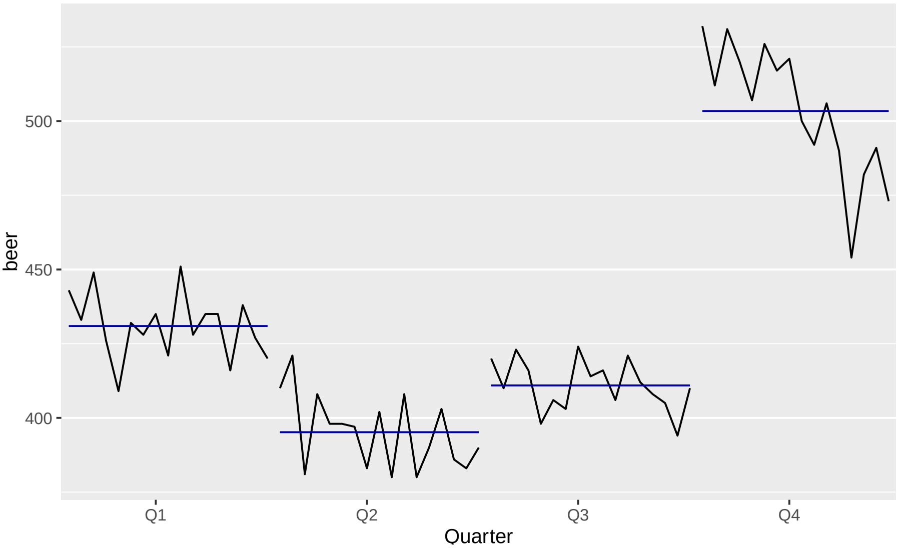
Quarterly Australian Beer Production



Quarterly Australian Beer Production



Quarterly Australian Beer Production



Outline

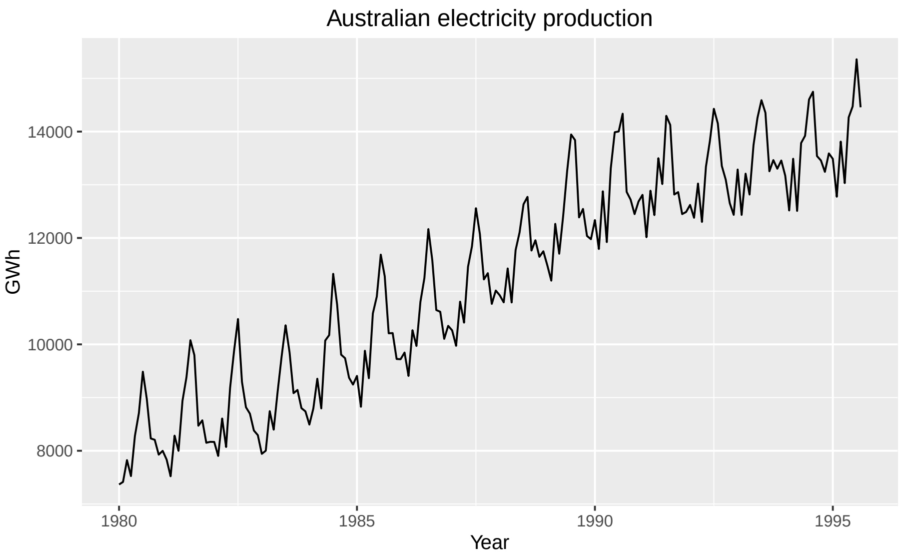
Time series patterns

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

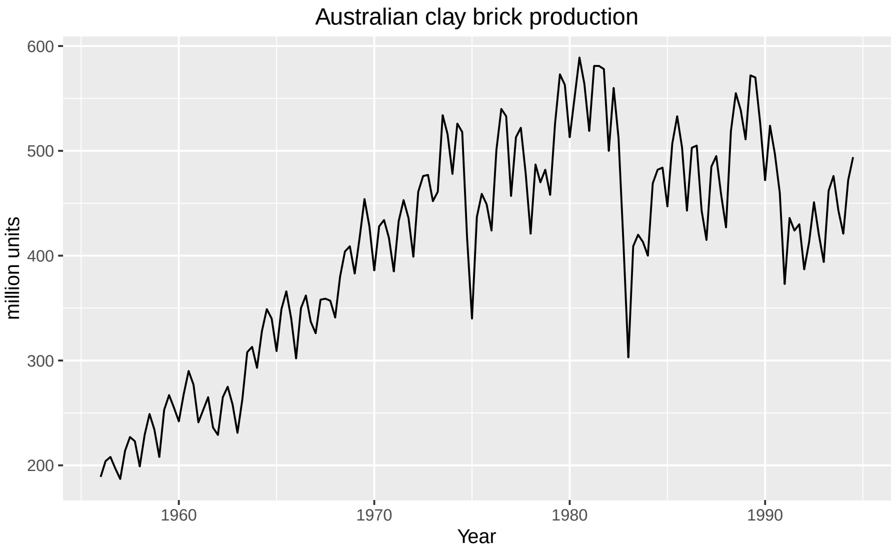
Seasonal pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).

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

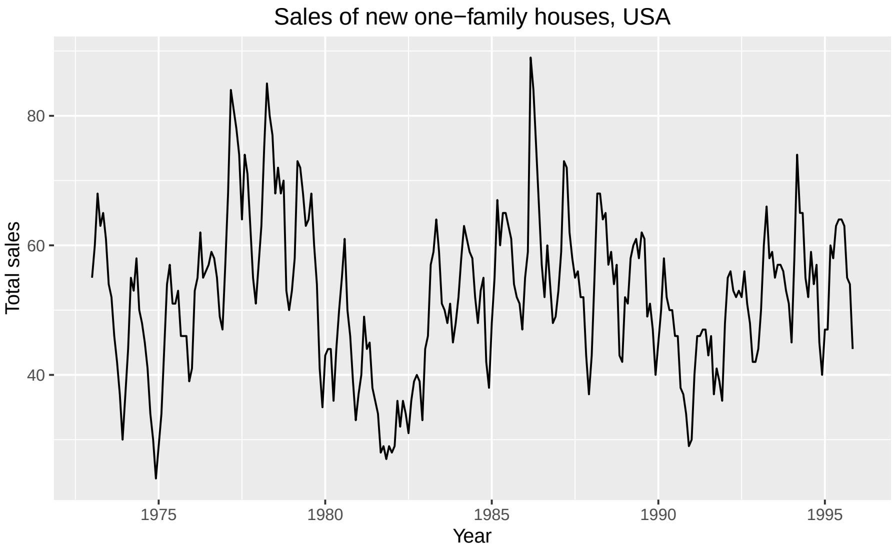
Time series patterns



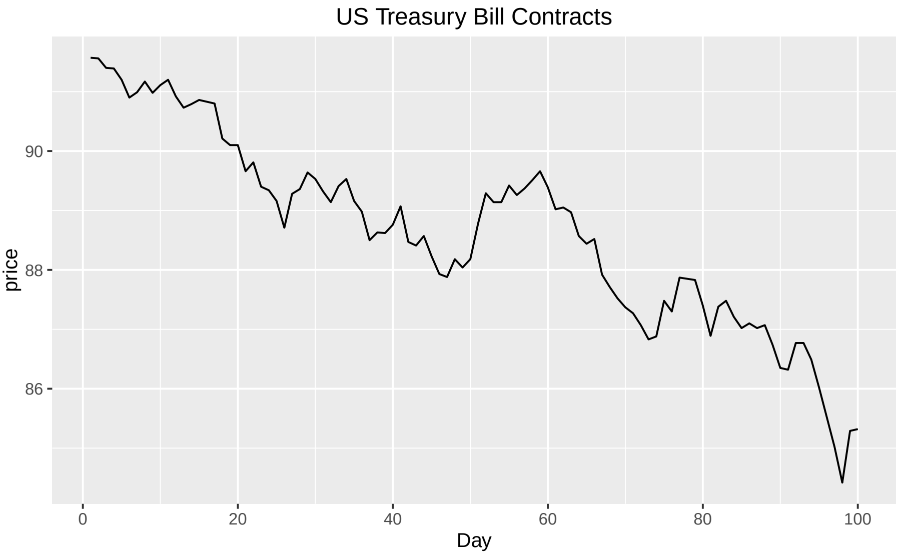
Time series patterns



Time series patterns



Time series patterns



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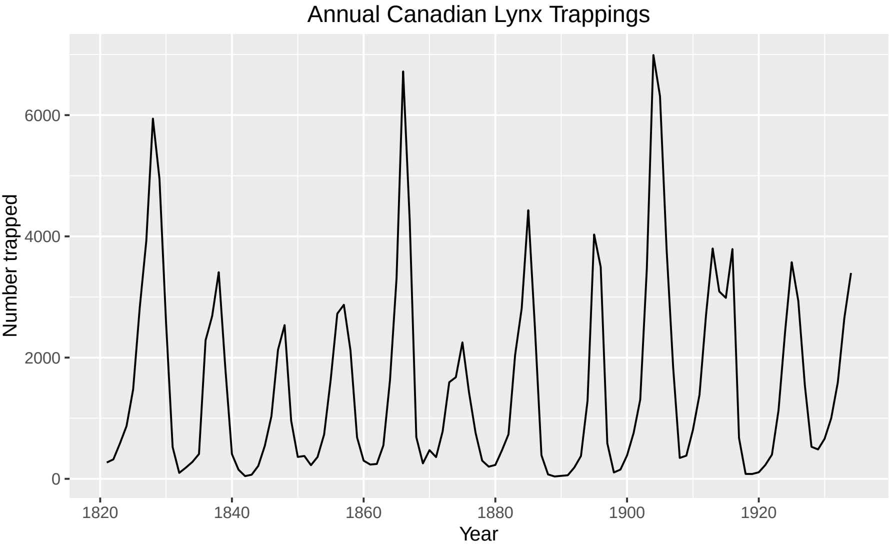

Seasonal or cyclic?

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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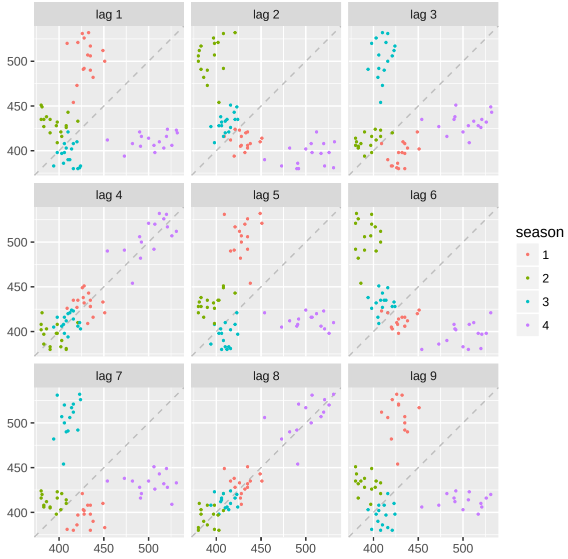
Outline

Example: Beer production

```
beer <- window(ausbeer, start=1992)
gglagplot(beer, lags=9, do.lines=FALSE, continu
```

Example: Beer production



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).

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.

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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 $$r_k = c_k/c_0$$

- 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}.

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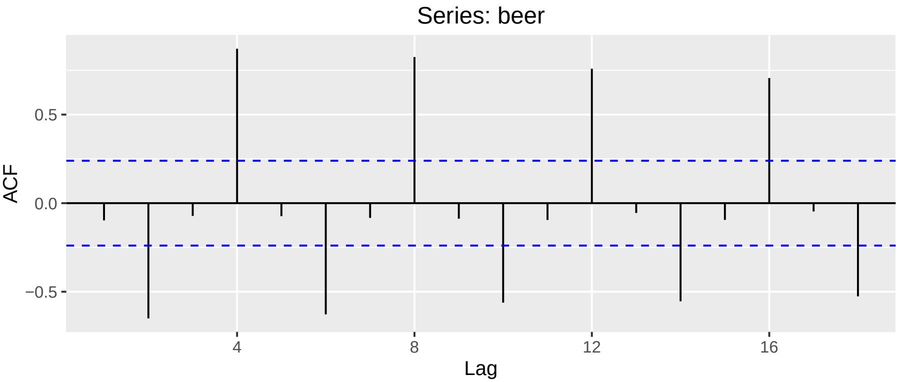
Autocorrelation

Results for first 9 lags for beer `data:/footnotesize`

r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r
-0.097	-0.651	-0.072	0.872	-0.074	-0.628	-0.083	0.825	-0.

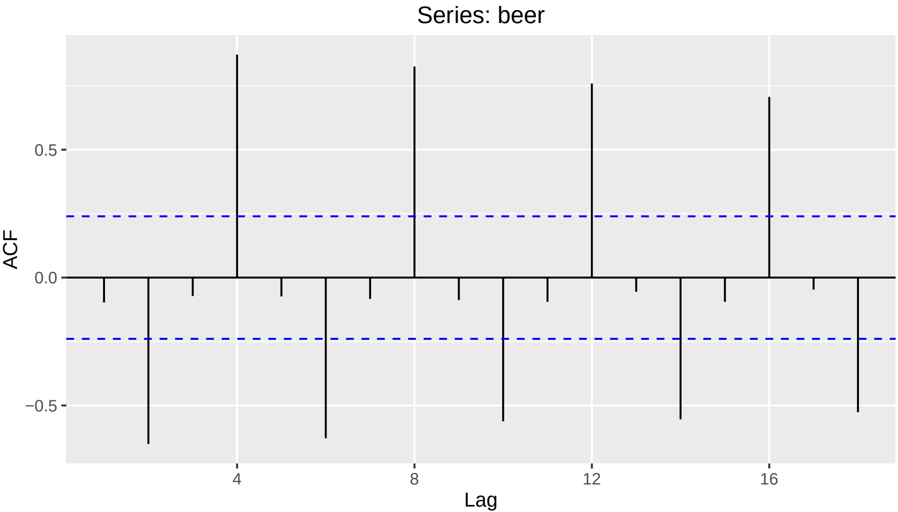


Autocorrelation

- 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, $\dots$, make up the *autocorrelation* or ACF.
- The plot is known as a **correlogram**

ACF

```r
ggAcf(beer)
```

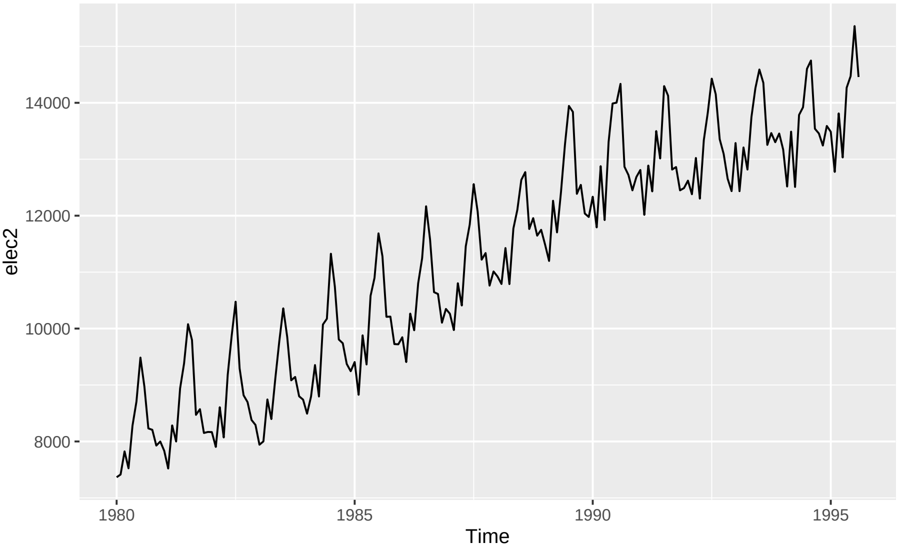


Recognizing seasonality in a time series

If there is seasonality, the ACF at the seasonal lag (e.g., 12 for monthly data) will be **large and positive**.

- For seasonal monthly data, a large ACF value will be seen at lag 12 and possibly also at lags 24, 36, …
- For seasonal quarterly data, a large ACF value will be seen at lag 4 and possibly also at lags 8, 12, …

Aus monthly electricity production



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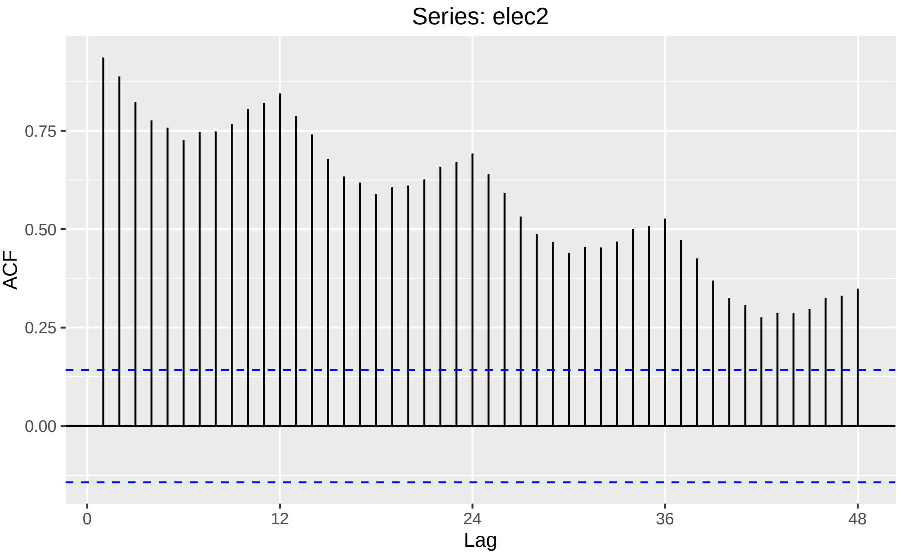


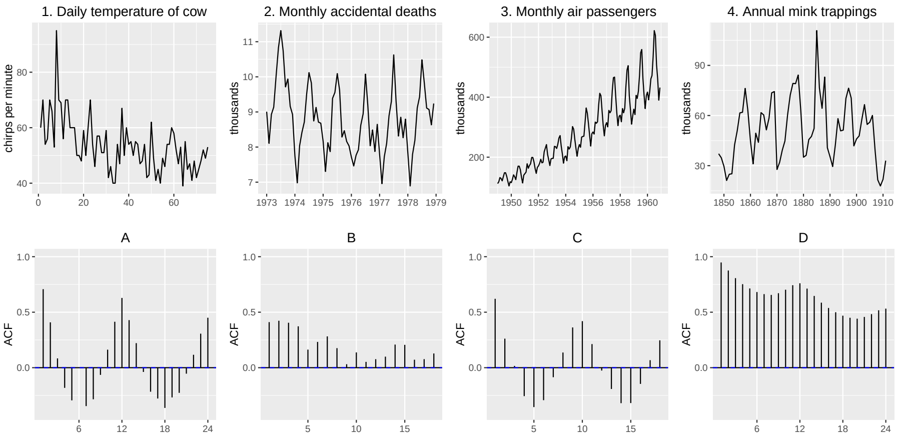
Aus monthly electricity production

Time plot shows clear trend and seasonality.

The same features are reflected in the ACF.

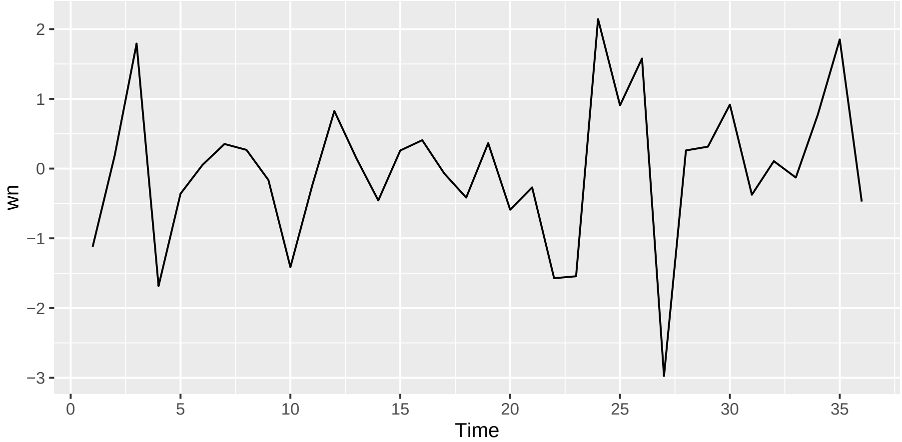
- The slowly decaying ACF indicates trend.
- The ACF peaks at lags 12, 24, 36, . . . , indicate seasonality of length 12.

Which is which?



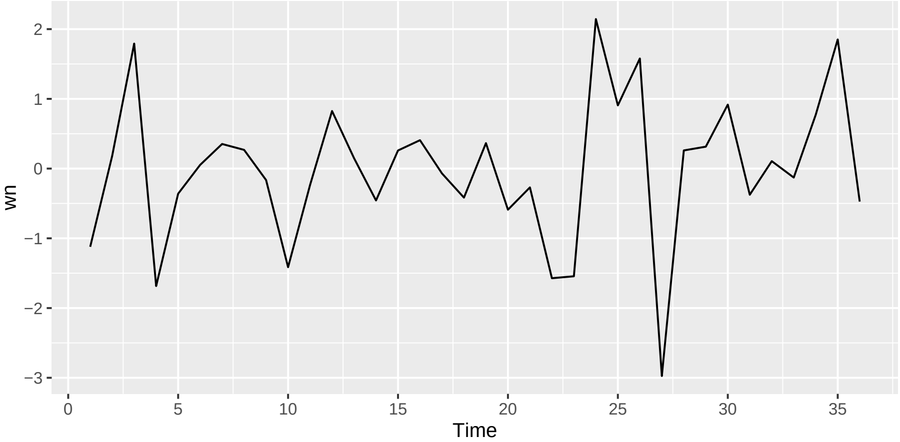
Outline

Example: White noise



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

Example: White noise



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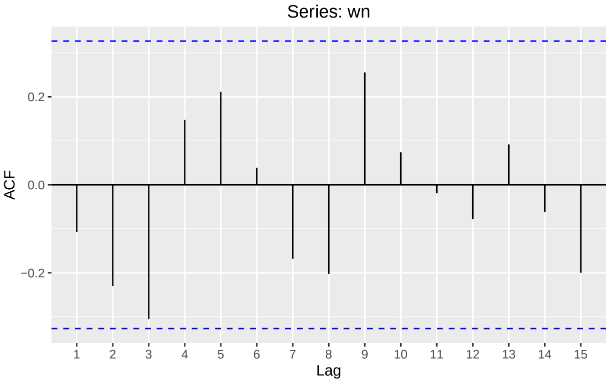
(Technically, we require independence as well.)

Example: White noise

r_1	-0.11
r_2	-0.23
r_3	-0.31
r_4	0.15
r_5	0.21
r_6	0.04
r_7	-0.17
r_8	-0.20
r_9	0.26
r_{10}	0.07



Sample autocorrelations for white noise series.

For uncorrelated data, we would expect each autocorrelation to be close to zero.

Sampling distribution of autocorrelations

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

- 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***.

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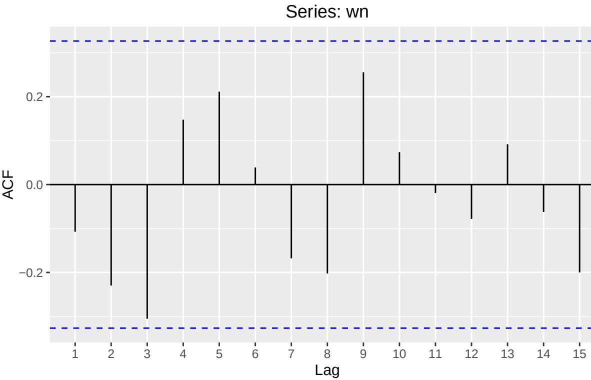
Autocorrelation

Example:

$T = 36$ and so critical values at $\pm 1.96/\sqrt{36} = \pm 0.327$.

All autocorrelation coefficients lie within these limits, confirming that the data are white noise. (More precisely, the data cannot be distinguished from white noise.)



Example: Pigs slaughtered

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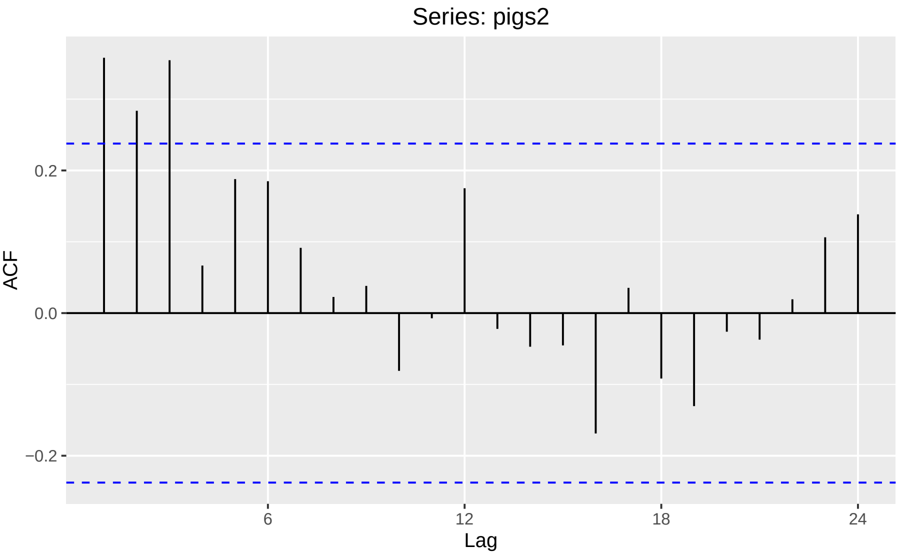

Example: Pigs slaughtered

Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 1990 through August 1995. (Source: Australian Bureau of Statistics.)

- Difficult to detect pattern in time plot.
- ACF shows some significant autocorrelation at lags 1, 2, and 3.
- r_{12} relatively large although not significant. This may indicate some slight seasonality.

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

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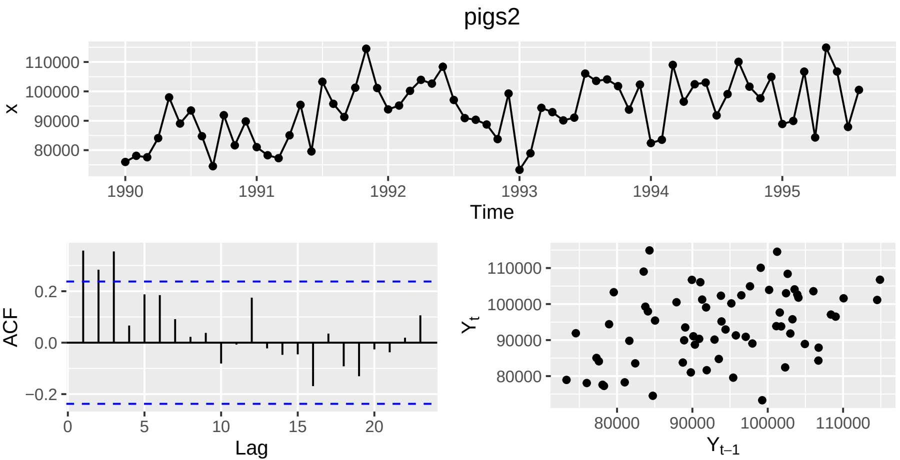
Combination graph

```
ggtsdisplay(pigs2, plot.type='scatter')
```



Outline

Lab Session 2