

MA 5124 Financial Time Series Analysis and Forecasting

Chapter 1: Introduction to time series and forecasting Lesson 1

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Types of Data

Cross-sectional data

Time series data

Pooled data

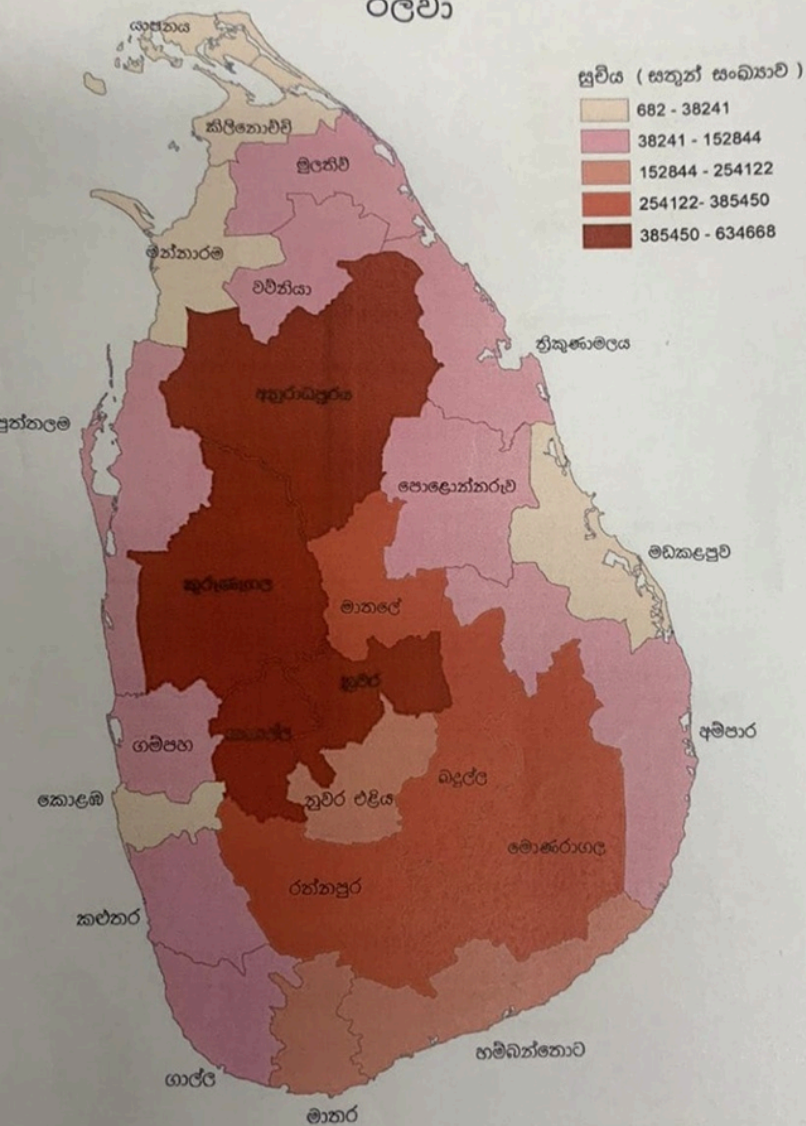
Panel data

1. Cross-sectional data

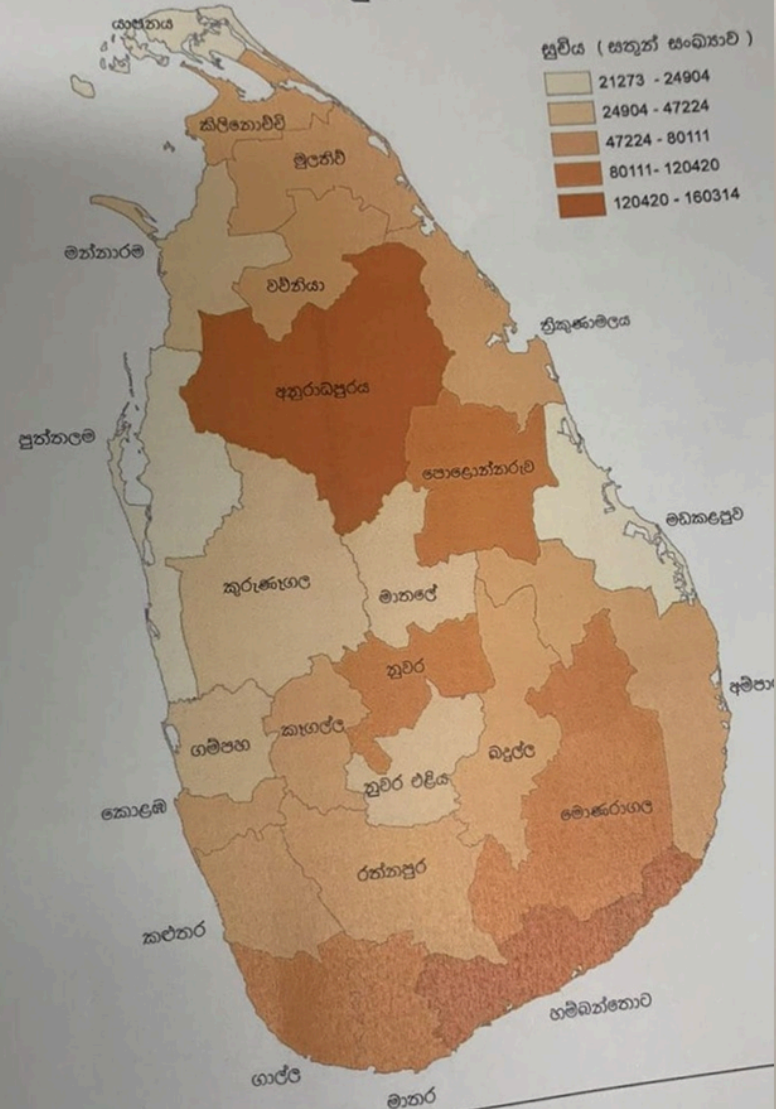
- ▶ A cross-sectional data set consists of a sample of individuals, households, countries or any other type of unit at **a specific point in time**.
- ▶ Sometimes, data across all units do not correspond to exactly the same time point.
- ▶ Example: A survey that collects data from questionnaire surveys of different units within a month.
- ▶ In this case, we can ignore the minor time differences in collection.

ID Monthly Income (in LKR)	
1	83000
2	150000
3	40000
4	65000

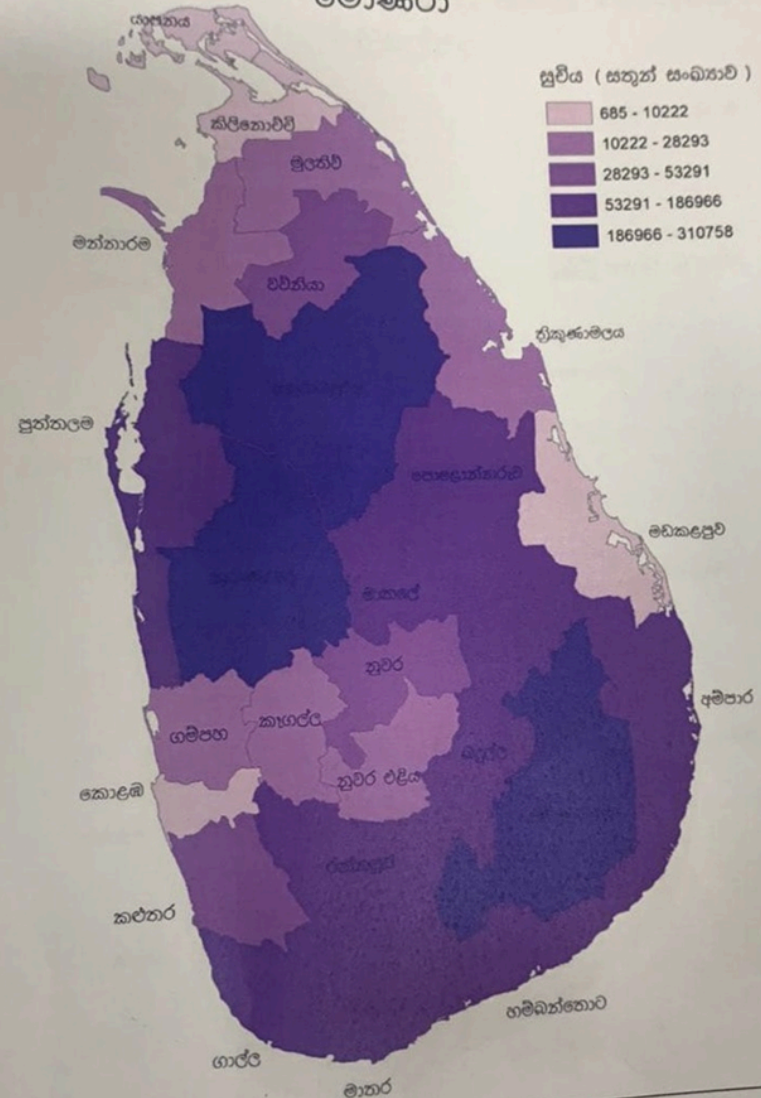
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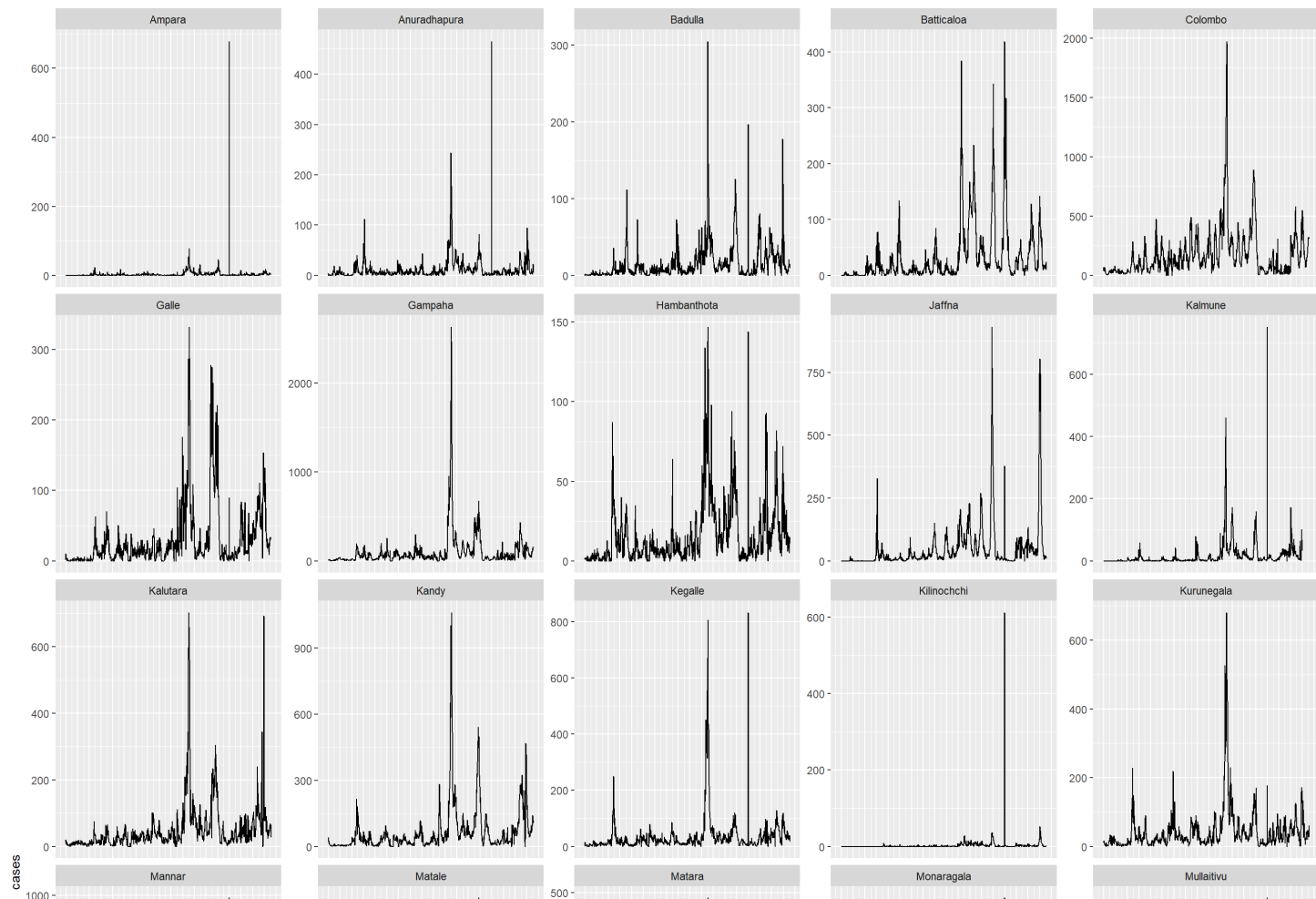
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2. Time series data

- ▶ A time series is a sequence of observations taken **sequentially in time**.
- ▶ Time series data are arranged in chronological order and can have different time frequencies (eg: biannual, annual, quarterly, monthly, weekly, daily, hourly, etc.)
- ▶ Examples of time series data
 - Annual Google profits
 - Monthly rainfall
 - Weekly retail sales
 - Daily confirmed dengue cases and deaths
 - Hourly electricity demand

District-wise weekly Dengue cases from 2006 to 2025



United States Dollar to Sri Lankan Rupee

308.4498

↑ 61.16%

+117.0615 5Y

Feb 6, 10:24:20 PM UTC · Disclaimer

1D

5D

1M

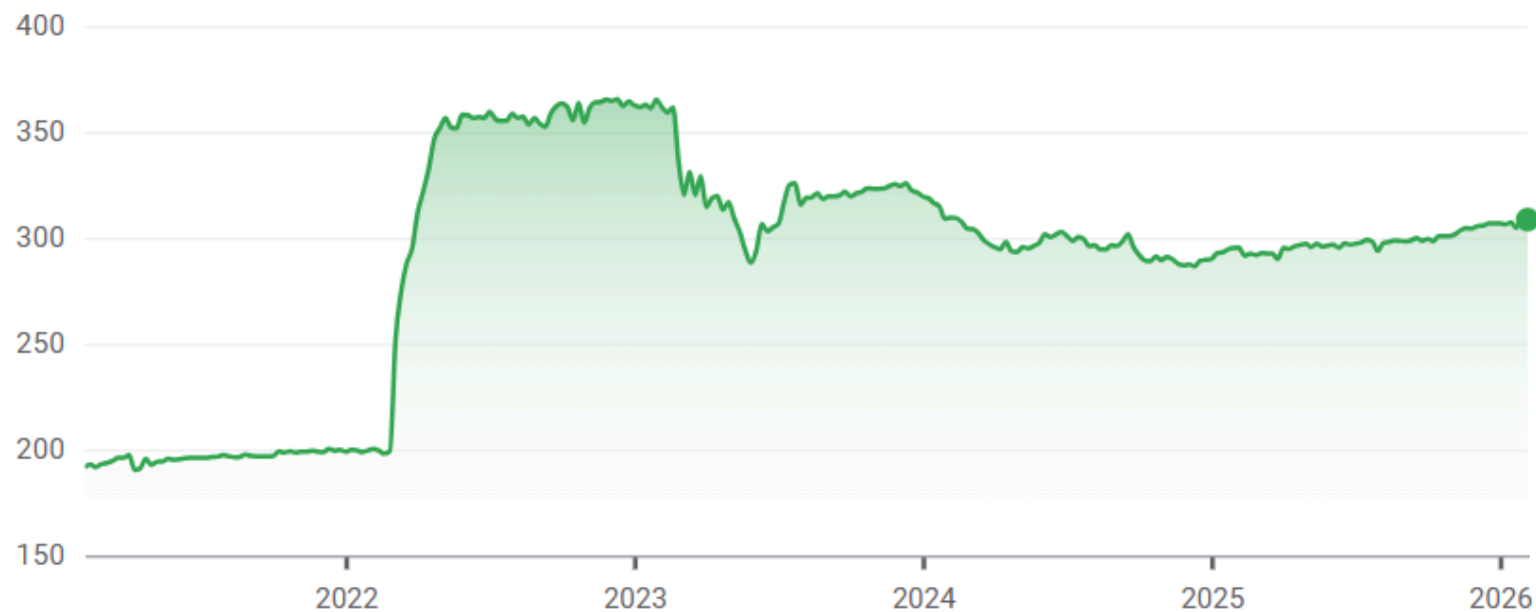
6M

YTD

1Y

5Y

MAX

[Compare to](#)

EUR / LKR

364.76

EUR

↑ 57.45%

JPY / LKR

1.96

JPY

↑ 8.13%

GBP / LKR

419.82

GBP

↑ 59.10%

AUD / LKR

216.37

AUD

↑ 47.30%



3. Pooled data

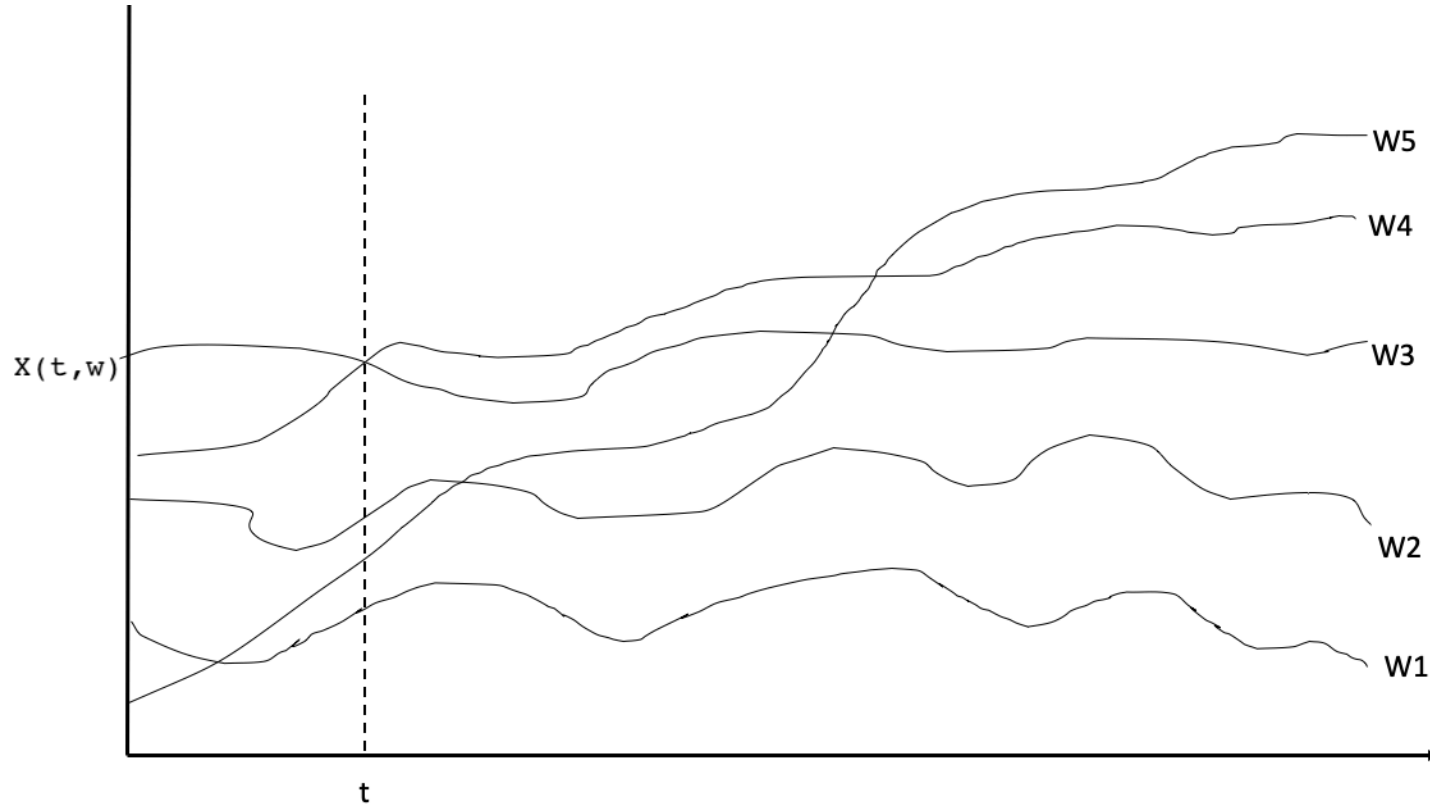
- ▶ Pooled data occur when we have a “time series of cross sections,” but the observations in each cross section do not necessarily refer to the same unit.

4. Panel data

- ▶ This is a **special type** of pooled data in which the samples of the same cross-sectional units observed over time.

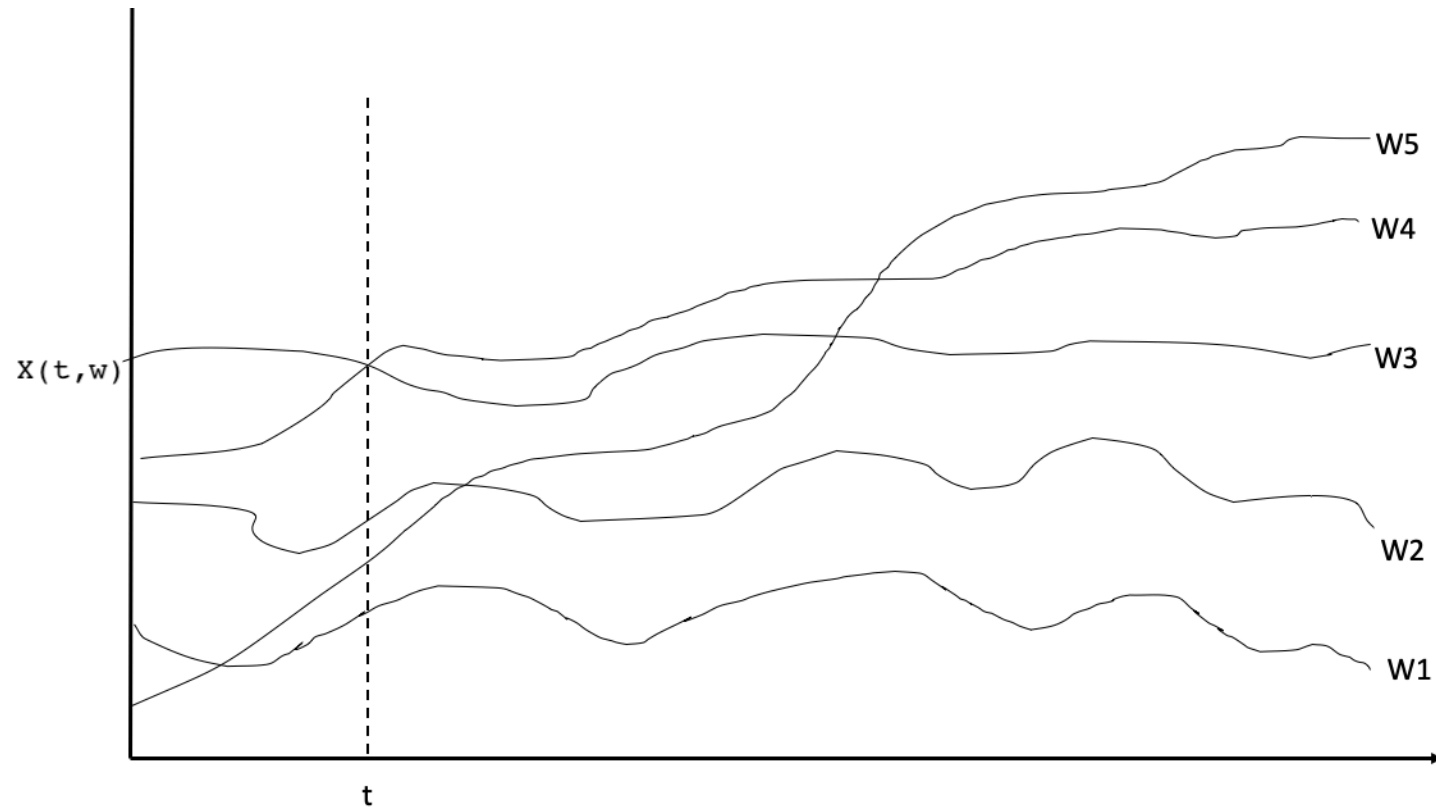
Stochastic Processes

A stochastic process is a family of indexed random variables $\{X(t, \omega); t \in T; \omega \in \Omega\}$ defined on a probability space $(\Omega, \beta, \mathbf{P})$ where T is an arbitrary set.



There are many ways of visualizing a stochastic process.

- (i) For each choice of $t \in T$, $X(t, \omega)$ is a random variable.
- (ii) For each choice of $\omega \in \Omega$, $X(t, \omega)$ is a function of t .
- (iii) For each choice of ω and t , $X(t, \omega)$ is a number.
- (iv) In general it is an ensemble (family) of functions $X(t, \omega)$ where t and ω can take different possible values.



Time series data

- ▶ The observed time series or time series to be analyzed is a particular realization of a stochastic process.
- ▶ Anything that is observed sequentially over time is a time series.
- ▶ In this course, we will only consider time series that are observed at regular intervals of time.
- ▶ Irregularly spaced time series can also be possible, but are beyond the scope of this course

Forecasting

- ▶ Forecasting is about predicting the future as accurately as possible, given all of the information available, including historical data and knowledge of any future events that might impact the forecasts.
- ▶ Forecasting is estimating how the sequence of observations will continue into the future.

Factors affecting forecastability

Something is easier to forecast if:

- ▶ we have a good understanding of the factors that contribute to it
- ▶ there is lots of data available;
- ▶ the forecasts cannot affect the thing we are trying to forecast.
- ▶ there is relatively low natural/unexplainable random variation.
- ▶ the future is somewhat similar to the past

Types of Methods

- ▶ **Qualitative** forecasts

- Judgmental forecasting is the only option if no historical data (for new product, new market conditions), or if the data available are not relevant to the forecasts.
- See fpp3 Chapter 6: <https://otexts.com/fpp3/judgmental.html>.

- ▶ **Quantitative** forecasts: can be applied

- if numerical information about the past is available
- if it is reasonable to assume that some aspects of the past patterns will continue into the future

Quantitative forecasts

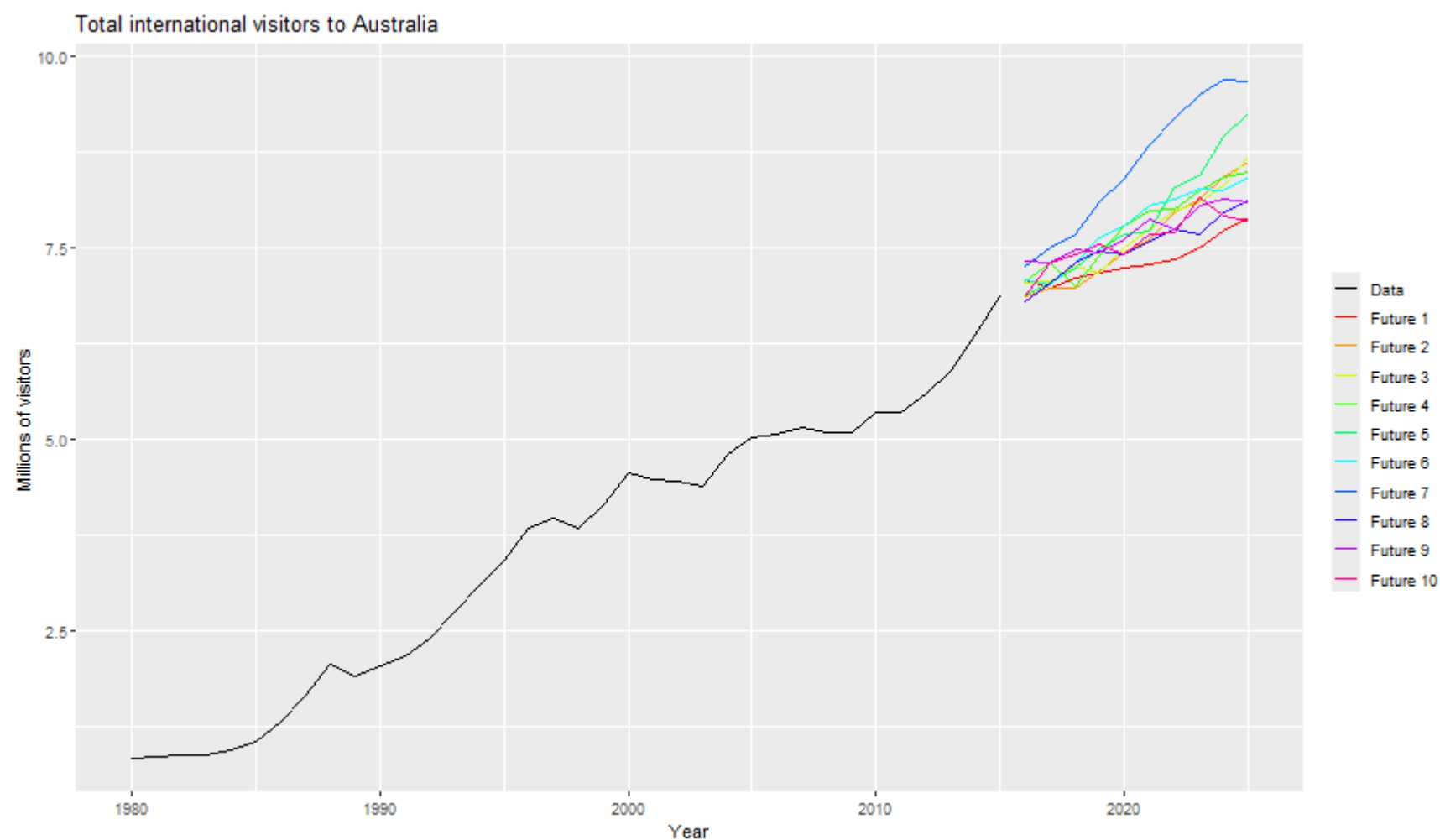
- ▶ Most quantitative forecasting problems use either
 - Time series data (collected at regular intervals over time).
 - Cross-sectional data (collected at a single point in time).

Basic steps in a forecasting task

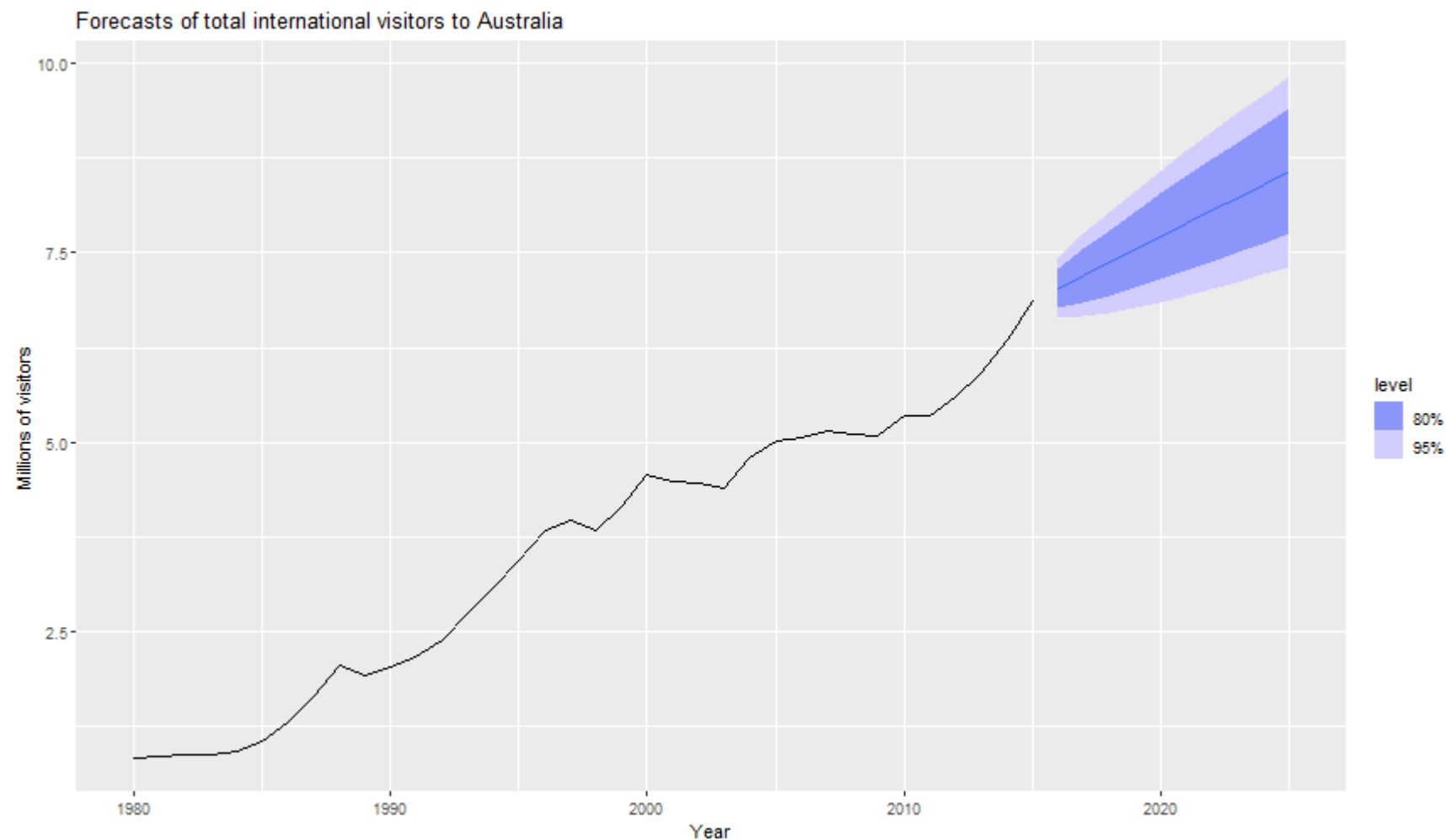
- ▶ Problem definition
- ▶ Collect data
- ▶ Preliminary (exploratory) analysis (data Visualization)
- ▶ Modelling
- ▶ Evaluate the fitted model

The statistical forecasting perspective

Sample futures



Forecast intervals



Statistical forecasting

- ▶ Thing to be forecast: a random variable, y_t .
- ▶ Forecast distribution: If \mathcal{I} is all observations, then $y_t|\mathcal{I}$ means "the random variable y_t given what we know in \mathcal{I} ".
- ▶ The **point forecast** is the mean (or median) of $y_t|\mathcal{I}$
- ▶ The **forecast variance** is $\text{var}[y_t|\mathcal{I}]$
- ▶ A prediction interval or **interval forecast** is a range of values of y_t with high probability.
- ▶ With time series, $y_{t|t-1} = y_t|\{y_1, y_2, \dots, y_{t-1}\}$.
- ▶ $\hat{y}_{T+h|T} = \text{E}[y_{T+h}|y_1, \dots, y_T]$ (an h -step forecast taking account of all observations up to time T).

Frequency of a time series: Seasonal periods

- ▶ **Frequency**: number of observation per natural time interval of measurement

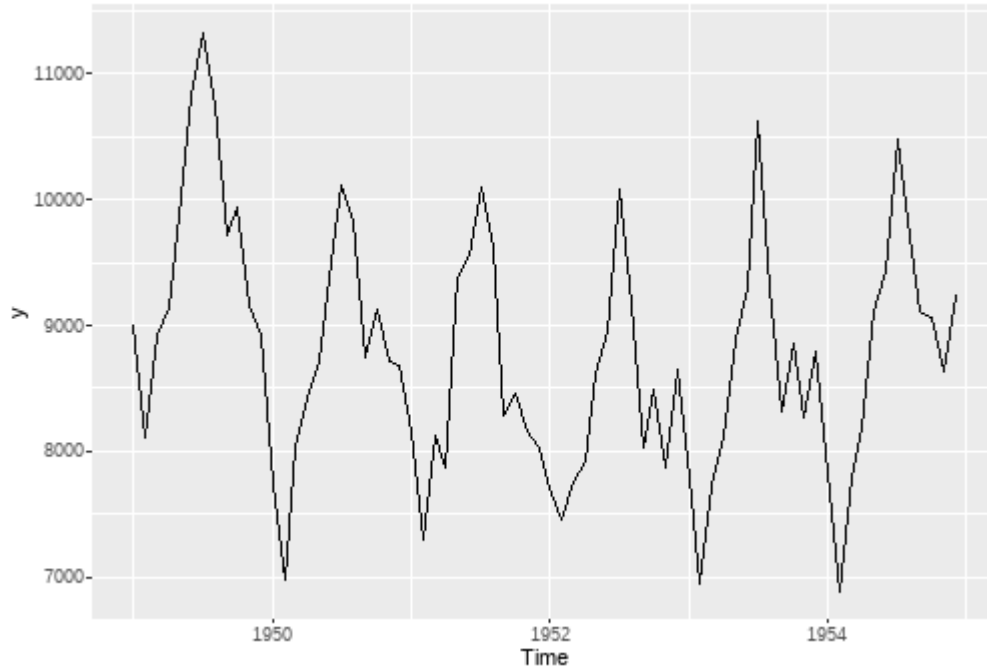
Data	Frequency
Annual	1
Quarterly	4
Monthly	12
Weekly	52 or 52.18

Frequency of a time series: Seasonal periods

- ▶ Multiple frequency setting

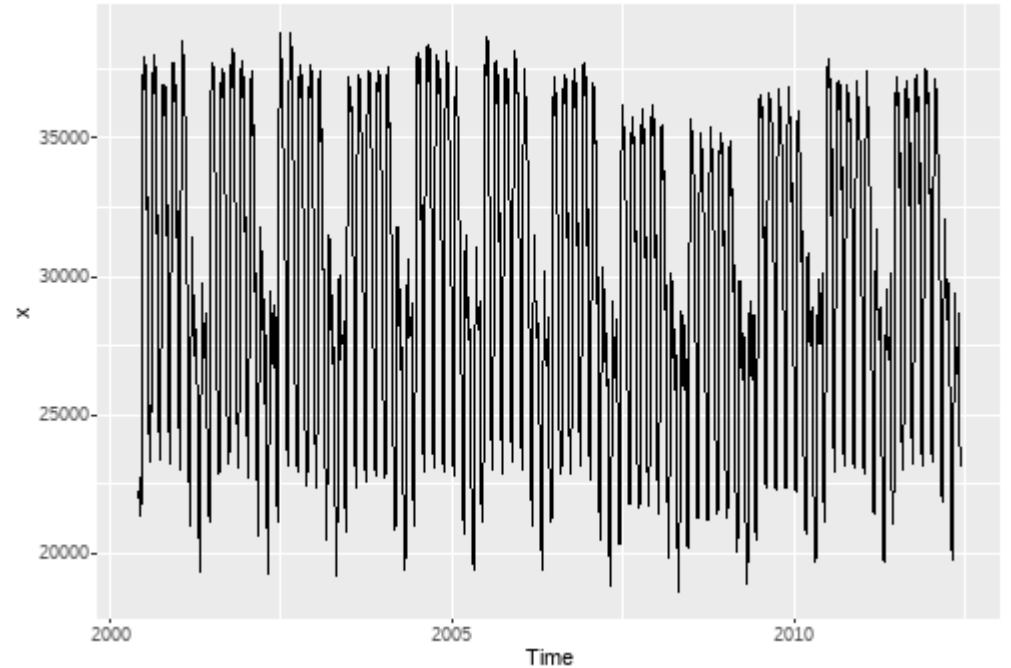
Data	Minute	Hour	Day	Week	Year
Daily				7	365.25
Hourly			24	168	8766
Half-Hourly			48	336	17532
Minutes		60	1440	10080	525960
Seconds	60	3600	86400	604800	31557600

Monthly time series



- ▶ Length of the series: 72
- ▶ Monthly seasonality

Half-hourly Time Series



- ▶ Length of the series: 4032
- ▶ Daily seasonality and weekly seasonality

Time series patterns

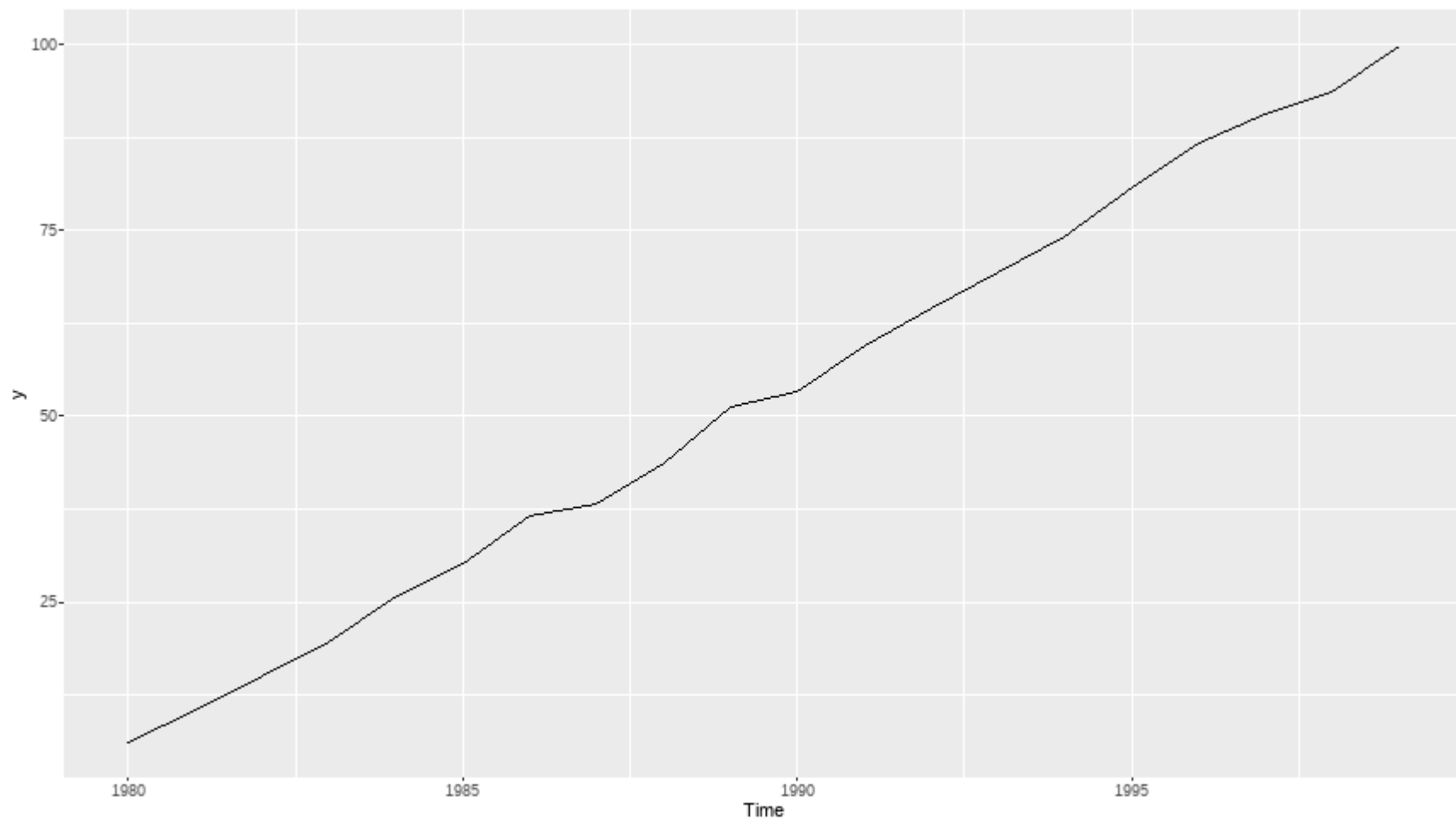
- ▶ **Trend** pattern exists when there is a long-term increase or decrease in the data.
- ▶ **Seasonal** pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).
- ▶ **Cyclic** pattern exists when data exhibit rises and falls that are not of fixed frequency (duration usually of at least 2 years).

Seasonal or cyclic?

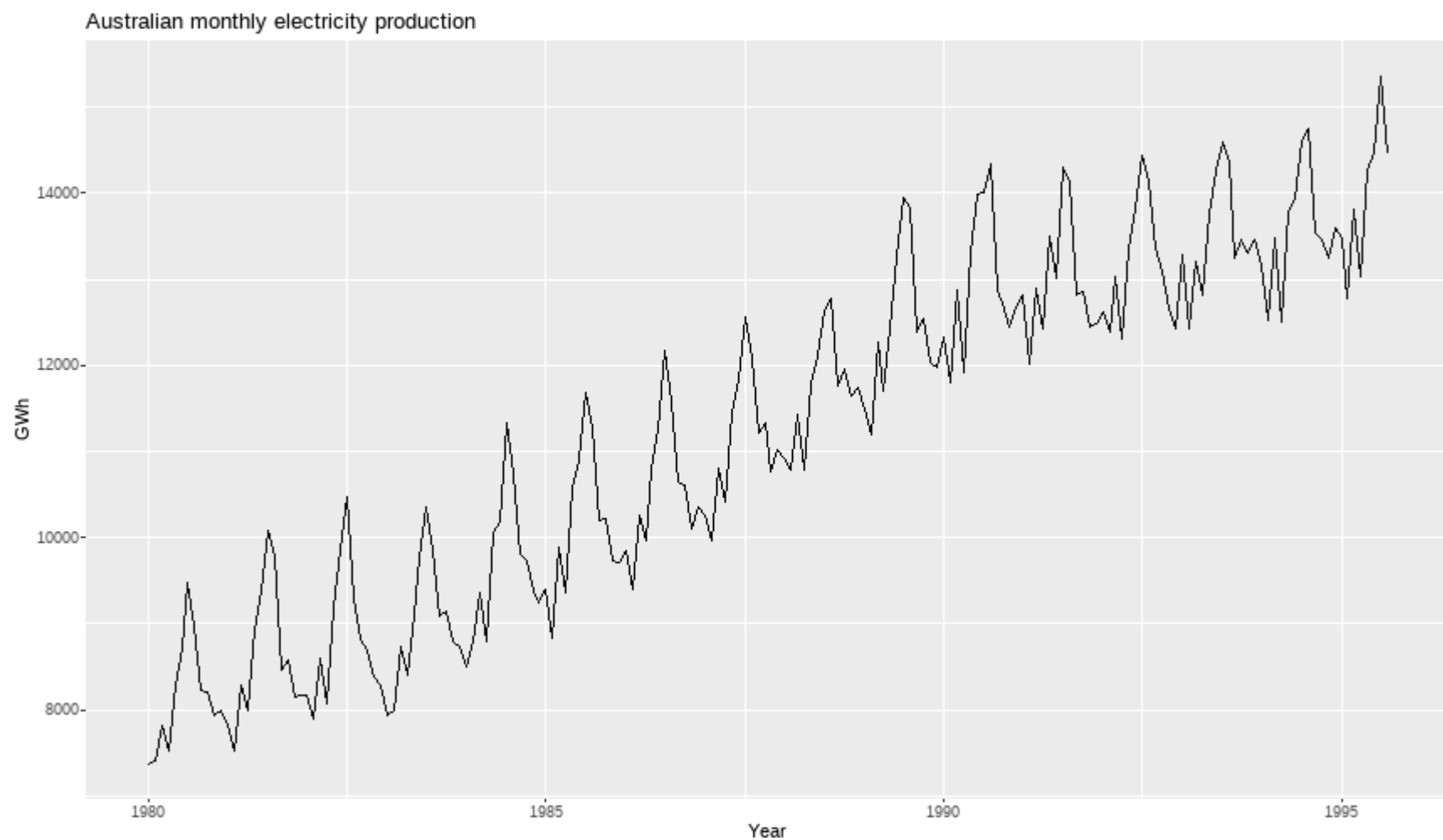
Differences between seasonal and cyclic patterns:

- ▶ 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.**

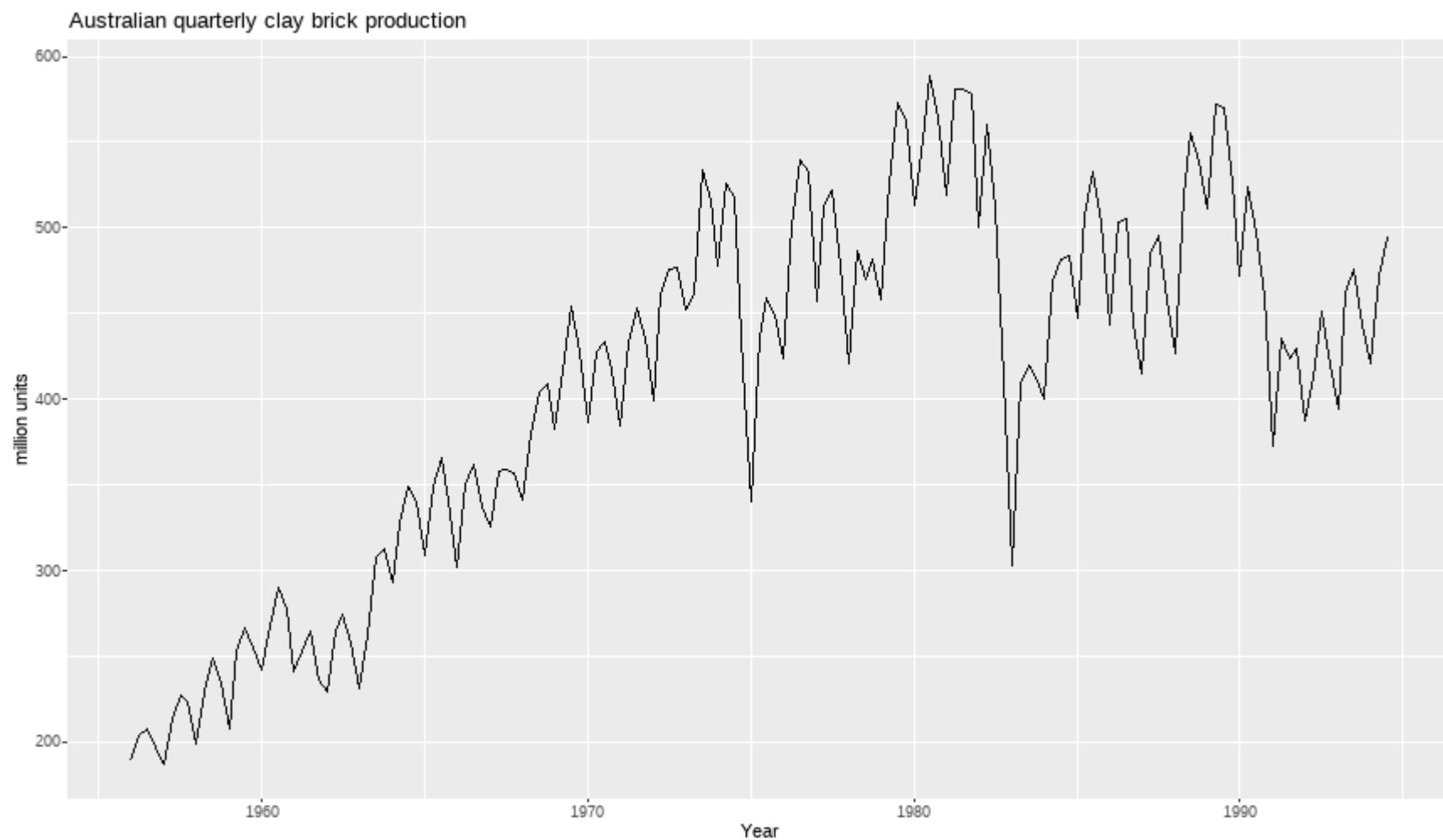
Time series patterns



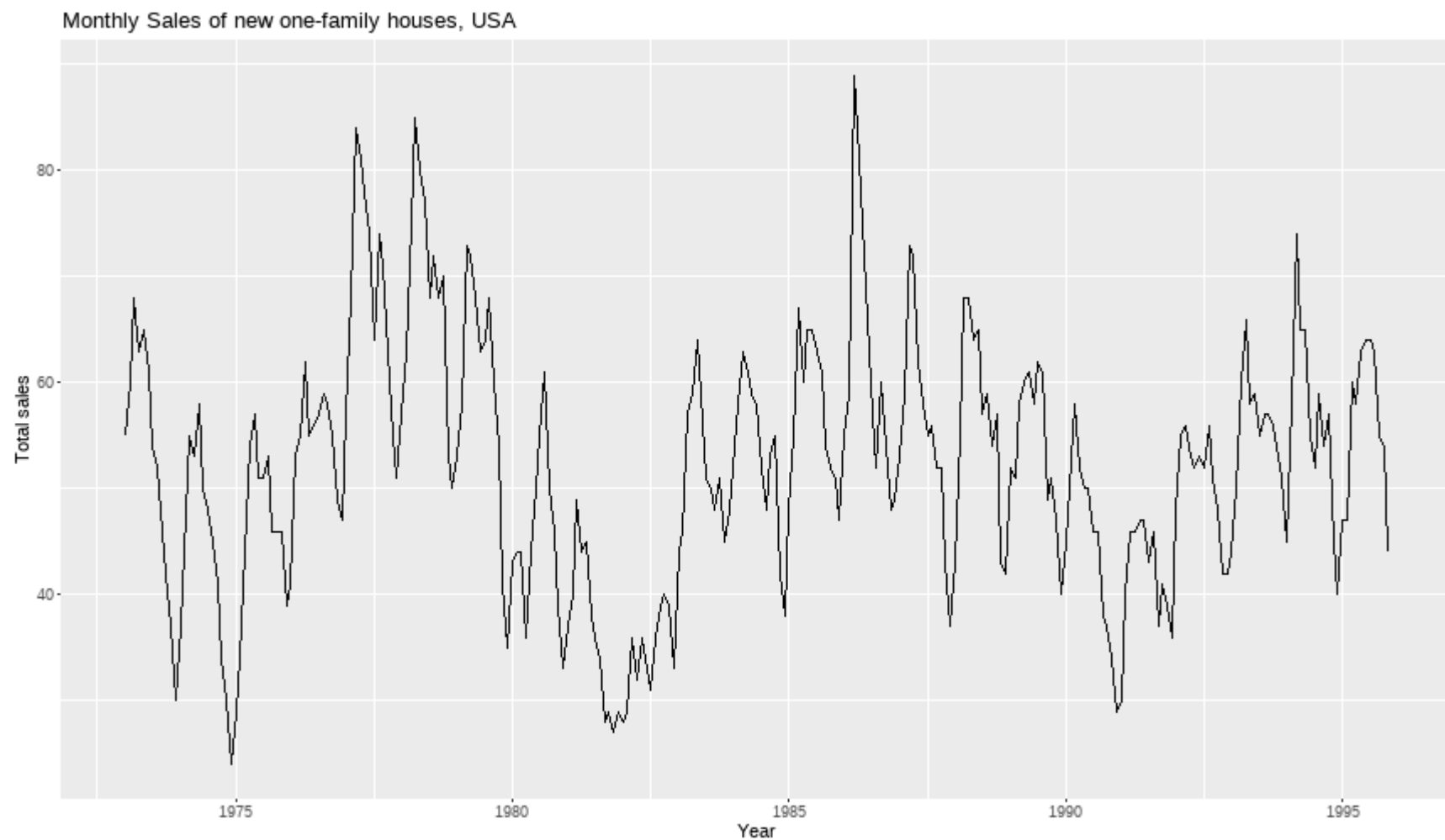
Time series patterns



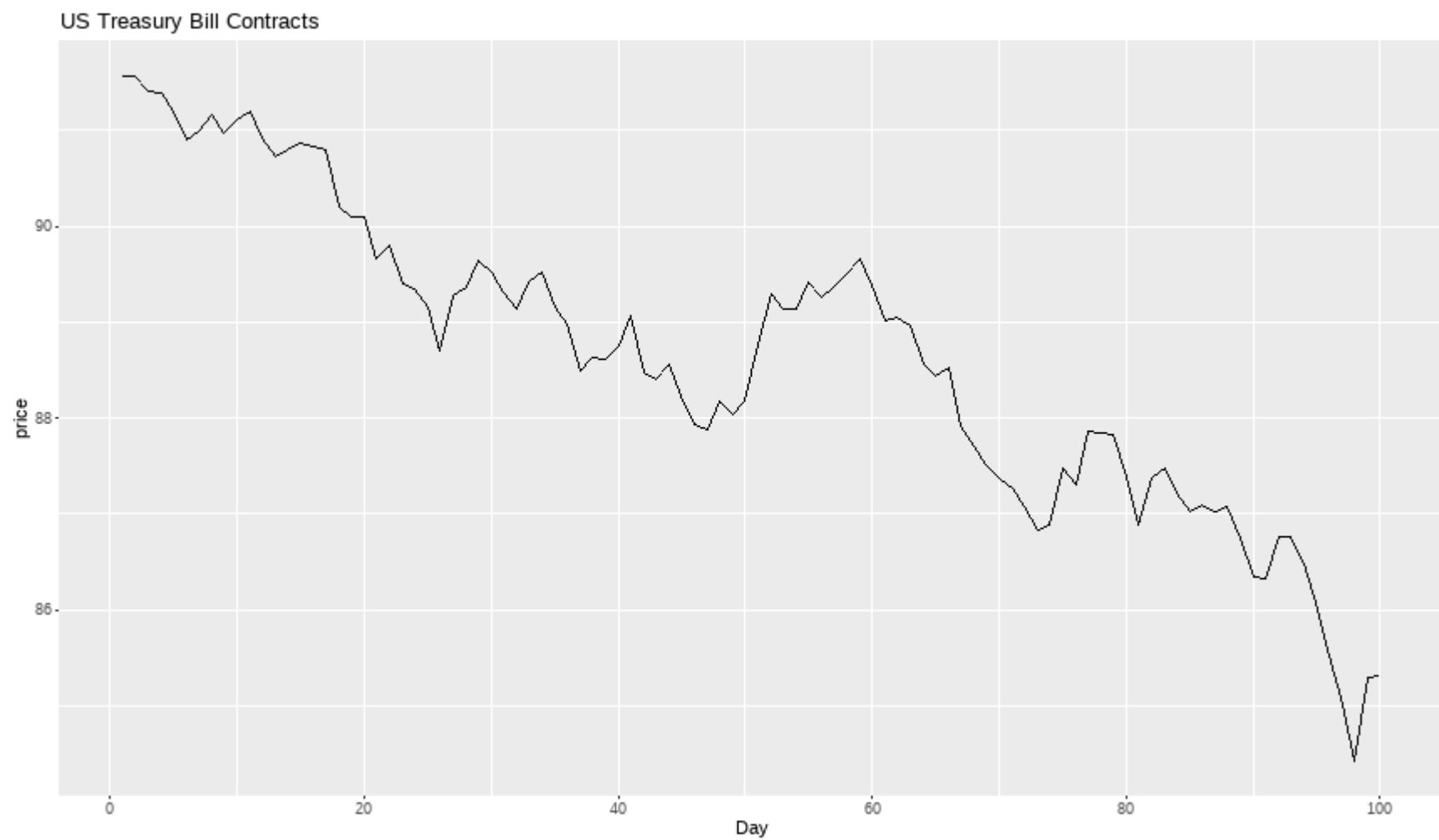
Time series patterns



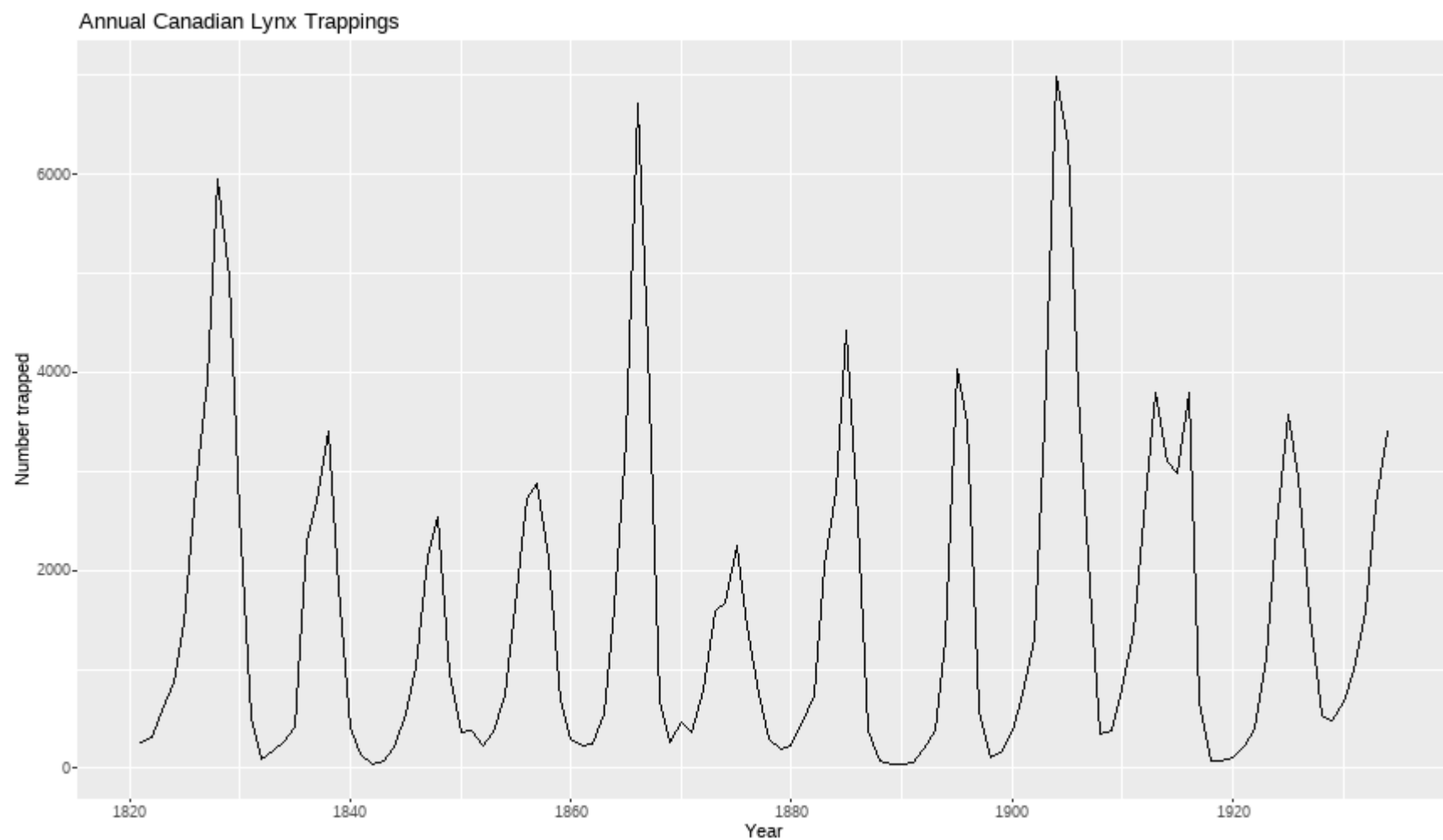
Time series patterns



Time series patterns



Time series patterns

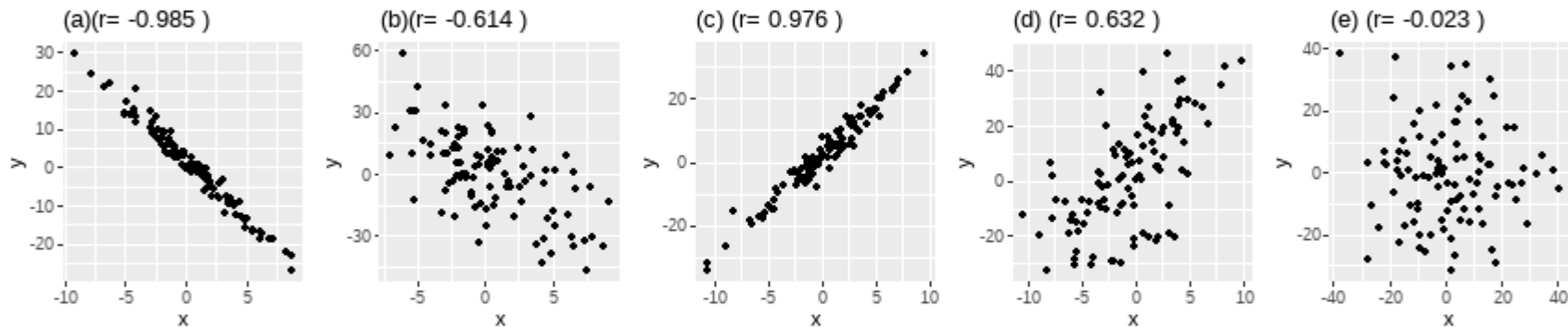


Numerical data summaries

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

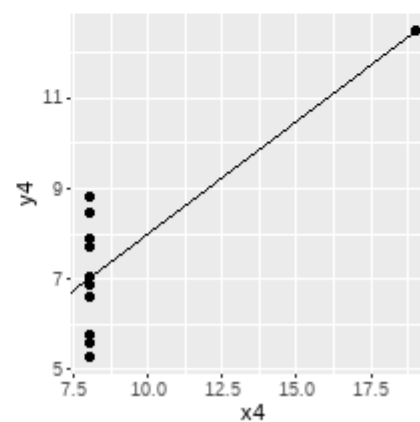
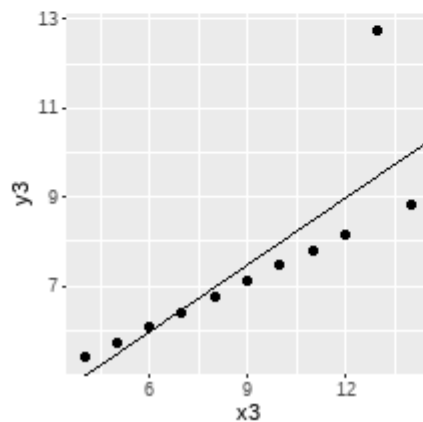
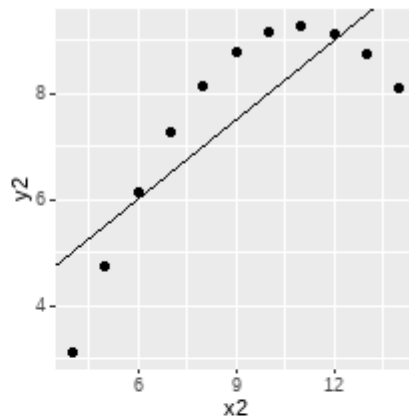
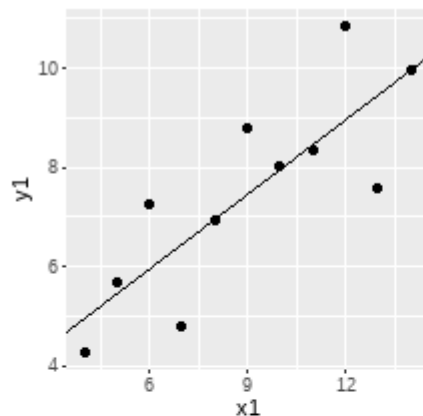
$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}}$$

- Lies between -1 and +1



Correlation coefficient

Which one has the highest correlation?



► All these have $r = 0.82$.

Autocorrelation

Autocovariance (c_k) and **auto**correlation (r_k): 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}

...

y_t and y_{t-k}

- ▶ We denote the sample autocovariance at lag k by c_k and the sample autocorrelation at lag k by r_k .

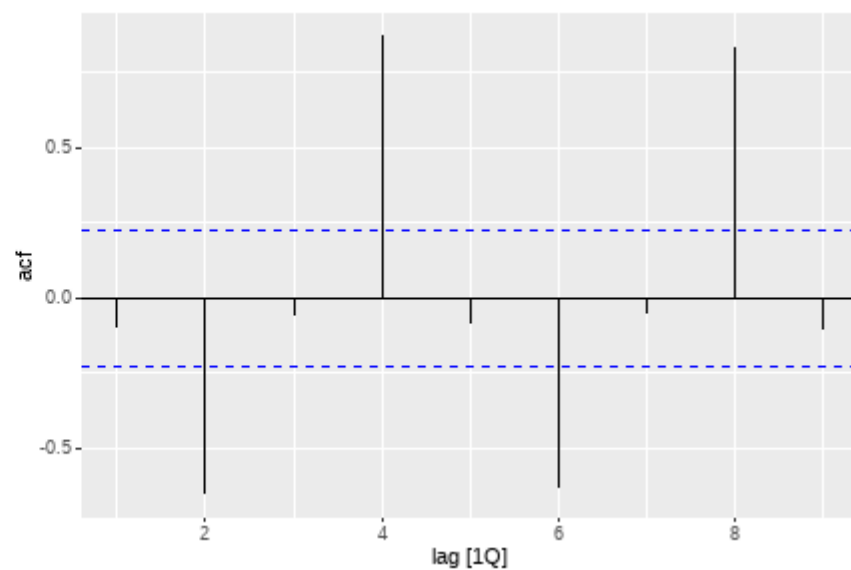
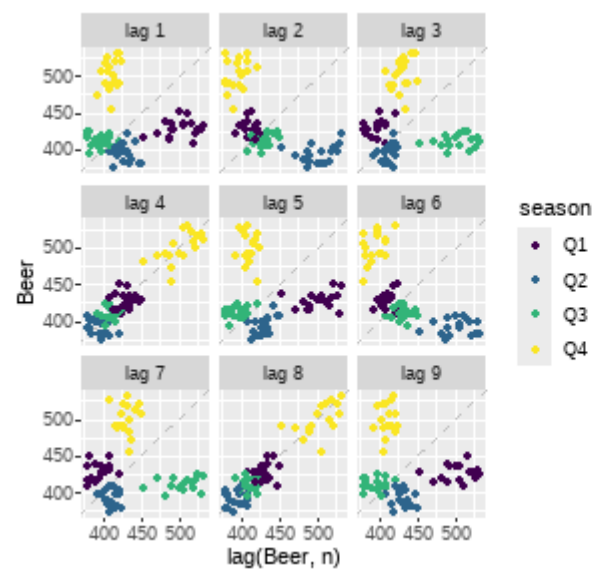
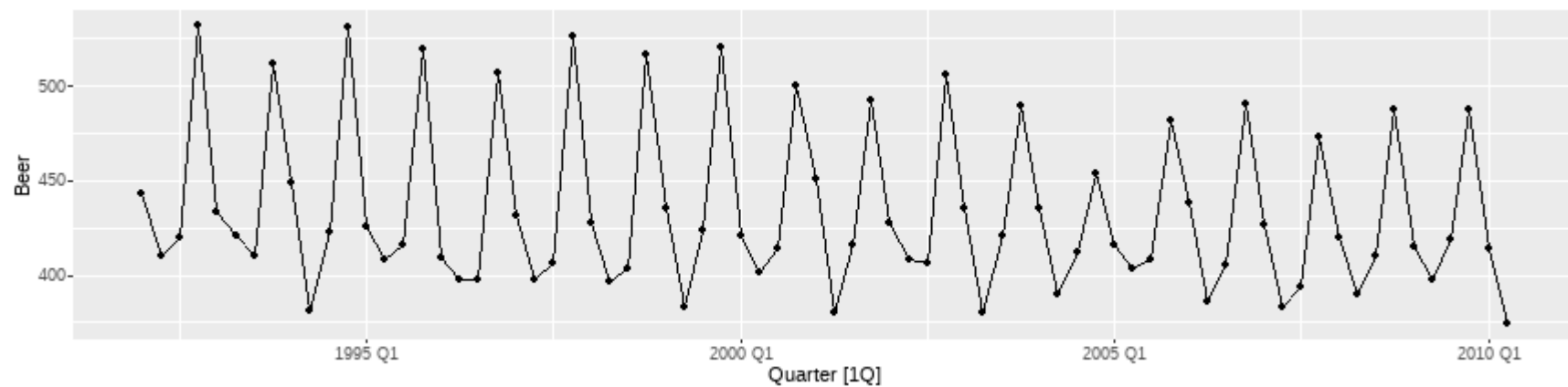
Then define

$$r_k = \frac{c_k}{c_0} = \frac{\sum_{t=k+1}^T (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^T (y_t - \bar{y})^2}$$

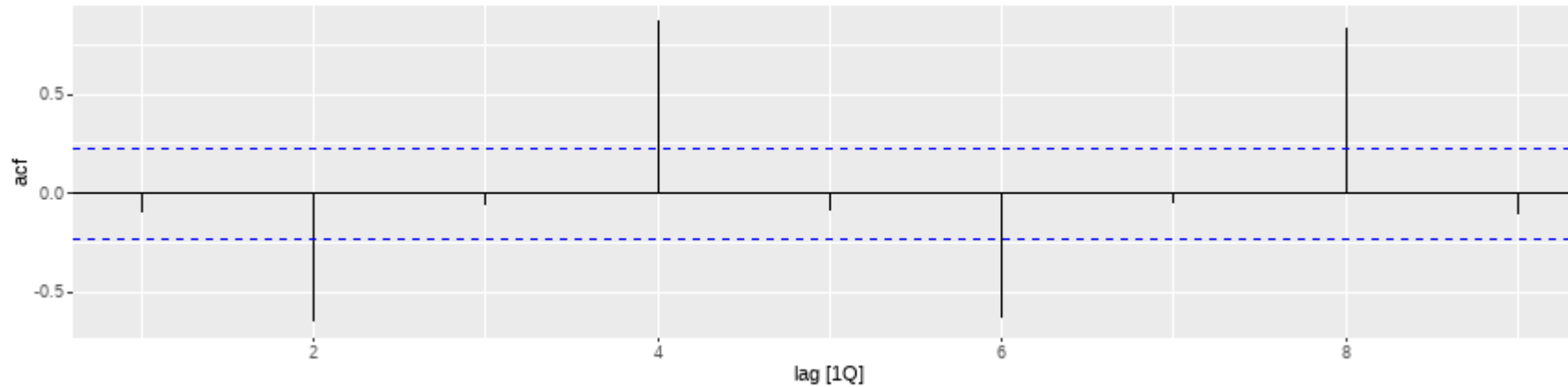
Autocorrelation

- ▶ 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:

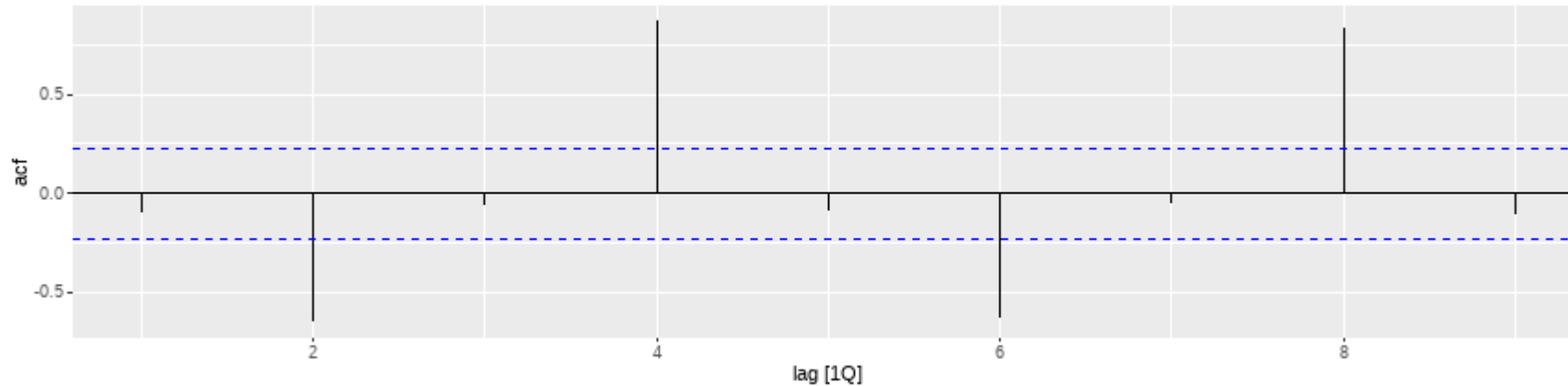


Autocorrelation: Results for first 9 lags for beer data:



- ▶ r_4 is **positive and higher** than for the other lags. This is due to the **seasonal pattern** in the data.
 - the peaks (troughs) tend to be 4 quarters apart.
 - the spikes every 4 lags after this (r_8, r_{12}, \dots) decrease in size as the lag number increases.

Autocorrelation: Results for first 9 lags for beer data:

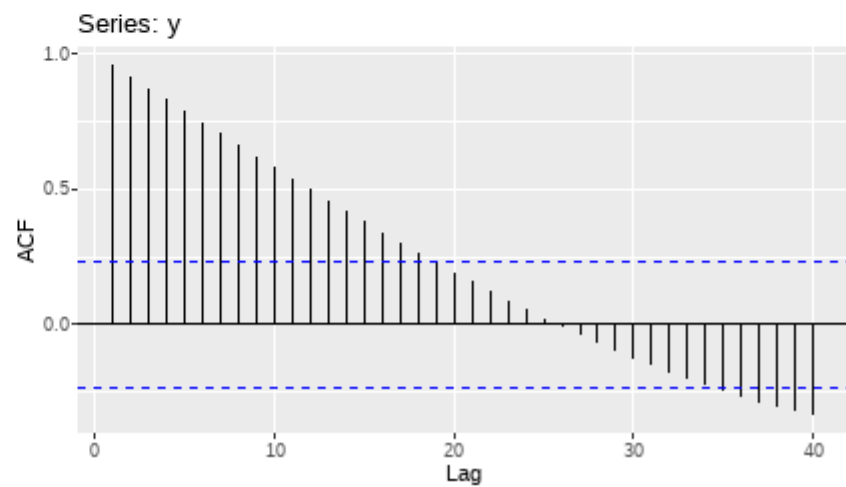
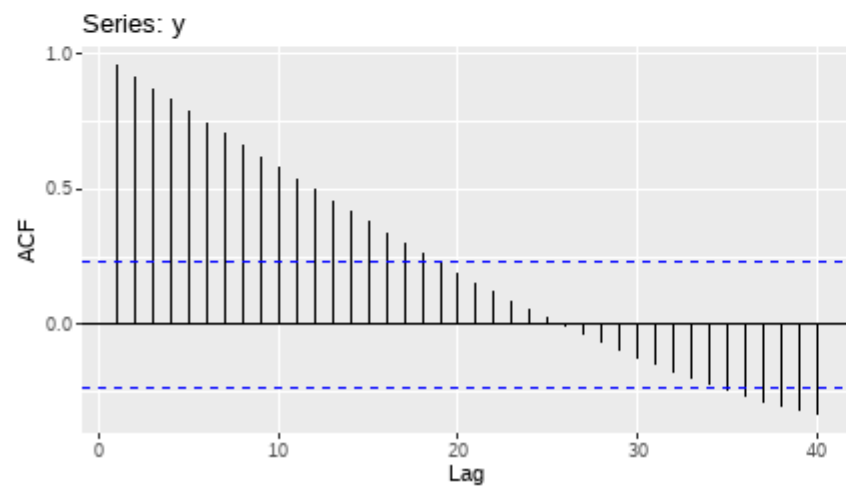
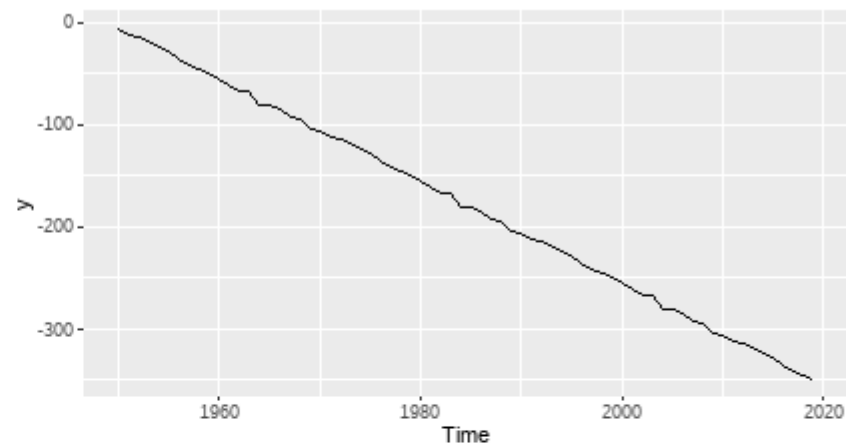
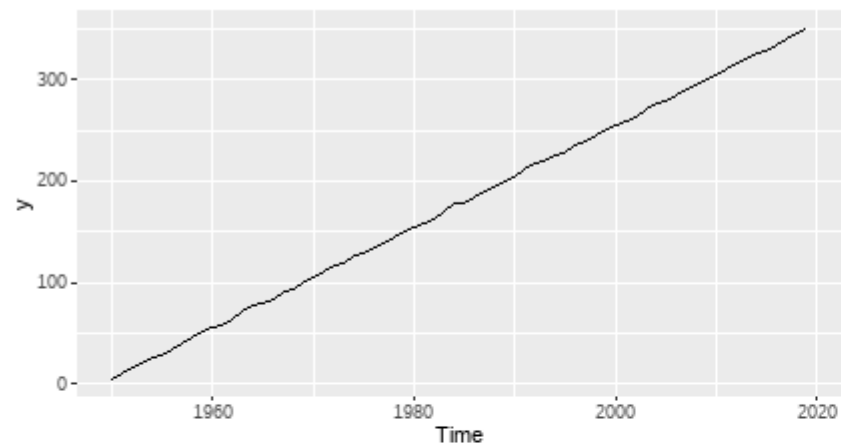


- ▶ r_2 is **more negative** than for the other lags because troughs and peaks tend to be 2 quarters apart.
 - The highest and the lowest productions are 2 quarters apart.
 - The spikes every 4 lags after this r_6, r_{10}, \dots decrease in size as the lag number increases.
- ▶ Together, the autocorrelations at lags 1, 2, \dots , make up the **autocorrelation** or **ACF**.
- ▶ The plot is known as a **correlogram**.
- ▶ The dashed blue lines indicate whether the correlations are significantly different from zero.

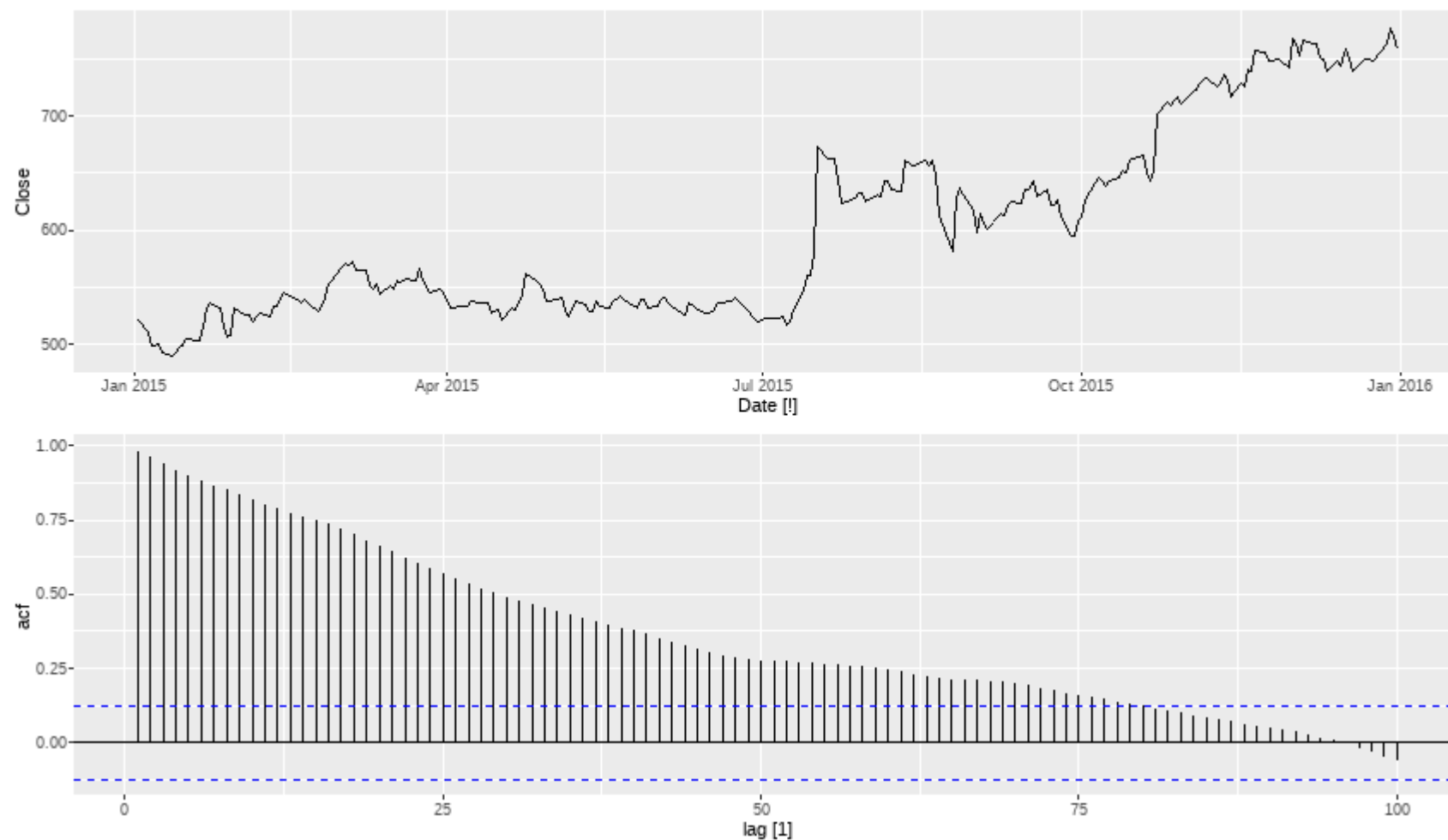
Trend and seasonality in ACF plots

- ▶ 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

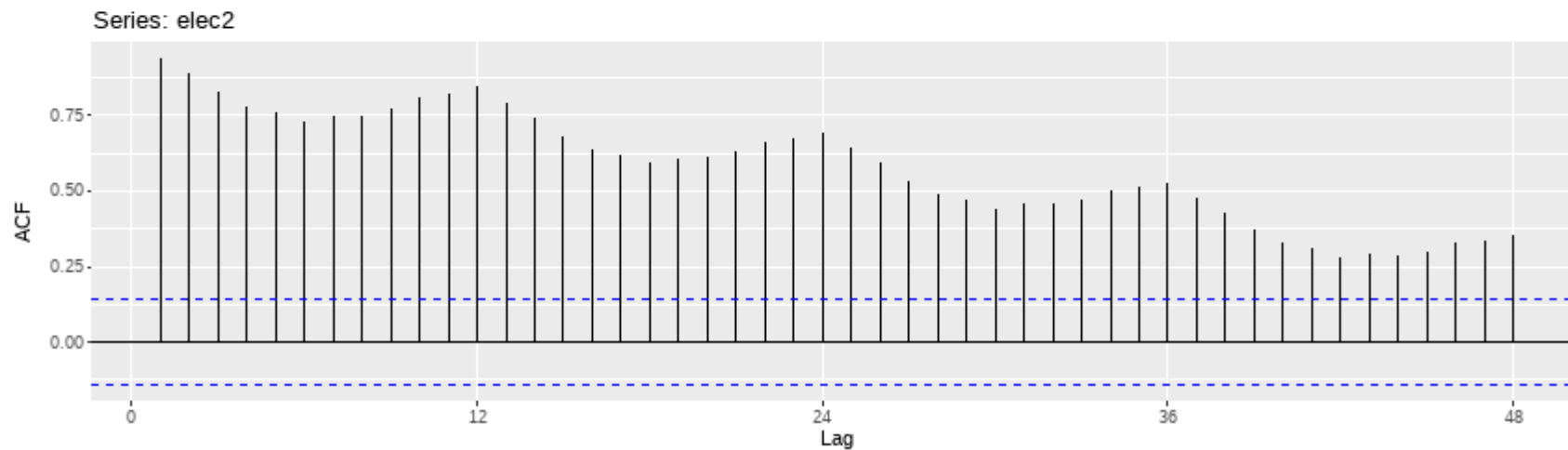
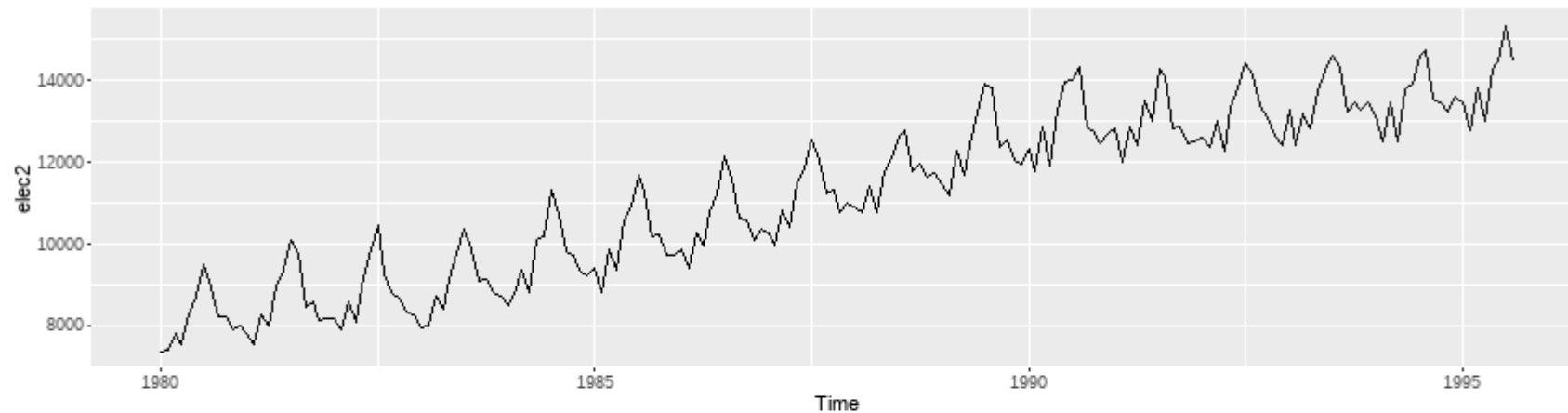
Trend



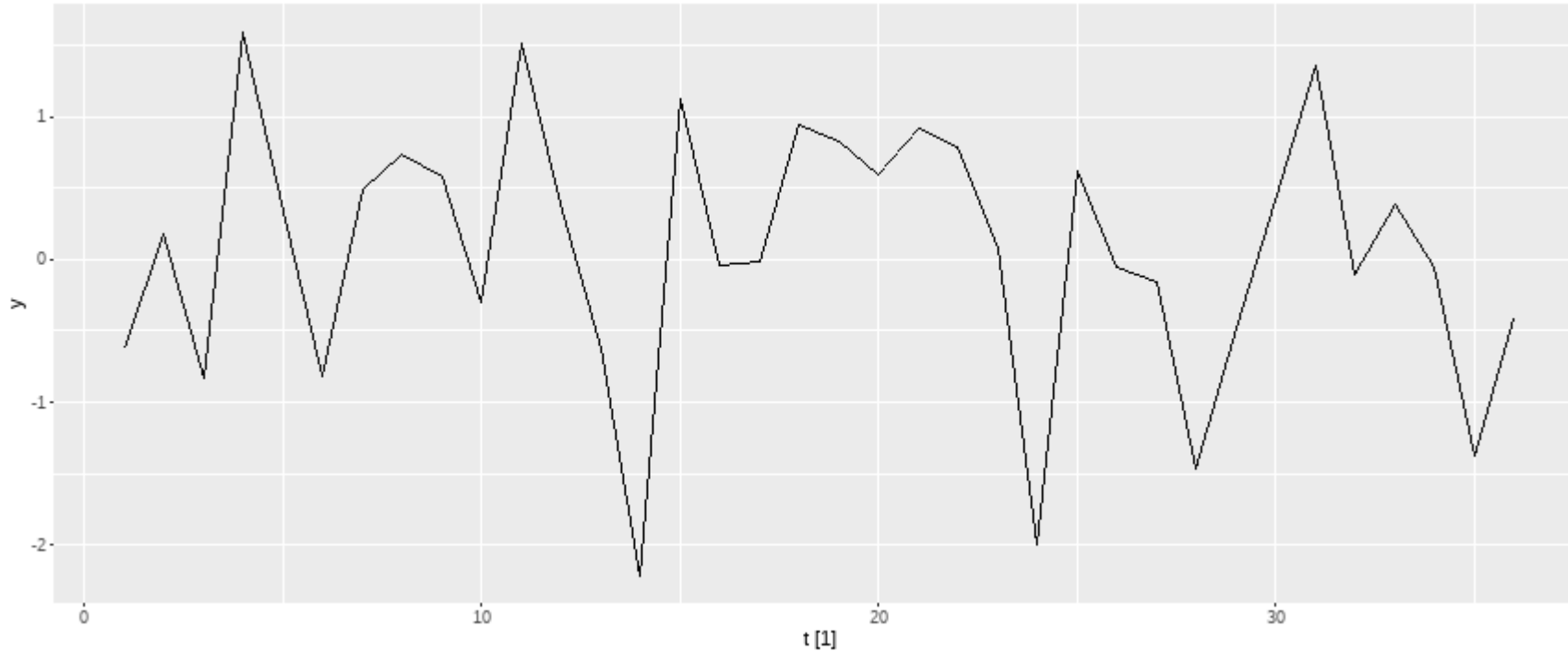
Google stock price



Australian monthly electricity production

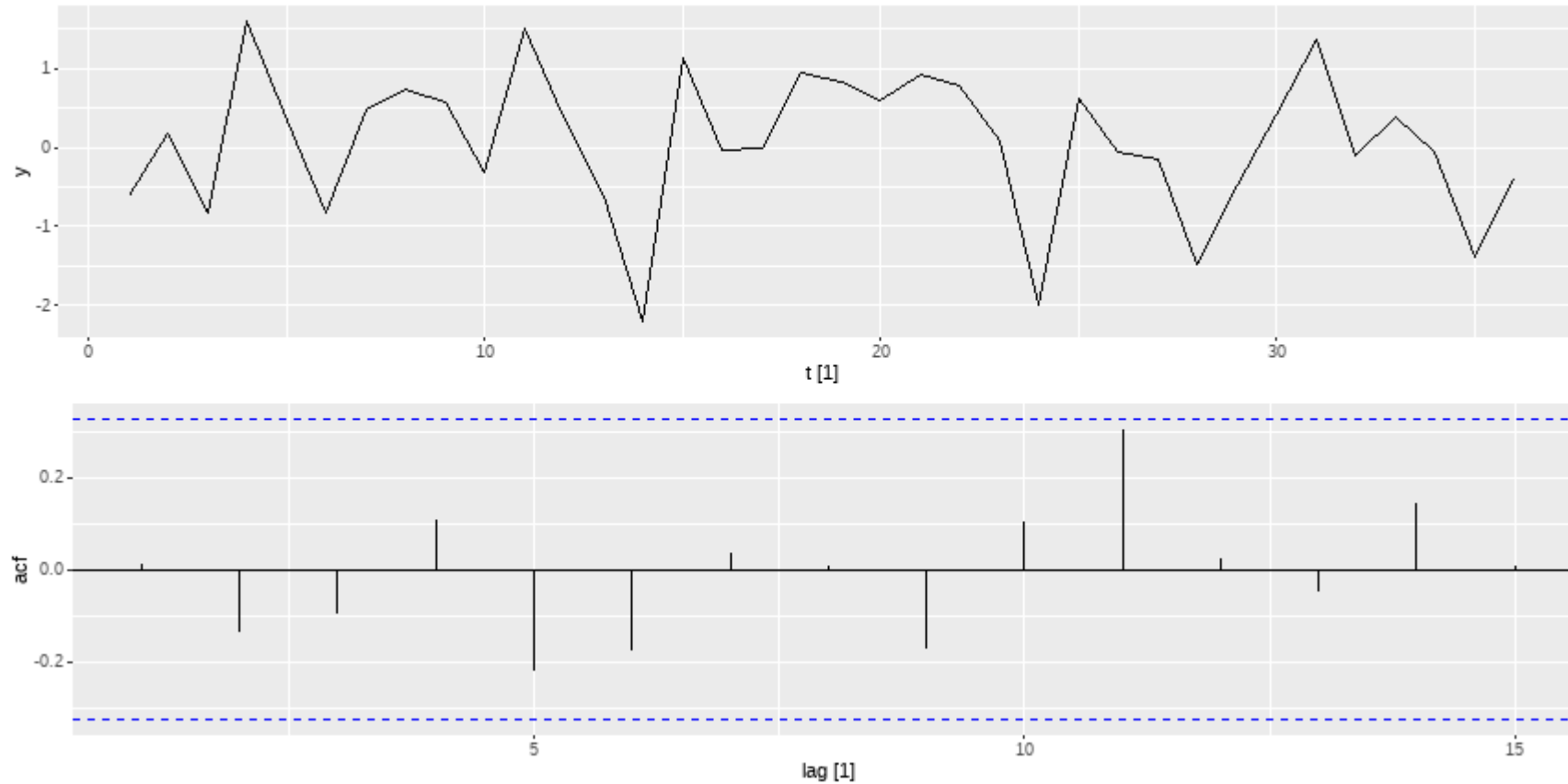


White noise



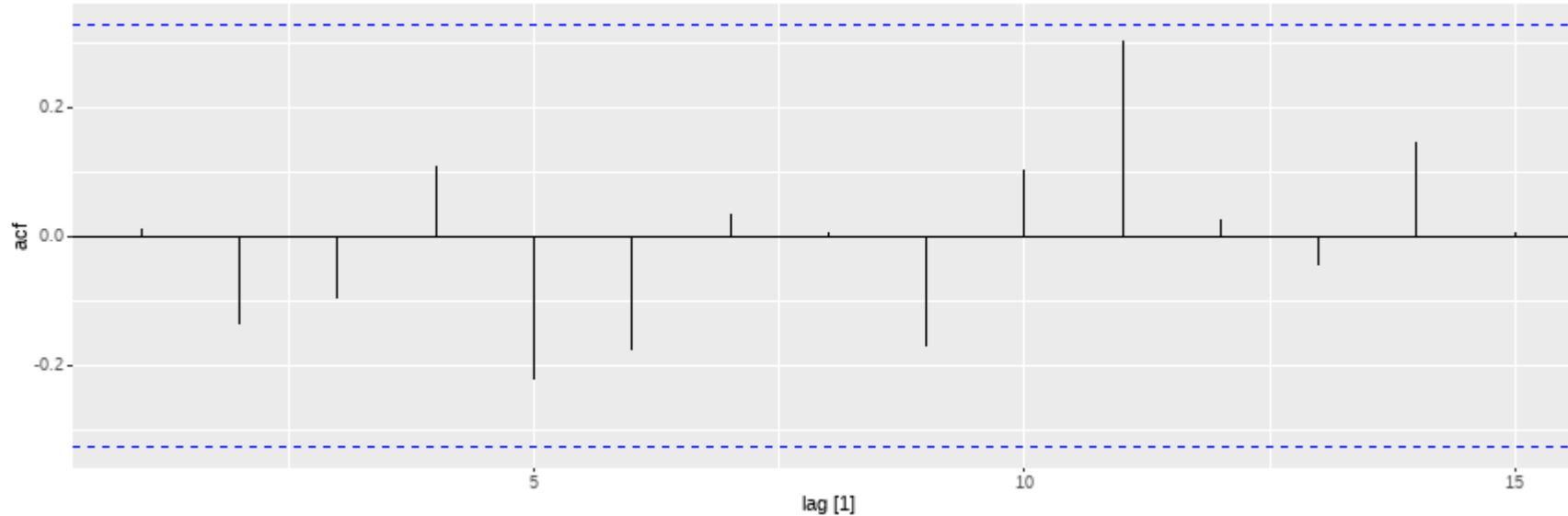
- ▶ **White noise data** is uncorrelated across time with zero mean and constant variance.
- ▶ Technically, we require independence as well.

Sample autocorrelations for white noise series



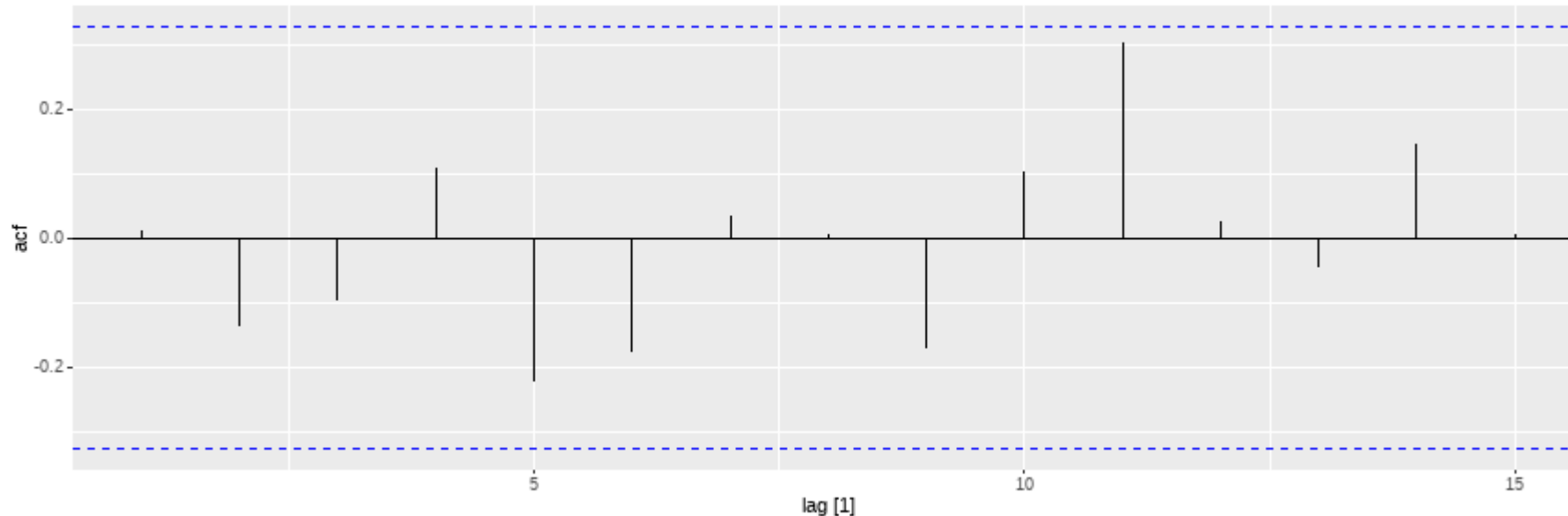
- ▶ For uncorrelated data, we would expect each one to be close to zero.
- ▶ Blue lines show 95% **critical values**.

Sampling distribution of autocorrelations



- ▶ 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**.

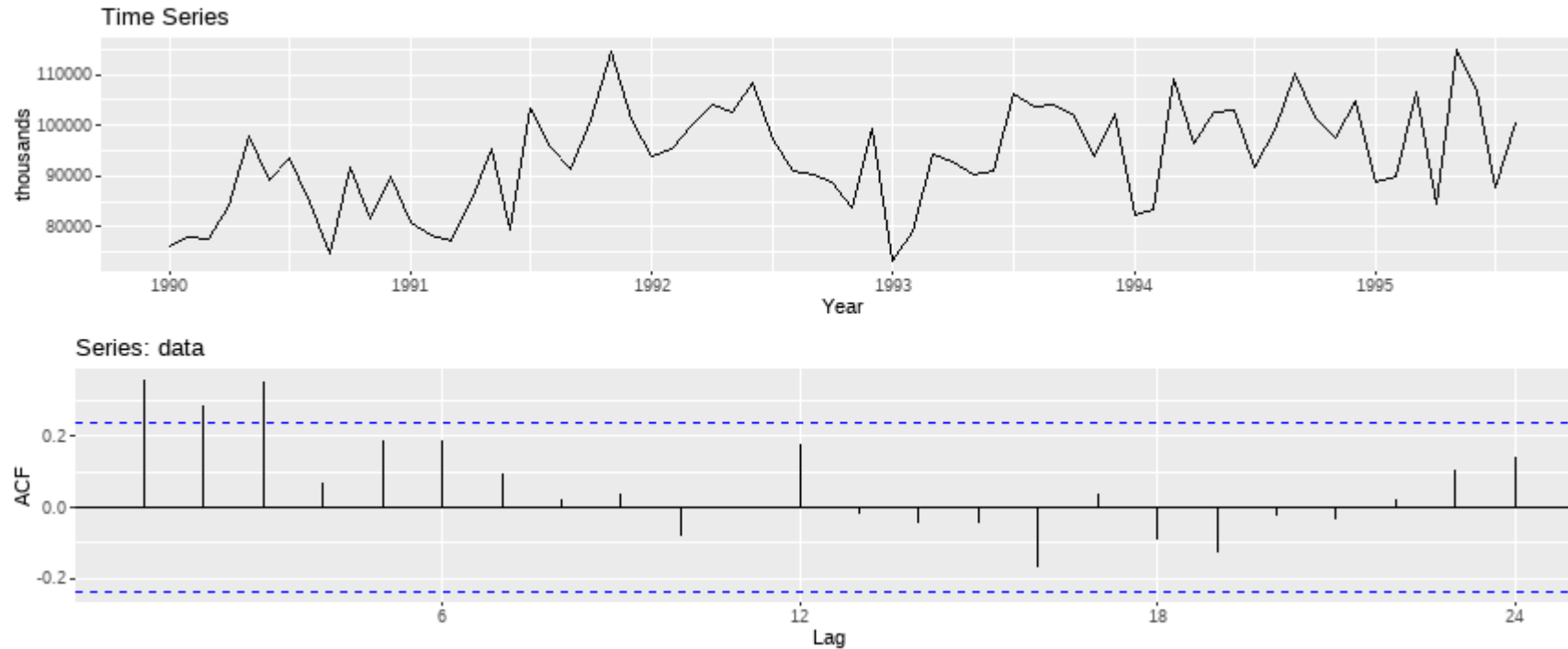
Sampling distribution of autocorrelations



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.)

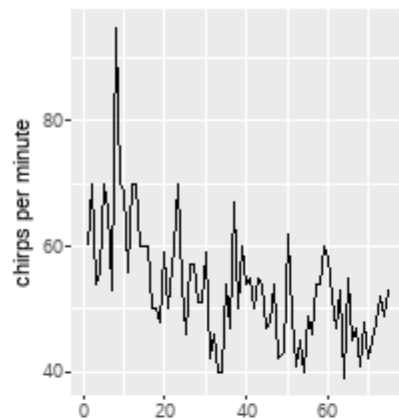
Example



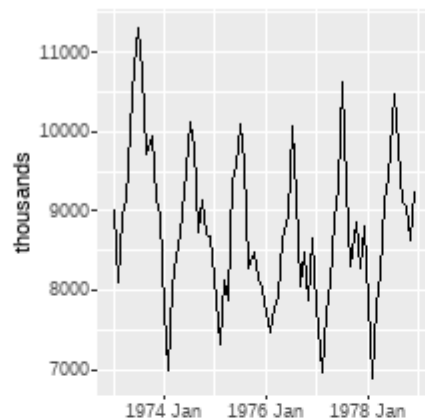
- ▶ Difficult to detect pattern in time plot.
- ▶ ACF shows some significant autocorrelation at lags 1, 2, and 3.
- ▶ r_{12} relatively large although not significant. This may indicate some slight seasonality.
- ▶ These show the series is **not a white noise series**.

Which is which?

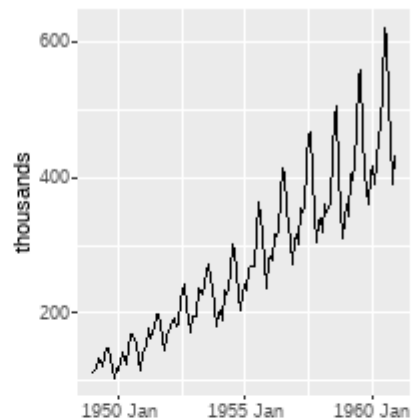
1. Daily temperature of cow



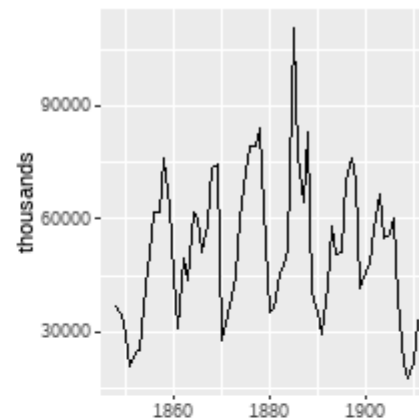
2. Monthly accidental deaths



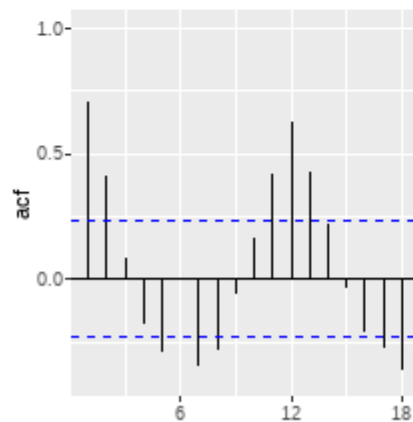
3. Monthly air passengers



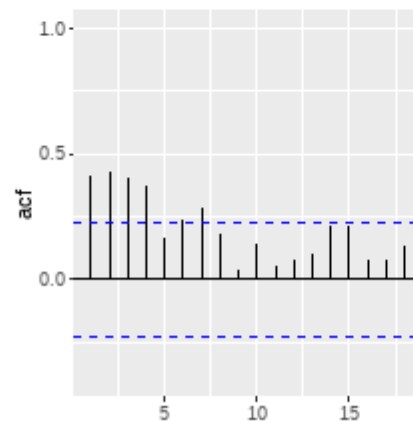
4. Annual mink trappings



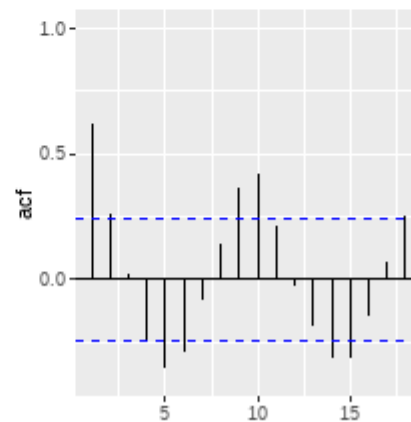
A



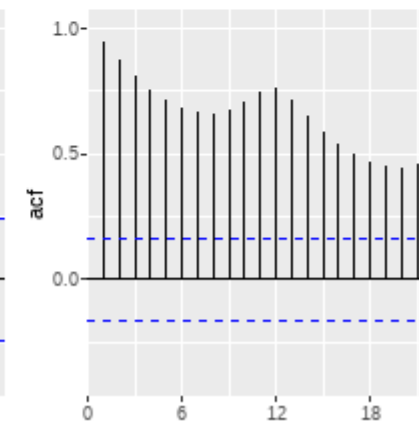
B



C



D



References

- ▶ Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: principles and practice. OTexts.
- ▶ Mathai, A. M., & Haubold, H. J. (2008). Applications to Stochastic Process and Time Series. Special Functions for Applied Scientists, 247-295.