MONASH University

MONASH BUSINESS SCHOOL

ETF3231/5231: Business forecasting

Ch2. Time series graphics

OTexts.org/fpp3/

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Outline

Outline

Time series in R

Included in week 1:

- `tsibble` objects
- The `tsibble` index

Outline

Graphics

- First in any modelling/forecasting task should be to plot your data.
- Plots allow us to identify:
  - Patterns;
  - Unusual observations;
  - Changes over time;
  - Relationships between variables.

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Patterns:

- trend
- seasonal
- cycles

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).

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

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The timing of peaks and troughs is predictable with seasonal data, but unpredictable in the long term with cyclic data.

Outline

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()`

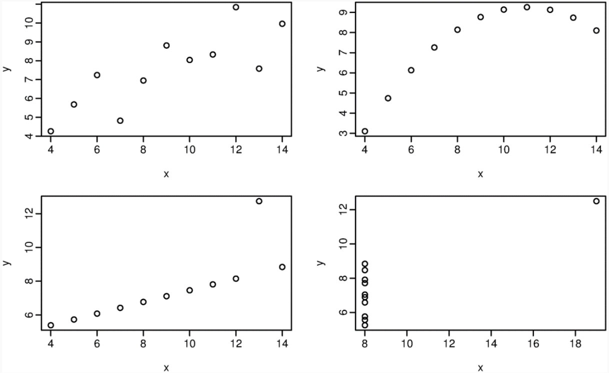
Seasonal subseries plots

- 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()`

Outline

Correlation coefficient

- Which one has the highest correlation?



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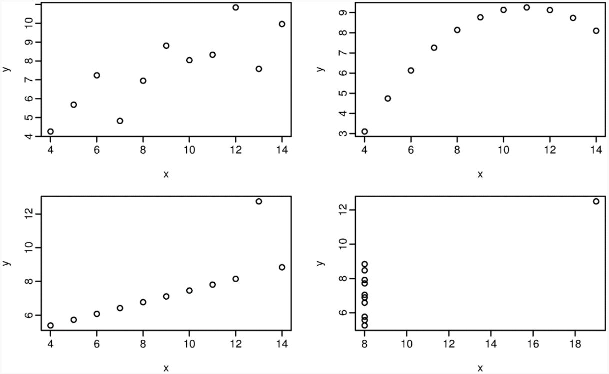

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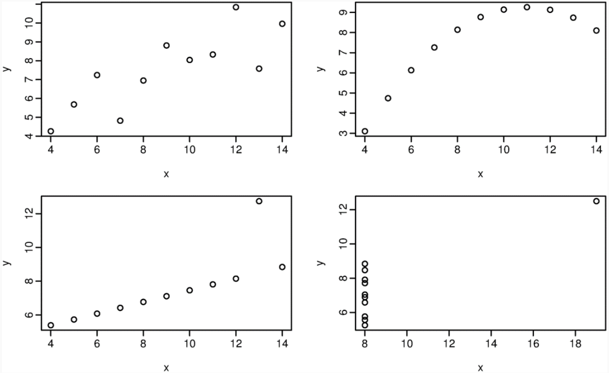

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All these have r = 0.82. Hence importance of plots.

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We measure the relationship between:

- y_t and y_{t-1}
- y_t and y_{t-2}
- y_t and y_{t-3}
- $\ldots$
- y_t and y_{t-k}
- etc.

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.

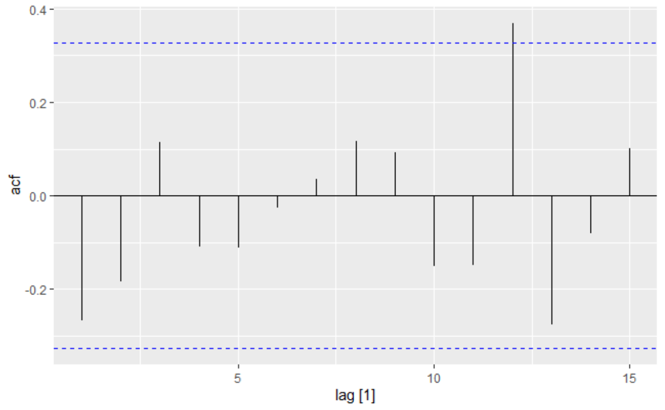
Outline

Example: White noise autocorrelation

Example:

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

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



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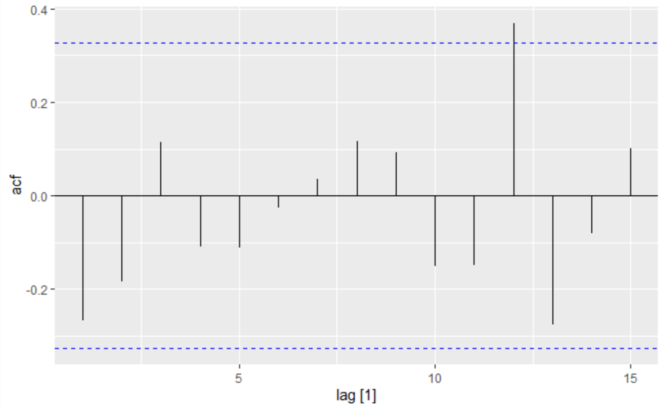


Note: 5% chance to be outside the critical values (Type I error). You want to see spikes a long way out or many of them. Don't get too excited for 1 just outside especially at longer lags.

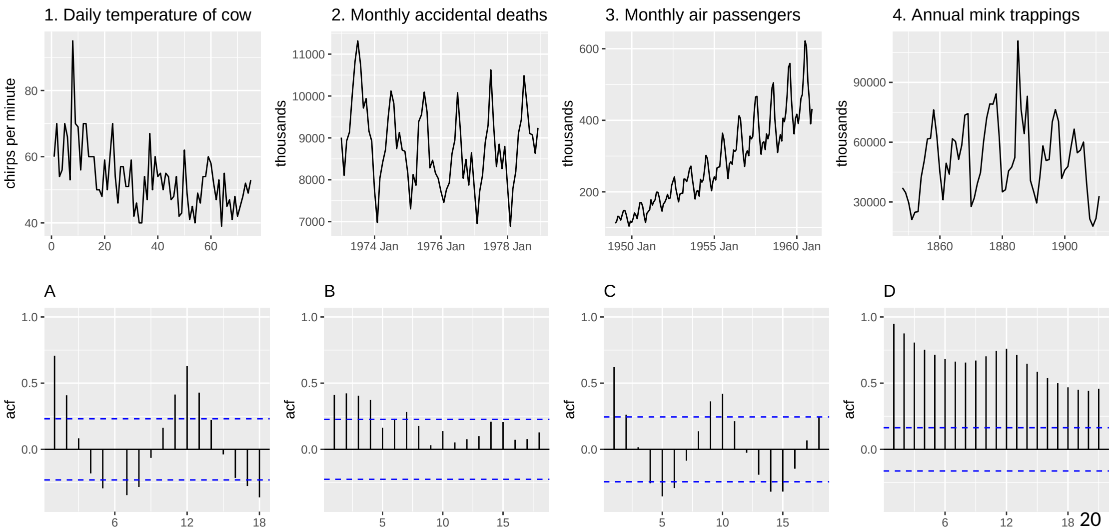
Your turn

1. We have introduced various functions for time series graphics include `autoplot()`, `gg_season()`, `gg_subseries()`, `gg_lag()` and `ACF`. Use these functions to explore the quarterly tourism data for the Snowy Mountains.

```r
snowy <- tourism |> filter(Region == "Snowy Mountains")
```

What do you learn?

Which is which?



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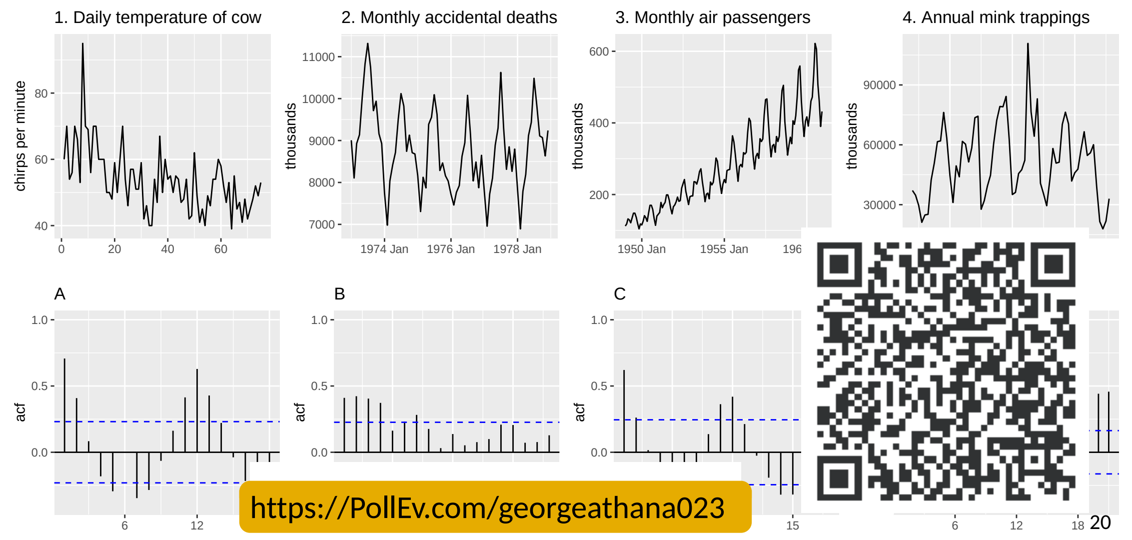

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Your turn

3. You can compute the daily changes in the Google stock price in 2018 using

```
dgoog <- gafa_stock |>
  filter(Symbol == "GOOG", year(Date) >= 2018) |>
  mutate(trading_day = row_number()) |>
  update_tsibble(index=trading_day, regular=TRUE) |>
  mutate(diff = difference(Close))
```

Does `diff` look like white noise?