Computing r_k

1. Plot the built-in `Nile` time series. Then make a lag plot of the series.
2. Compute the correlation of `Nile` with itself at lag $k = 1$.
3. Compute the autocorrelation of `Nile` at lag $k = 1$ with the formula $r_k = \frac{\sum(y_t - \bar{y})(y_{t+k} - \bar{y})}{\sum(y_t - \bar{y})^2}$
4. Compute the autocorrelation of `Nile` at lag $k = 1$ with `ACF` and compare with (2) and (3).
5. Plot the autocorrelogram of the `Nile` series.

souvenirs

The tsibble `souvenirs` is part of the `fpp3` package. It has monthly souvenir sales for a store in Australia.

1. Make a time plot of the series. Describe the seasonality.
2. The variance is clearly growing as the sales increase, so compute the log of the Sales variable.
3. Make an autocorrelogram of the log of Sales.
4. Take an STL decomposition of the log of Sales, and plot the components.
5. Make an autocorrelogram of the remainder component. Are there significant autocorrelations?
6. Perform a Ljung-Box hypothesis test using 24 lags to determine if the remainder is white noise.

Simulated models

For each time series model, do the following:

1. Generate the time series.
2. Plot a time plot of the series.
3. Plot a lag plot of the series out to lag 12.
4. Plot the autocorrelogram.
5. Discuss how the autocorrelogram relates to the model.

Here are three models:

- **Random walk:** Generate 100 standard random normals and then cumulatively sum them with `cumsum` to get $y_1, \ldots, y_{100}$.
- **Periodic:** Generate 11 standard random normals and then repeat those values (with `rep`) 9 times to get $y_1, \ldots, y_{99}$.
- **Moving Average:** Generate 101 standard random normals and then take a 2-MA to get $y_1, \ldots, y_{100}$.