The following Time Series Problems and Solutions are provided from the Textbook:

Forecasting: Principles and Practice (3rd ed)

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> Figure 1 shows the ACFs for 36 random numbers, 360 random numbers and 1,000 random numbers.

> a. Explain the differences among these figures. Do they all indicate that the data are white noise?

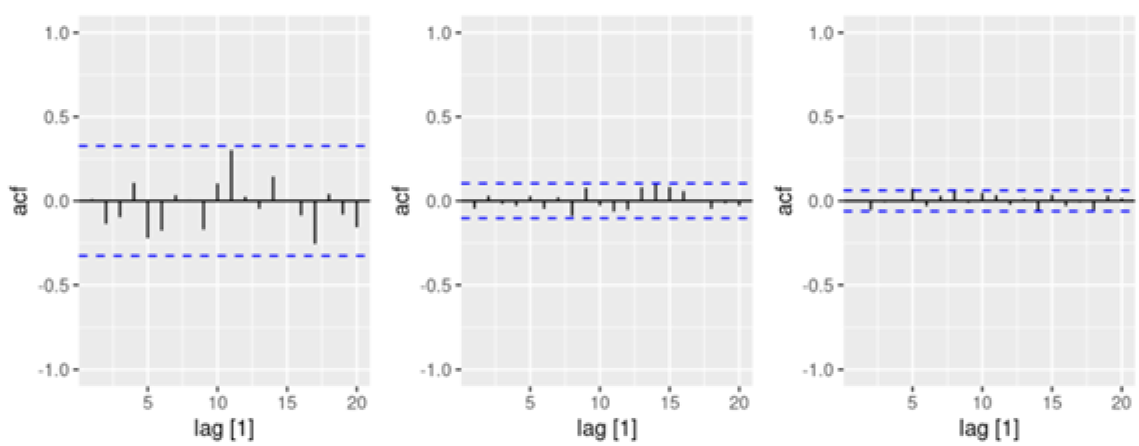


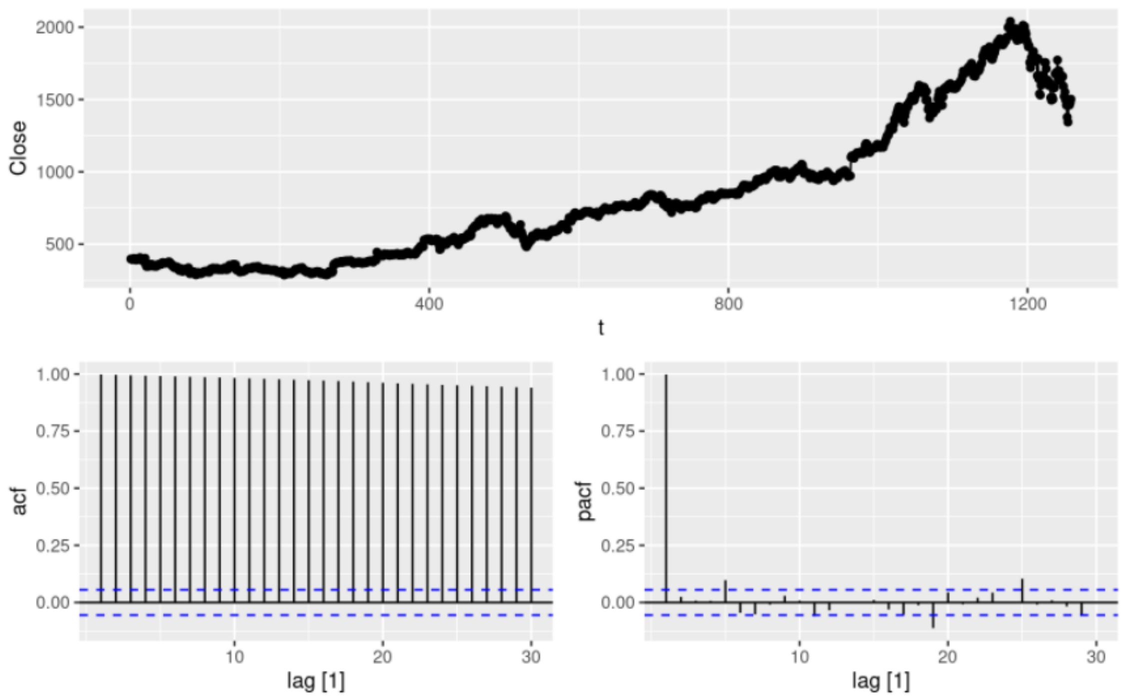
Figure 1: Left: ACF for a white noise series of 36 numbers. Middle: ACF for a white noise series of 360 numbers. Right: ACF for a white noise series of 1,000 numbers.

- The figures show different critical values (blue dashed lines).
- All figures indicate that the data is white noise.

> b. Why are the critical values at different distances from the mean of zero? Why are the autocorrelations different in each figure when they each refer to white noise?

- The critical values are at different distances from zero because the data sets have different number of observations. The more observations in a data set, the less noise appears in the correlation estimates (spikes). Therefore the critical values for bigger data sets can be smaller in order to check if the data is not white noise.

> A classic example of a non-stationary series are stock prices. Plot the daily closing prices for Amazon stock (contained in `gafa_stock`), along with the ACF and PACF. Explain how each plot shows that the series is non-stationary and should be differenced.



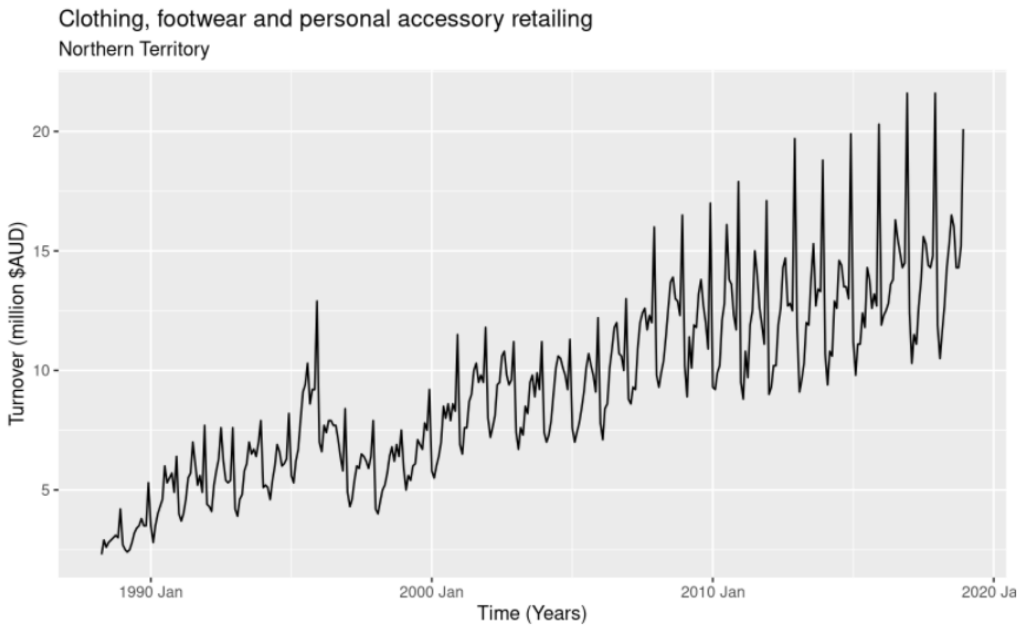
The time plot shows the series “wandering around”, which is a typical indication of non-stationarity. Differencing the series should remove this feature.

ACF does not drop quickly to zero, moreover the value r_1 is large and positive (almost 1 in this case). All these are signs of a non-stationary time series. Therefore it should be differenced to obtain a stationary series.

PACF value r_1 is almost 1. All other values $r_i, i > 1$ are small. This is a sign of a non-stationary process that should be differenced in order to obtain a stationary series.

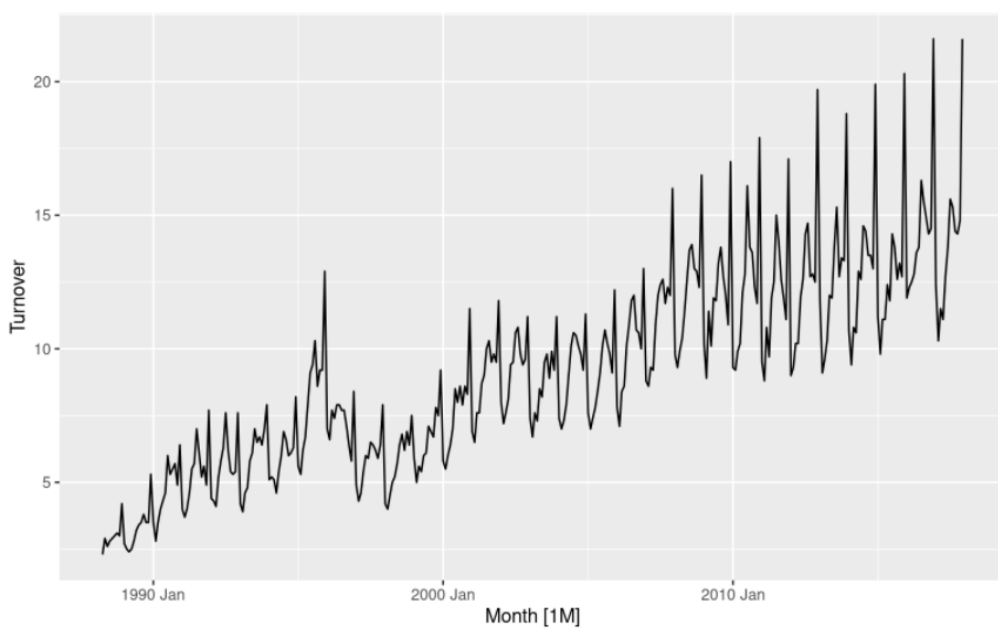
ACF(r1, *k*) = the ACF value at lag *k* for the time series in range r1
Learn more [here](#).

Monthly Australian retail data is provided in aus_retail.

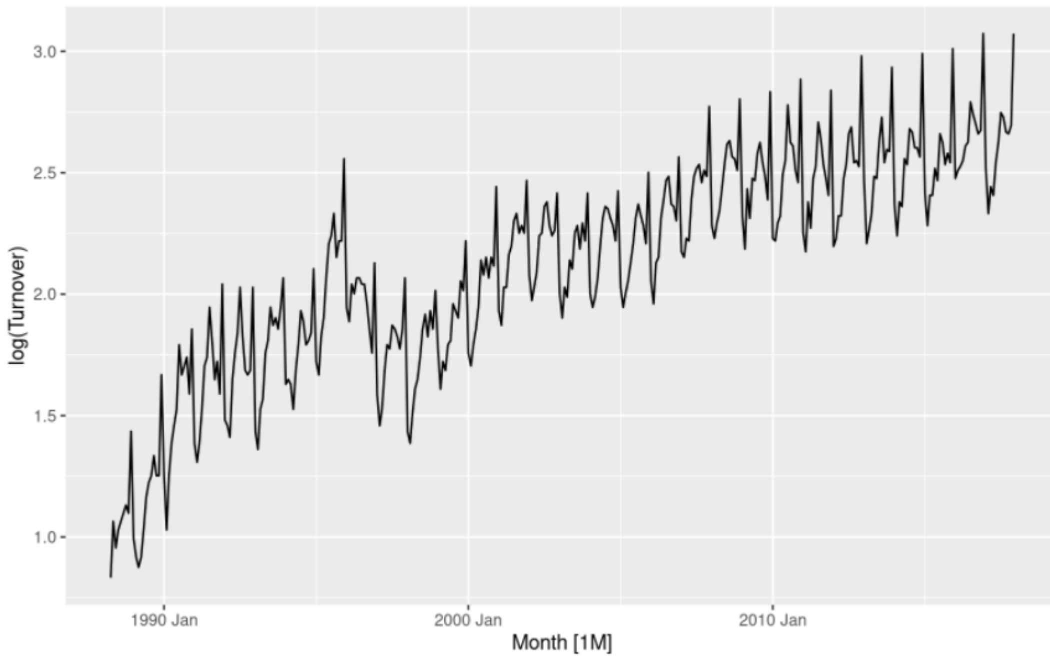


The data features a non-linear upward trend and a strong seasonal pattern. The variability in the data appears proportional to the amount of turnover (level of the series) over the time period.

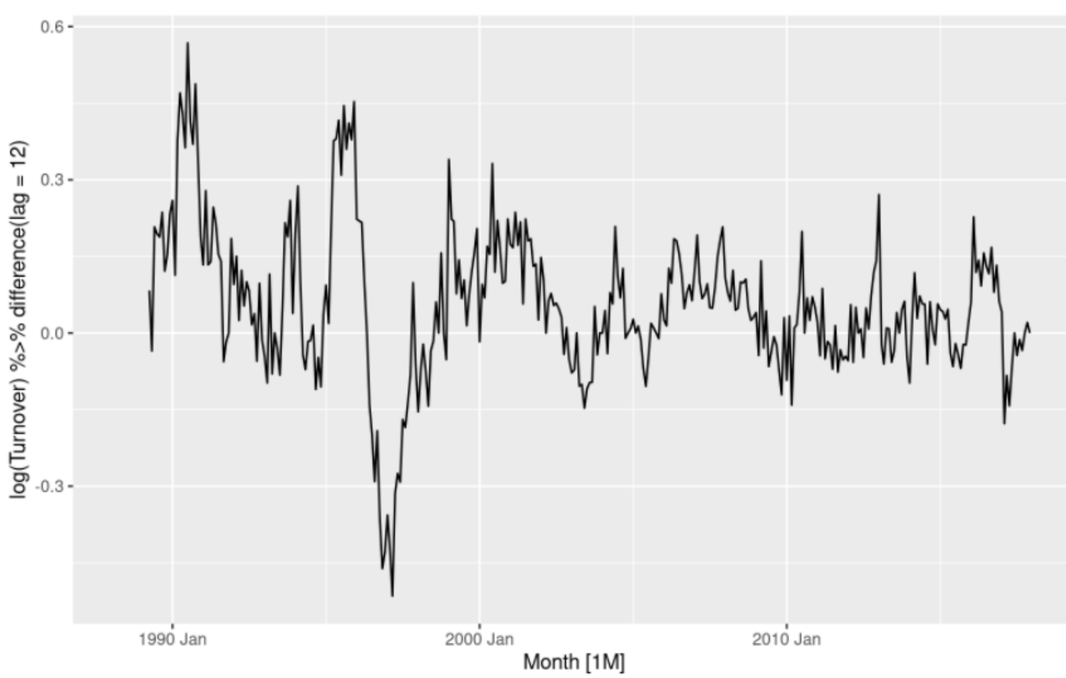
Find the appropriate order of differencing (after transformation if necessary) to obtain stationary data.



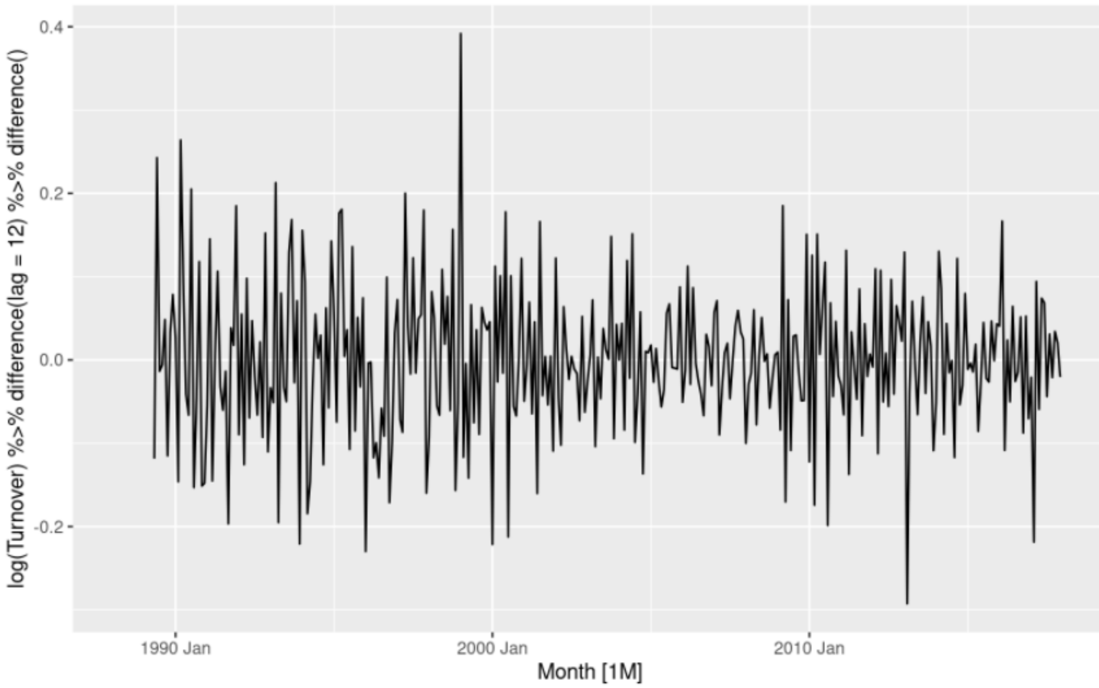
Data requires a transformation as the variation is proportional to the level of the series. A log transformation will be okay, although it does seem to be too strong.



Data contains seasonality, so a seasonal difference is required.



Data still appears to have extended periods of high values and low values. A first order differencing may be useful.



The dataset is now clearly stationary. Either just a seasonal difference, or both a seasonal and first difference, could be used here.