Stationarity and differencing

Stationary time series is a time series that does not depend on the time at which a series is observed. Trend and seasonality make it non-stationary; cyclic patterns are considered stationary. Generally, stationary time series will be roughly horizontal and constant variance.

Log transformations help stabilize a time series by reducing variance and differencing helps to stabilize the mean of a time series by removing changes in the level of a time series eliminating/reducing trend and seasonality.

To help determine stationarity, we use the ACF and PACF plots. In a stationary time series, the ACF plot will drop to zero quickly versus gradually for non-stationary plots. The value of r1 is generally large and positive for non-stationary also.

Unit root test can be utilized to determine if differencing need to be done. By running the ur.kpss() function in r, you are assuming a null hypothesis of the data being stationary. So if the test-stat is less than 0.5 the data is stationary

AutoRegression models

The term autoregression indicates that it is a regression of a variable against itself. So the variable of interest is plotted linearly with a combination of past values of the same variable. Referred to as **AR(p) model.**

Moving average models

Moving average models utilize past forecast errors in a regression-like model instead of using past values. Referred to as **MA(q) model**.

Non-seasonal ARIMA model

We can combine difference, autoregression, and moving average models to create the ARIMA model. ARIMA stands for AutoRegressive Integrated Moving Average. Referred to as **ARIMA(p,d,q) model.**

* P – order of the autoregressive part
* D – degree of first differencing involved
* Q – order of the moving average part

Special case ARIMA models

* White noise – ARIMA(0, 0, 0)
* Random Walk – ARIMA(0, 1, 0) with no constant
* Random Walk with drift – ARIMA(0, 1, 0) with a constant
* Autoregression – ARIMA(p, 0, 0)
* Moving Average – ARIMA(0, 0, q)