ETC3550/ETC5550 Applied forecasting

Week 8: ARIMA models

ARIMA models

AR: autoregressive (lagged observations as inputs)
I: integrated (differencing to make series stationary)
MA: moving average (lagged errors as inputs)

An ARIMA model is rarely interpretable in terms of visible data structures like trend and seasonality. But it can capture a huge range of time series patterns.

Stationarity

Definition

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Transformations help to **stabilize the variance**.

For ARIMA modelling, we also need to **stabilize the mean**.

Non-stationarity in the mean

Identifying non-stationary series

- time plot.
- The ACF of stationary data drops to zero relatively quickly
- The ACF of non-stationary data decreases slowly.
- For non-stationary data, the value of r_1 is often large and positive.

Differencing

Differencing

- Differencing helps to **stabilize the mean**.
- First differencing: *change* between consecutive observations: $y'_t = y_t - y_{t-1}$.
- Seasonal differencing: *change* between years: $y'_t = y_t - y_{t-m}$.
- Sometimes two differences need to be applied (but never more).

Automatic differencing

Statistical tests to determine the required order of differencing.

1. Augmented Dickey Fuller test: null hypothesis is that the data are **non-stationary** and non-seasonal.
2. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test: null hypothesis is that the data are **stationary** and non-seasonal.

Seasonal strength

STL decomposition: $y_t = T_t + S_t + R_t$

Seasonal strength $F_s = \max\left(0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(S_t + R_t)}\right)$

If $F_s > 0.64$, do one seasonal difference.

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R commands

- Lag 1 difference: `difference(y)`
- Seasonal difference: `difference(y, lag = 4)`
- KPSS test: `unitroot_kpss(y)`
- Seasonal strength: `feat_stl(y, .period = 4)`
- Automatic first differencing: `unitroot_ndiffs(y)`
- Automatic seasonal differencing: `unitroot_nsdiffs(y, .period = 4)`

Relationship to random walks

A random walk is the process:

$$y_t = y_{t-1} + \varepsilon_t$$

where ε_t is a white noise variable.

So if data did come from such a process, differencing would give white noise:

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Relationship to random walks

A seasonal random walk is the process

$$y_t = y_{t-m} + \varepsilon_t$$

where ε_t is a white noise variable.

So if data did come from such a process, seasonal differencing would give white noise:

$$y_t - y_{t-m} = \varepsilon_t$$