Time Series ARMA

Moving Average (MA) models

For AR models we considered models of the form:

$$y_t = w_0 + w_1 y_{t-1} + \ldots + w_p y_{t-p} + \text{noise}_t$$

So the past *p* observations were used as inputs. In MA(q) models we take a different approach:

$$y_t = \text{noise}_t + \theta_1 \text{noise}_{t-1} + \ldots + \theta_q \text{noise}_{t-q}$$

MA(q) models are more difficult to fit because the noise terms are not observed.

CAMBRIDGE SPARK

Autoregression Moving Average (ARMA) models

These try to combine AR and MA models together!

Idea: AR model accounts for autoregressive component. Then MA fits any trends in the noise which we cannot explain with the AR model!

Idea: sometimes we can use the error at time *t-1* as a valuable predictor for time *t*!

Example: assume we have an AR(p) model that does a reasonable job, but always over-predicts according to the latest error! We can use an MA model to account for this!

CAMBRIDGE SPARK

Autoregression with more features

These try to combine AR and MA models together!

Idea: AR model accounts for autoregressive component. Then MA fits any trends in the noise which we cannot explain with the AR model!

$$y_t = c + \underbrace{\phi_1 y_{t-1} + \cdots + \phi_p y_{t-p}}_{AR(p)} + \underbrace{\theta_1 e_{t-1} + \cdots + \theta_q e_{t-q}}_{MA(q)} + e_t,$$

This cannot be mapped directly to a Linear Regression therefore finding the coefficients is more complicated.

CAMBRIDGE SPARK

Hands-on session

time_series_autoregression.ipynb

CAMBRIDGE SPARK