ADVANCED FINACIAL MODELING
LECTURE 4: PARAMETRIC AND NONPARAMETRIC MODELING: MODELING APPROACHES FOR TIME SERIES

Modelling approaches

- Persistence
- Climatology
- Linear regression
- Autoregressive (AR) models
- Moving average (MA) models
- Autoregressive moving average (ARMA) models
- Seasonal ARMA (SARMA) models
- Regime switching models (TAR, SETAR, MS-AR)
- Analogue prediction models
- Exponential smoothing (Single, Trend, Trend/Seasonality)

Forecasting: Principles and Practise

- Understanding key forecasting terminologies
- Tools for analysing time series
- Importance of using naïve benchmarks
- Parameter estimation based on in-sample probabilistic forecast accuracy
- Direct versus iterative forecasting scheme
- Generating multistep ahead probabilistic forecasts using nonlinear models
- Model evaluation based on point, quantile and density forecasts
- Modelling time series with multiple seasonal cycles
- Evaluating forecasts across different horizons (leadtimes) using performance scores

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- Rule-based forecasting
- Handling anomalous, missing, and irregular sampled observations
- Machine learning algorithms for time series forecasting

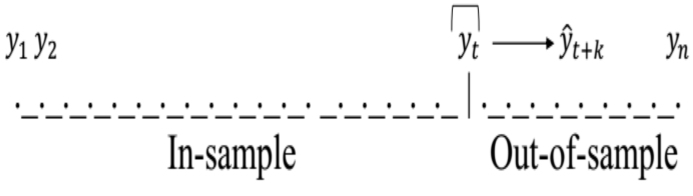
Forecast benchmarks

- It is important to compare models against naïve benchmarks
- Any new method may appear useful until it is compared to some simple benchmarks
- These benchmarks serve to establish levels of forecast performance that can be easily achieved without a complicated mathematical model
- They should also be robust
- We discuss the seasonal and non-seasonal variants of the following two benchmarks – persistence and climatology

Persistence (Random walk benchmark)

- The persistence forecast corresponds to assuming that the underlying dynamics are generated by a random walk
- The best guess forecast is simply the last available observation

$$y_t \to \hat{y}_{t+k}$$



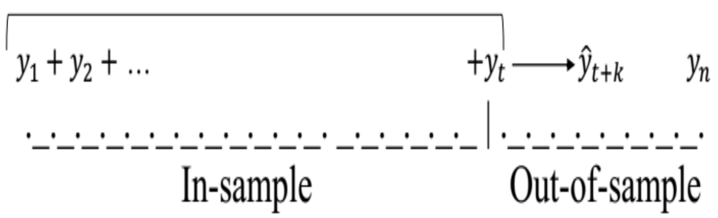
Persistence

- The persistence benchmark is common in meteorology
- To issue a forecast for tomorrow's stock price at say 1pm, issue today's stock price observed at 1pm as a forecast
- If the time series have an underlying seasonality, then the persistence forecast should take this into account (seasonal random walk)

Climatology (Unconditional mean benchmark)

- The unconditional average represents the expected value of the unconditional distribution. For density forecasting, issue the distribution of in-sample observations as a forecast for out-of-sample data.

$$\frac{1}{t}\sum_{i=1}^{t} y_i \rightarrow \hat{y}_{t+k}$$

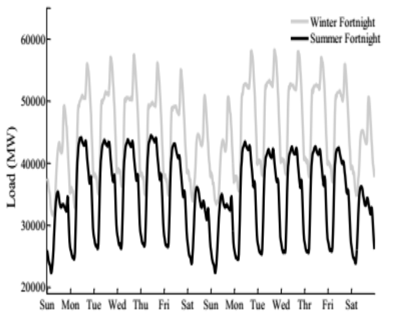


Climatology

- This forecast assumes that the time ordering of the observations do not provide any additional information
- In meteorology, this is the climate forecast
- One may consider taking mean of only previous p observations, where p is estimated using cross-validation
- It is also important to include seasonal effects
- A statistical model is useful for horizons up to which it is significantly more accurate than the naïve benchmarks

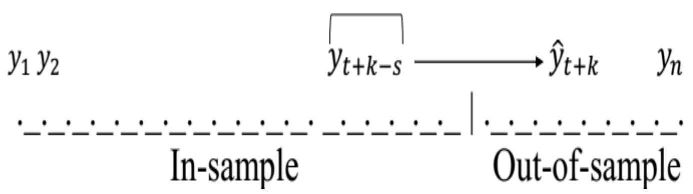
Seasonal random walk

- We need to adapt the persistence and climatology benchmarks for seasonal time series



- If a time series exhibits seasonality (having period s), using seasonal random walk, we issue the most recent observation belonging to the same period of the seasonal cycle as a forecast. For example, to issue a forecast for tomorrow's (Wednesday) load at say 1pm, issue load observed on last Wednesday at 1pm as a forecast

$$y_{t+k-s} \rightarrow \hat{y}_{t+k}$$



Seasonal moving average

- If a time series exhibits seasonality (having period s), using seasonal moving average, we issue the mean of p most recent available observation belonging to the same period as a forecast. For example, to issue a forecast for tomorrow's (Wednesday) load at say 1pm, issue load observed at 1pm on last p Wednesday's as a forecast

$$\frac{1}{p}\sum_{i=1}^{p} y_{t+k-i\times s} \rightarrow \hat{y}_{t+k}$$