

Time Series Analysis

Basics

Sample Autocorrelations

$$\begin{aligned}\gamma_0 &= \frac{1}{N} \sum_{t=1}^N (x_t - \bar{x})^2 \\ \gamma_k &= \frac{1}{N} \sum_{t=1}^{N-k} (x_t - \bar{x})(x_{t+k} - \bar{x}) \\ \rho_0 &= 1 \\ \rho_k &= \frac{\gamma_k}{\gamma_0} \\ \hat{\sigma}_X^2 &= \frac{\hat{\sigma}^2}{n} \left(1 + 2 \sum_{k=1}^{n-1} \left(1 - \frac{|k|}{n} \hat{\rho}_k \right) \right) \\ CI : \bar{X} \pm 1.96 \sqrt{\frac{\hat{\sigma}^2}{n} \left(1 + 2 \sum_{k=1}^{n-1} \left(1 - \frac{|k|}{n} \hat{\rho}_k \right) \right)}\end{aligned}$$

Autoregressive Models

AR(1) Models

$$\begin{aligned}X_t - \phi X_{t-1} &= a_t \\ (1 - \phi z) &= 0 \\ \rho_0 &= 1 \\ \rho_k &= \phi_1^k \\ \sigma_X^2 &= \frac{\sigma_a^2}{1 - \phi_1^2}\end{aligned}$$

AR(1) Properties

- Positive ϕ
 - Realizations appear to be wandering (aperiodic)
 - Autocorrelations are damped exponentials
 - Spectral densities have peaks at zero
- Negative ϕ
 - Realizations appear to be oscillating
 - Autocorrelations are damped oscillating exponentials
 - Spectral densities have peaks at $f = 0.5$

AR(2) Models

$$\begin{aligned}X_t - \phi_1 X_{t-1} - \phi_2 X_{t-2} &= a_t \\ (1 - \phi_1 z - \phi_2 z^2) &= 0 \\ \rho_0 &= 1 \\ \rho_1 &= \frac{\phi_1}{1 - \phi_2} \\ \rho_2 &= \frac{\phi_1^2 + \phi_2 - \phi_2^2}{1 - \phi_2} \\ \sigma_X^2 &= \frac{1}{1 - \phi_1 \rho_1 - \phi_2 \rho_2}\end{aligned}$$

AR(2) Properties

- Two Real Roots - Both Pos
 - The realization will appear to be wandering
 - The autocorrelations will be exponentially damped
 - There will be a peak at 0
- Two Real Roots - Both Neg
 - The realization will appear to be oscillating
 - The autocorrelations will be damped oscillating exponentials
 - There will be a peak at 0.5
- Two Real Roots - One Each
 - The realization will appear to be wandering and an oscillation will run on the realization
 - The autocorrelations will be exponentially damped with a hint of oscillation
 - There will be peaks at 0 and 0.5 in the spectral density
- One Complex
 - The realization will appear to have a pseudo-cyclic behavior with a cycle length of $\frac{1}{f_0}$
 - The autocorrelations will be damped exponentials oscillating in a sinusoid envelope with a frequency of f_0
 - There will be a peak at f_0 (between 0 and 0.5)

$$f_0 = \frac{1}{2\pi} \cos^{-1} \left(\frac{\phi_1}{2\sqrt{-\phi_2}} \right)$$

AR(p) Models

$$\begin{aligned}X_t - \beta + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots + \phi_p X_{t-p} &= a_t \\ x_t - \phi_1 B X_t - \phi_2 B^2 X_t - \dots - \phi_p B^p X_t &= a_t\end{aligned}$$

Key Concepts

- An AR(p) model is stationary if and only if all the roots of the characteristic equation are outside the unit circle.
- Any AR(p) characteristic equation can be numerically factored into 1st and 2nd order elements.
- These factors are interpreted as contributing AR(1) and AR(2) behaviors to the total behavior of the AR(p) model.

Factor Contributions

AR(p) models reflect a contribution of AR(1) and AR(2) contributions. Roots that are close to the unit circle will be the dominate behavior.

- First order factors $(1 - \phi_1 B)$
 - Associated with real roots
 - Contribute AR(1)-type behavior to the AR(p) model
 - Associated with a system frequency of 0 if ϕ_1 is positive or 0.5 if ϕ_1 is negative
- Second order factors $(1 - \phi_1 B - \phi_2 B^2)$
 - Associated with complex roots
 - Contribute cyclic AR(2) behavior to the AR(p) model
 - Associated with a system frequency of f_0

Moving Average Models

MA(1) Models

$$\begin{aligned}X_t &= a_t - \theta a_{t-1} \\ (1 - \theta_1 z) &= 0 \\ \rho_0 &= 1 \\ \rho_1 &= \frac{-\theta_1}{1 + \theta_1^2} \\ \rho_k &= 0 |_{k>1} \\ \sigma_X^2 &= \sigma_a^2 (1 + \theta_1^2)\end{aligned}$$

MA(2) Models

$$\begin{aligned}X_t &= a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} \\ (1 - \theta_1 z - \theta_2 z^2) &= 0 \\ \rho_0 &= 1 \\ \rho_1 &= \frac{-\theta_1 + \theta_1 \theta_2}{1 + \theta_1^2 + \theta_2^2} \\ \rho_2 &= \frac{-\theta_2}{1 + \theta_1^2 + \theta_2^2} \\ \rho_k &= 0 |_{k>2} \\ \sigma_X^2 &= \sigma_a^2 (1 + \theta_1^2 + \theta_2^2)\end{aligned}$$

MA(q) Models

X_t = a_t - \theta_1 a_{t-1} - ... - \theta_q a_{t-q}

x_t = a_t - \theta_1 B a_t - ... - \theta_q B^q X_t

Key Concepts

- MA models are a finite GLP
- MA models are always stationary
- MA models are invertable iff all the roots are outside of the unit circle.

MA Inversion

- Real Root: use 1/\theta
- Complex Roots: use \theta_1 = r_1^{-1} + r_2^{-1} and \theta_2 = -r_1^{-1} r_2^{-1}

ARMA(p,q) Models

X_t = \beta + \phi_1 X_{t-1} + ... + \phi_p X_{t-p} = a_t - \theta_1 a_{t-1} - ... - \theta_q a_{t-q}

x_t - \phi_1 B X_t - ... - \phi_p B^p X_t = a_t - \theta_1 B a_t - ... - \theta_q B^q X_t

Key Concepts

- Valid when the model is stationary and invertable
 - Stationary: roots of \phi(z) are outside the unit circle
 - Invertable: roots of \theta(z) are outside the unit circle
- \phi(z) and \theta(z) have no common factors (check)

ARIMA

General Form

\phi(B)(1-B)^d X_t = \theta(B) a_t

Properties

- The roots on the unit circle dominate the behavior of the realization
- The autocorrelations are defined to have a magnitude of 1 (\rho_k = 1)
- The variance of ARIMA is not well defined

ARUMA

ARUMA is an generalization of ARIMA that includes a term or term(s) for seasonality.

\phi(B)(1-B)^d(1-B^s) X_t = \theta(B) a_t

Monthly Seasonality

(1-B^4) = (1-B)(1+B)(1+B^2)

General Linear Processes

General Form

Use psi.weights.wge to calculate \psi s

X_t - \mu = \sum_{j=0}^{\infty} \psi_j a_{t-j}

- An MA model can be represented as finite GLP
- An AR model can be represented as infinite GLP

Forecasting

Notation

- t_0 - origin of the forecast
- l - number of time units to forecast (lead time)
- \hat{X}_{t_0}(l) - the forecast of X_{t_0+l} given data up to t_0

ARMA Forecasting

Use fore.arma.wge() for forecasting.

\hat{X}_{t_0}(l) = \sum_{i=1}^p \phi_i \hat{X}_{t_0}(l-i) - \sum_{j=1}^q \theta_j \hat{a}_{t_0+l-j} + \bar{x} \left[1 - \sum_{i=1}^p \phi_i \right]

\hat{\sigma}_a^2 = \frac{1}{n-p} \sum_{t=p+1}^n \hat{a}_t^2

Facts

e_{t_0}(l) = X_{t_0+l} - \hat{X}_{t_0}(l)

var[e_{t_0}(l)] = \sigma_a^2 \sum_{j=0}^{l-1} \psi_j^2

FI : \hat{X}_{t_0}(l) \pm z_{1-\alpha/2} \sigma_a \left[\sum_{k=0}^{l-1} \psi_k^2 \right]^{1/2}

ARIMA Forecasting

Use fore.aruma.wge() for forecasting.

- Limits become unbounded as l increases
- A factor of (1-B) does not forecast a trend. An order of d > 1 is required to forecast a trend.

ARIMA with Seasonality Forecasting

The forecast for step l is same as the last s value. Use fore.aruma.wge() for forecasting.

- Limits become unbounded as l increases
- A factor of (1-B) does not forecast a trend. An order of d > 1 is required to forecast a trend.
- (1-B)(1-B^s) = a_t is called an airline model.

Linear Forecasting

Use fore.sigplusnoise.wge() for forecasting.

- Fit an OLS to X_t
- Fit an AR(p) to the residuals (Z_t)

\hat{X}_{t_0}(l) = b_0 + b_1 t + \hat{Z}_{t_0}(l)

FI : b_0 + b_1 t + \hat{Z}_{t_0}(l) \pm z_{1-\alpha/2} \hat{\sigma}_a \left[\sum_{k=0}^{l-1} \psi_k^2 \right]^{1/2}

Filtering

Filters transform time series.

Z_t \rightarrow H(B) \rightarrow X_t

X(t) = Z(t)H(B)

There are four basic types of filters.

- High pass - filters out low frequencies
- Low pass - filters out high frequencies
- Band pass - filters out frequencies outside the band
- Band stop - filters out frequencies inside the band

Difference Filter

The first order difference is expressed by the following

X_t = Z_t - Z_{t-1}

H(B) = B^0 - B

This is a high pass filter.

Moving Average Filter

A 5-point moving average filter can be expressed as

X_t = \frac{Z_{t+2} + Z_{t+1} + Z_t + Z_{t-1} + Z_{t-2}}{5}

H(B) = \frac{B^{-2} + B^{-1} + B^0 + B + B^2}{5}

This is a low pass filter.

Band-Type Filter

High pass and low pass filters can be combined to produce band pass and band stop filters.