Time Series Analysis

Teaching Session II: ARIMA models-3 Seasonal models

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- Seasonal patterns
 - ► Yearly (ocean temperature)
 - ► Daily, weekly (Server workload)
- Strong correlation of x_t and x_{t+s}
 - ► *s* = 12, 24, ...

- Applications
 - ► Physics, biology, economics, computer science

• Pure seasonal $ARMA(P, Q)_s$

$$\Phi_p(B^s)x_t = \theta_Q(B^s)w_t$$

Seasonal autoregressive operator

$$\Phi_p(B^s) = 1 - \Phi_1(B^{(1 \cdot s)}) - \dots - \Phi_p B^{P \cdot s}$$

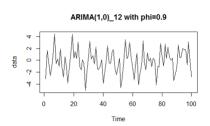
Seasonal moving average operator

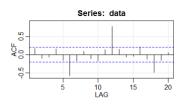
$$\Theta_Q(B^s) = 1 + \Theta_1(B^{(1 \cdot s)}) - \dots - \Theta_Q B^{Q \cdot s}$$

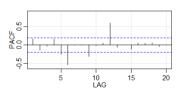
- Same principles for causality and invertibility
- Example: $ARMA(1,0)_{12}$ and $ARMA(0,1)_{12}$
 - Autocovariance



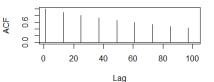
• Example: Simulated $ARMA(1,0)_{12}, \Phi = 0.9$

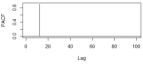






- Example: Simulated $ARMA(1,0)_{12}, \Phi = 0.9$
 - ► Theoretical ones





	$AR(P)_s$	$MA(Q)_s$	$ARMA(P,Q)_s$
ACF*	Tails off at lags ks , $k = 1, 2, \dots$,	Cuts off after $\log Qs$	Tails off at lags ks
PACF*	Cuts off after $\log Ps$	Tails off at lags ks $k = 1, 2, \dots,$	Tails off at lags ks

^{*}The values at nonseasonal lags $h \neq ks$, for k = 1, 2, ..., are zero.

Multiplicative seasonal ARMA

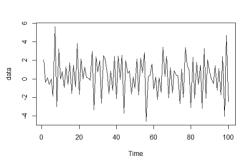
- Problem: in real data, it is hard to assume x_t is dependent on x_{t-kh} only...
 - ► Combinal seasonal and nonseasonal!
- Multiplicative Seasonal $ARMA(p,q) \times (P,Q)_s$

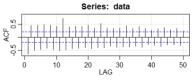
$$\Phi_p(B^s)\phi(B)x_t = \Theta_Q(B^s)\theta(B)w_t$$

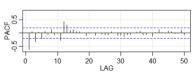
• Example Expression for $ARMA(p,q) \times (P,Q)_s$

Multiplicative seasonal ARMA

• Example $x_t = 0.8x_{t-12} + w_t - 0.5w_{t-1}$

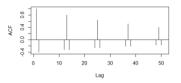


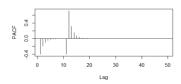




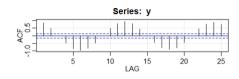
Multiplicative seasonal ARMA

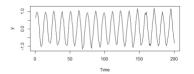
- Example $x_t = 0.8x_{t-12} + w_t 0.5w_{t-1}$
 - ► Theoretical

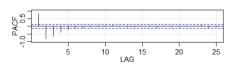




 What if there is a seasonal pattern which differs a little between the series







Note: ACF almost decays very slowly at peaks 12h

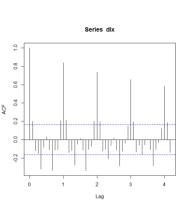
• Multiplicative seasonal autoregressive integrated moving average model $ARIMA(p, d, q) \times (P, D, Q)_s$

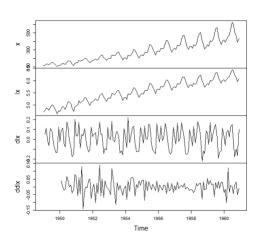
$$\Phi_p(B^s)\phi(B)\nabla_s^D\nabla^d x_t = \delta + \Theta_Q(B^s)\theta(B)w_t$$

$$\nabla_s^D = (1 - B^s)^D$$

- How to identify SARIMA?
 - Perform differencing first (trend)
 - 2 Investigate ACF \rightarrow slowly decays at peaks?
 - $exttt{1}$ Yes o Additional differencing by $abla_s^D$
 - Model non-seasonal part
 - 4 Model seasonal part (check peaks), check ACF and PACF of residuals

• Example: Air passangers





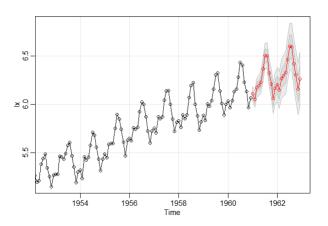
Remove AR term!

Is one model much better the other one?

sigma^2 estimated as 0.001341: log likelihood = 244.95, aic = -481.9

```
> m1$fit
                                                               Call:
                                                                stats::arima(x = xdata, order = c(p, d, g), seasonal = list(order = c(p, D,
                                                                   Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
                                                                   REPORT = 1, reltol = tol))
                                                               Coefficients:
(1,1,1) \times (1,1,0)_{12}
                                                                     0.0547 -0.4886 -0.4731
                                                                s.e. 0.2161 0.1933 0.0800
                                                                sigma^2 estimated as 0.001425: log likelihood = 241.73, aic = -475.47
                                                                > m2$fit
                                                               Call:
                                                                stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(p, D,
(1,1,1) \times (0,1,1)_{12}
                                                                   Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
                                                                   REPORT = 1, reltol = tol))
                                                                Coefficients:
                                                                        ar1
                                                                                 ma1
                                                                     0.1960 -0.5784 -0.5643
                                                                s.e. 0.2475 0.2132 0.0747
```

Forecasting



Read home

Shumway and Stoffer, section 3.9

• R code: sarima, sarima.for, runs