# ARIMA(R,d,M) Models

Part II

#### Yule-Walker Equations

$$\gamma_{k} = E[Y_{t-k}(\phi_{1}Y_{t-1} + \phi_{2}Y_{t-2} + \dots + \phi_{R}Y_{t-R} + e_{t})]$$
when  $k = 0,1,\dots,R,\dots$ 

$$\gamma_{0} = \phi_{1}\gamma_{1} + \phi_{2}\gamma_{2} + \dots + \phi_{R}\gamma_{R} + \sigma_{e}^{2}$$

$$\gamma_{1} = \phi_{1}\gamma_{0} + \phi_{2}\gamma_{1} + \dots + \phi_{R}\gamma_{R-1}$$

$$\dots$$

$$\gamma_{R} = \phi_{1}\gamma_{R-1} + \phi_{2}\gamma_{R-2} + \dots + \phi_{R}\gamma_{0}$$

$$\dots$$

$$\gamma_{k} = \phi_{1}\gamma_{k-1} + \phi_{2}\gamma_{k-2} + \dots + \phi_{R}\gamma_{k-R} \quad k > R$$

#### Yule-Walker Equations

$$\rho_1 = \phi_1 \rho_0 + \phi_2 \rho_1 + \dots + \phi_R \rho_{R-1}$$

• • •

$$\rho_{R} = \phi_{1}\rho_{R-1} + \phi_{2}\rho_{R-2} + \dots + \phi_{R}\rho_{0}$$

• • •

$$\rho_{k} = \phi_{1}\rho_{k-1} + \phi_{2}\rho_{k-2} + \dots + \phi_{R}\rho_{k-R} \quad k > R$$

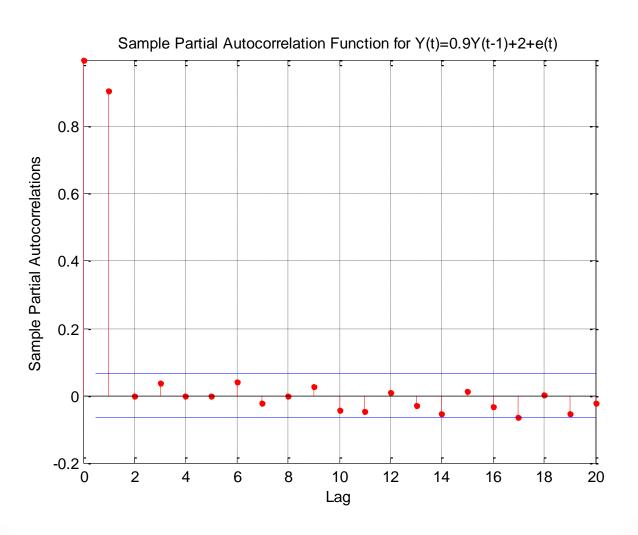
#### Yule-Walker Equations

- We can solve the equations for  $\rho_k$ , but also for  $\phi_i$ .
- In the second case the estimates of  $\phi_i$  for i>R will have values close to zero

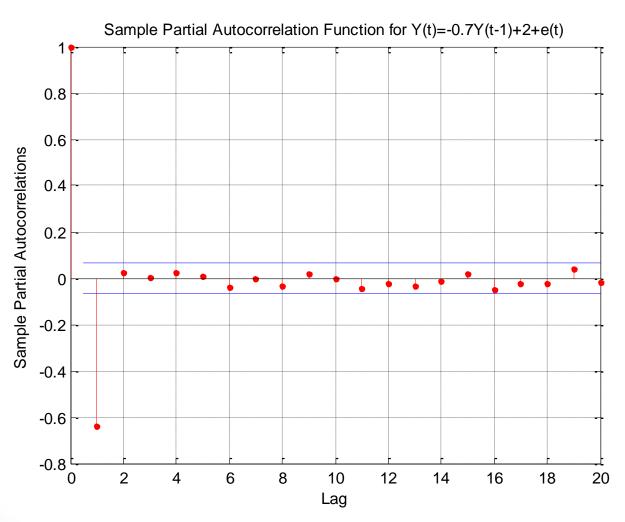
### Partial Autocorrelation Coefficients

- These estimated  $\phi_i$ , from Yule-Walker equations will be called Partial Autocorrelation Coefficients
- The Partial Autocorrelation Coefficients are very useful for determination of the AR model order

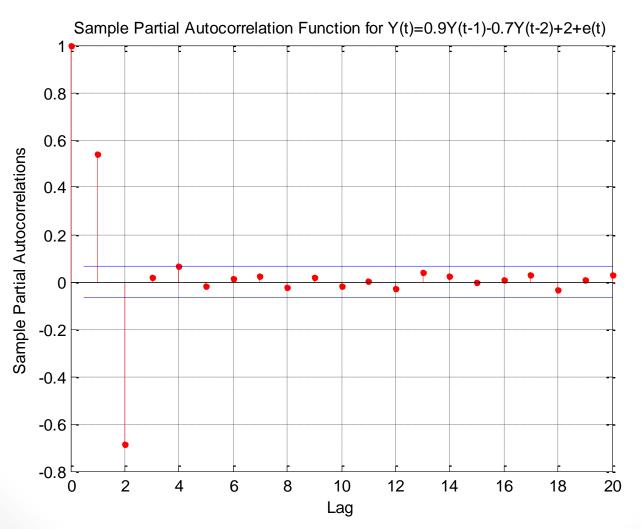
$$Y_t = 0.9Y_{t-1} + 2 + e_t$$



$$Y_t = -0.7Y_{t-1} + 2 + e_t$$



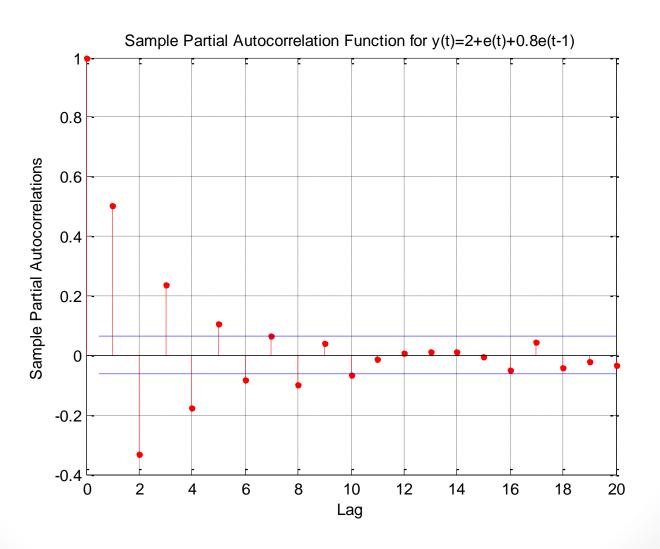
$$Y_{t} = 0.9Y_{t-1} - 0.7Y_{t-2} + 2 + e_{t}$$



### Partial Autocorrelation Coefficients for MA models

 The Partial Autocorrelation Coefficients diminish quickly for MA models

$$Y_t = 2 + e_t + 0.8e_{t-1}$$



$$Y_t = 2 + e_t + 0.6e_{t-1} - 0.3e_{t-2}$$

Sample Partial Autocorrelation Function for Y(t)=2+e(t)+0.6e(t-1)-0.3e(t-2)0.8 Sample Partial Autocorrelations 0.6 0.4 0.2 -0.2 -0.4 2 12 14 20 8 10 4 6 16 18

Lag

#### Combined ARMA(R,M)

$$Y_{t} = c + \phi_{1}Y_{t-1} + \phi_{2}Y_{t-2} + \dots + \phi_{R}Y_{t-R} + e_{t} + \theta_{1}e_{t-1} + \theta_{2}e_{t-2} + \dots + \theta_{M}e_{t-M}$$

$$\mu = c + \mu + \phi_1 \mu + \phi_2 \mu + \dots + \phi_R \mu \Longrightarrow$$

$$\mu = \frac{c}{1 - \phi_1 - \phi_2 - \dots - \phi_R}$$

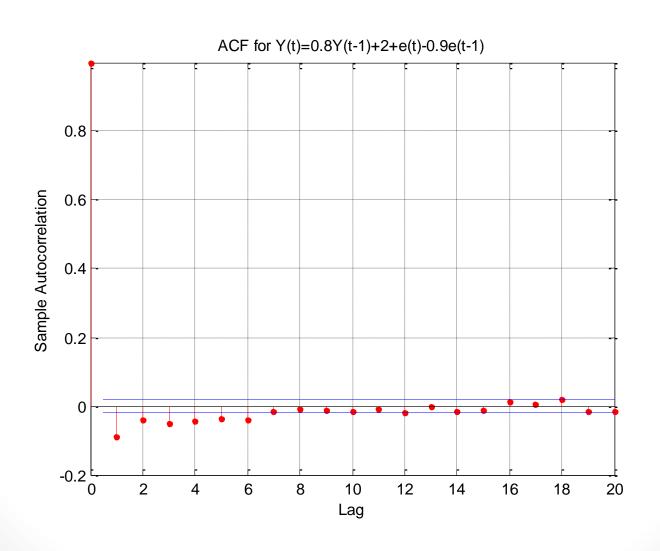
#### ARMA(1,1) model

$$\begin{split} Y_{t} &= c + \phi_{1}Y_{t-1} + e_{t} + \theta_{1}e_{t-1} \\ \gamma_{0} &= E[(\phi_{1}Y_{t-1} + e_{t} + \theta_{1}e_{t-1})^{2}] = \phi_{1}^{2}\gamma_{0} + 2\phi_{1}\theta_{1}\sigma_{e}^{2} + \sigma_{e}^{2} + \theta_{1}^{2}\sigma_{e}^{2} \Rightarrow \\ \gamma_{0} &= \frac{1 + \theta_{1}^{2} + 2\phi_{1}\theta_{1}}{1 - \phi_{1}^{2}}\sigma_{e}^{2} \\ \gamma_{1} &= \frac{(1 + \phi_{1}\theta_{1})(\phi_{1} + \theta_{1})}{1 - \phi_{e}^{2}}\sigma_{e}^{2} \end{split}$$

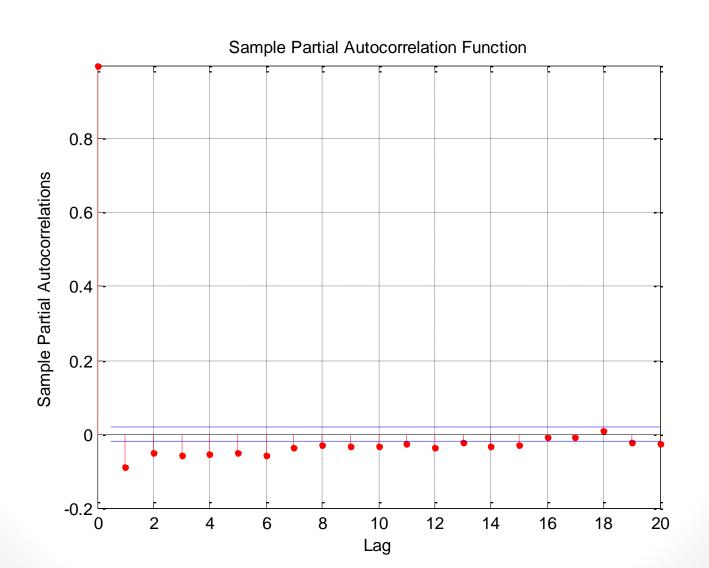
$$\gamma_2 = \phi_1 \gamma_1 \quad \dots \quad \gamma_k = \phi_1 \gamma_{k-1} \quad \text{for } k > 2$$

$$Y_{t} = 0.8Y_{t-1} + 2 + e_{t} - 0.9e_{t-1}$$

**ACF** for 
$$Y_t = 0.8Y_{t-1} + 2 + e_t - 0.9e_{t-1}$$



### **PACF** for $Y_t = 0.8Y_{t-1} + 2 + e_t - 0.9e_{t-1}$



# ACF for ARMA(R,M) model when $k \ge M+1$

$$\gamma_k = \phi_1 \gamma_{k-1} + \phi_2 \gamma_{k-2} + \dots + \phi_R \gamma_{k-R} \quad k \ge M + 1$$

$$\rho_{k} = \phi_{1}\rho_{k-1} + \phi_{2}\rho_{k-2} + \dots + \phi_{R}\rho_{k-R} \quad k \ge M + 1$$

### Lag (Backshift) operator

$$Be_{t} = e_{t-1}, B^{2}e_{t} = e_{t-2}, \dots, B^{M}e_{t} = e_{t-M}$$

$$MA(M): Y_{t} = \mu + (1 + \theta_{1}B + \theta_{2}B^{2} + \dots + \theta_{M}B^{M})e_{t}$$

$$Y_{t} = \mu + \theta(B)e_{t}$$

$$AR(R): (1 - \phi_{1}B - \phi_{2}B^{2} - \phi_{3}B^{3} - \dots - \phi_{R}B^{R})Y_{t} = c + e_{t}$$

$$\phi(B)Y_{t} = c + e_{t}$$

$$ARMA(R, M): \phi(B)Y_{t} = c + \theta(B)e_{t}$$

#### Difference operator

$$\Delta Y_t = Y_t - Y_{t-1}, \quad \Delta^2 Y_t = \Delta Y_t - \Delta Y_{t-1}$$
$$\Delta Y_t = (1 - B)Y_t$$

# Generalized form for ARIMA models

$$ARIMA(R,d,M)$$
: 
$$\phi(B)\Delta^{d}Y_{t} = c + \theta(B)e_{t}$$
 
$$\phi(B)(1-B)^{d}Y_{t} = c + \theta(B)e_{t}$$

#### Stationarity conditions

$$\begin{split} \widetilde{Y}_t &= Y_t - \mu \\ \phi(B)\widetilde{Y}_t &= \theta(B)e_t \\ \widetilde{Y}_t &= \phi(B)^{-1}\theta(B)e_t \\ 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_R B^R &= 0 \\ z &= \frac{1}{B} \Rightarrow \\ z^R - \phi_1 z^{R-1} - \phi_2 z^{R-2} - \dots - \phi_R &= 0 \end{split}$$

#### Stationarity conditions

All roots of equation(1) to lie out of the unit circle

$$1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_R B^R = 0 \tag{1}$$

or

All roots of equation (2) to lie in the unit circle

$$z^{R} - \phi_{1}z^{R-1} - \phi_{2}z^{R-2} - \dots - \phi_{R} = 0$$
 (2)

```
Y_{t} = 0.9Y_{t-1} - 0.7Y_{t-2} + e_{t}
p1=[1-0.9+0.7]
roots(p1)
ans =
  0.4500 + 0.7053i
  0.4500 - 0.7053i
abs(roots(p1))
ans =
  0.8367
  0.8367
```

```
Y_{t} = 0.9Y_{t-1} + 0.5Y_{t-2} + e_{t}
p1=[1 -0.9 -0.5]
roots(p1)
ans =
1.2882
-0.3882
ar2=arima('c',2,'var',1,'ar',[0.9 0.5])
Error using arima/validateModel (line 1306)
The non-seasonal autoregressive polynomial is
unstable.
```

#### Invertibility conditions

$$\begin{split} \widetilde{Y}_t &= Y_t - \mu \\ \phi(B)\widetilde{Y}_t &= \theta(B)e_t \\ \theta^{-1}(B)\phi(B)\widetilde{Y}_t &= e_t \\ 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_R B^M &= 0 \end{split}$$

#### Invertibility conditions

All roots of equation (1) to lie out of the unit circle

$$1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_M B^M = 0 \tag{1}$$

or

All roots of equation (2) to lie in the unit circle

$$z^{M} + \theta_{1}z^{M-1} + \theta_{2}z^{M-2} + \dots + \theta_{M} = 0$$
 (2)

$$Y_t = 2 + e_t + 0.6e_{t-1} - 0.3e_{t-2}$$

$$p2=[1 \ 0.6 \ -0.3]$$

roots(p2)

ans =

-0.9245 0.3245

```
Y_t = 2 + e_t + 0.7e_{t-1} - 0.3e_{t-2} p2 = \begin{bmatrix} 1 \ 0.7 \ -0.3 \end{bmatrix} roots(p2) ans = -1.0000 0.3000
```

ma2=arima('c',2,'var',1,'ma',[0.7 -0.3]) Error using arima/validateModel (line 1314) The non-seasonal moving average polynomial is non-invertible. ARIMA(R,d,M) Estimation. Box-Jenkins Approach.

#### Estimation of ARIMA models

$$e_{t} = Y_{t} - \sum_{i=1}^{R} \phi_{i} Y_{t-i} - \sum_{i=1}^{M} \theta_{i} e_{t-i}$$

$$\sum_{t=1}^{T} e_t^2 = f(\phi_1, \phi_2, ..., \phi_R, \theta_1, \theta_2, ..., \theta_M)$$

$$LLF = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(\sigma_{t}^{2}) - \frac{1}{2}\sum_{t=1}^{T}\frac{e_{t}^{2}}{\sigma_{t}^{2}}$$

#### Estimation of ARIMA models

- Initial values for  $Y_t$  and  $e_t$
- Initial values for  $\Phi$  and  $\Theta$  polynomials
- Optimization parameters

### Initial values for $Y_t$ and $e_t$

$$Y_i = \overline{Y}$$
 for  $i = -R, -R+1, ..., 0$   
 $e_i = 0$  for  $i = -M, -M+1, ..., 0$ 

# Initial values for $\Phi$ and $\Theta$ polynomials

- Yule-Walker equations
- Nonlinear equations for  $\theta$  after filtering the autoregression part

#### Optimization parameters

- MaxFunEvals
- MaxIter
- TolFun
- TolX
- TolCon

#### Box-Jenkins Approach

- Determination of ARIMA(R,d,M) model structure
- Estimation and model selection
- Test for model adequacy

# Determination of ARIMA(p,d,q) model structure

- Determination of d.
- Determination of autoregression order R.
- Determination of moving average order
   M.
- Selection of an initial models set.

#### Estimation and model selection

- Estimation of the selected models.
- Significance test for the estimated parameters.
- Application of AIC and BIC criteria for model selection.
- Selection of appropriate model/models.

#### Test for model adequacy

- Test for residuals autocorrelation presence.
- Lyung-Box test.
- Final model selection.

#### Information Criteria

**Akaike Criterion** 

$$-2logL + 2numParam$$

**Bayesian Criterion** 

-2logL + numParam \* log(numObs)