

ÖZYEĞİN ÜNİVERSİTESİ

M7

Predictive Analytics

ENİS KAYIŞ

Seasonal ARIMA models

- ▶ We can add seasonal terms to original ARIMA:

$$\text{ARIMA } \underbrace{(p, d, q)}_{\substack{\uparrow \\ \left(\begin{array}{c} \text{Non-seasonal part} \\ \text{of the model} \end{array} \right)}} \underbrace{(P, D, Q)_m}_{\substack{\uparrow \\ \left(\begin{array}{c} \text{Seasonal part} \\ \text{of the model} \end{array} \right)}}$$

where m is the number of periods per season.

- ▶ Use backshift operator to write concisely.
- ▶ Example: $\text{ARIMA}(1,1,1)(1,1,1)_4$

$$\underbrace{(1 - \phi_1 B)}_{\substack{\uparrow \\ \left(\begin{array}{c} \text{Non-seasonal} \\ \text{AR}(1) \end{array} \right)}} \underbrace{(1 - \Phi_1 B^4)}_{\substack{\uparrow \\ \left(\begin{array}{c} \text{Seasonal} \\ \text{AR}(1) \end{array} \right)}} \underbrace{(1 - B)}_{\substack{\uparrow \\ \left(\begin{array}{c} \text{Non-seasonal} \\ \text{difference} \end{array} \right)}} \underbrace{(1 - B^4)}_{\substack{\uparrow \\ \left(\begin{array}{c} \text{Seasonal} \\ \text{difference} \end{array} \right)}} y_t = \underbrace{(1 + \theta_1 B)}_{\substack{\uparrow \\ \left(\begin{array}{c} \text{Non-seasonal} \\ \text{MA}(1) \end{array} \right)}} \underbrace{(1 + \Theta_1 B^4)}_{\substack{\uparrow \\ \left(\begin{array}{c} \text{Seasonal} \\ \text{MA}(1) \end{array} \right)}} e_t.$$

Seasonal ARIMA models

► Example: $\text{ARIMA}(1,1,1)(1,1,1)_4$

$$(1 - \phi_1 B)(1 - \Phi_1 B^4)(1 - B)(1 - B^4)y_t = (1 + \theta_1 B)(1 + \Theta_1 B^4)\varepsilon_t$$

All the factors can be multiplied out and the general model written as follows:

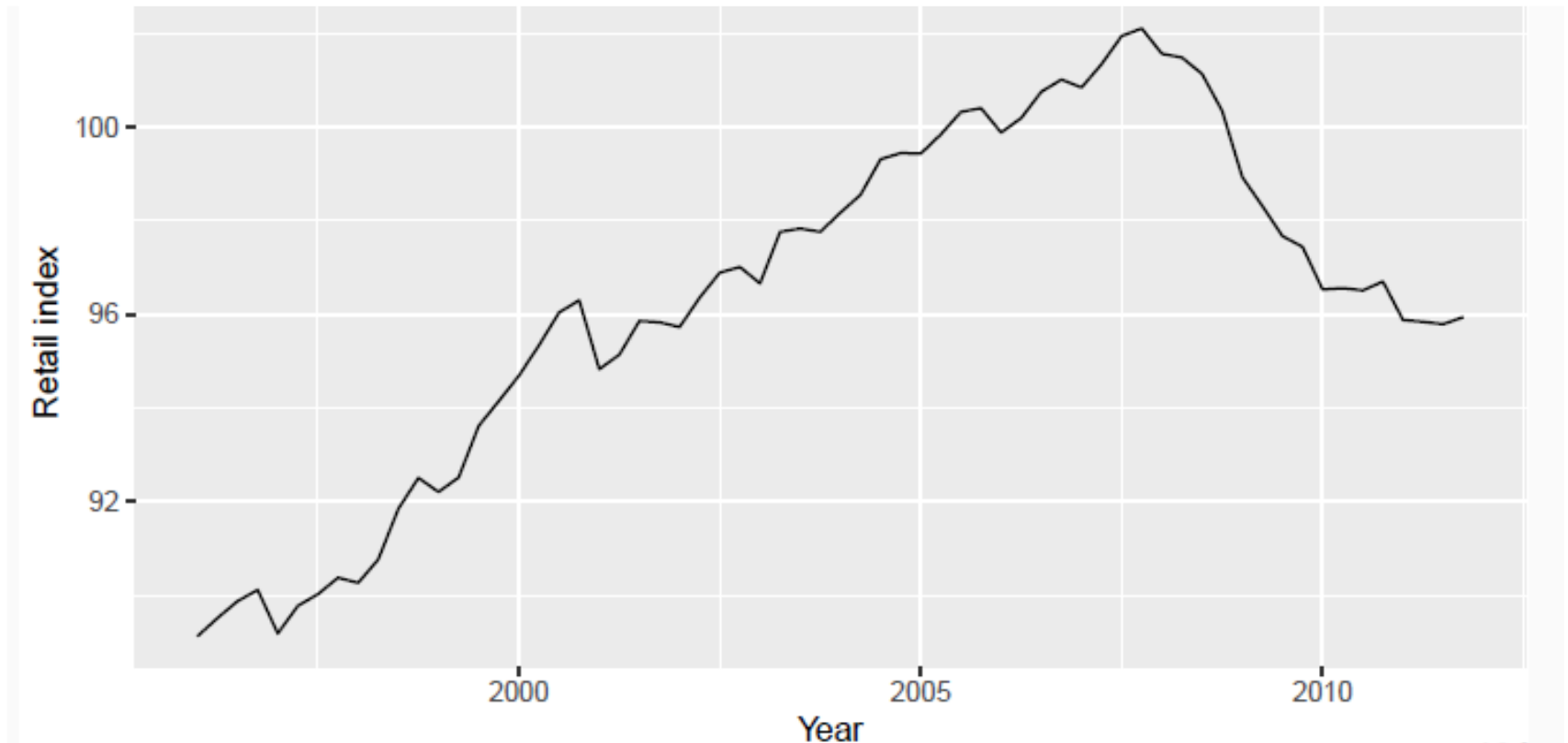
$$\begin{aligned} y_t = & (1 + \phi_1)y_{t-1} - \phi_1 y_{t-2} + (1 + \Phi_1)y_{t-4} \\ & - (1 + \phi_1 + \Phi_1 + \phi_1 \Phi_1)y_{t-5} + (\phi_1 + \phi_1 \Phi_1)y_{t-6} \\ & - \Phi_1 y_{t-8} + (\Phi_1 + \phi_1 \Phi_1)y_{t-9} - \phi_1 \Phi_1 y_{t-10} \\ & + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \Theta_1 \varepsilon_{t-4} + \theta_1 \Theta_1 \varepsilon_{t-5}. \end{aligned}$$

Seasonal ARIMA models

- ▶ How to interpret ACF/PACF plots with seasonal data?
- ▶ The seasonal part of an AR or MA model will be seen in the seasonal lags of the PACF and ACF.
- ▶ Examples:
 - ▶ $\text{ARIMA}(0,0,0)(0,0,1)_{12}$ will show:
 - ▶ ACF will show a spike at lag 12 but no other significant spikes.
 - ▶ PACF will show exponential decay in the seasonal lags; that is, at lags 12, 24, 36,...
 - ▶ $\text{ARIMA}(0,0,0)(1,0,0)_{12}$ will show:
 - ▶ ACF will show exponential decay in the seasonal lags.
 - ▶ PACF will show a single significant spike at lag 12.

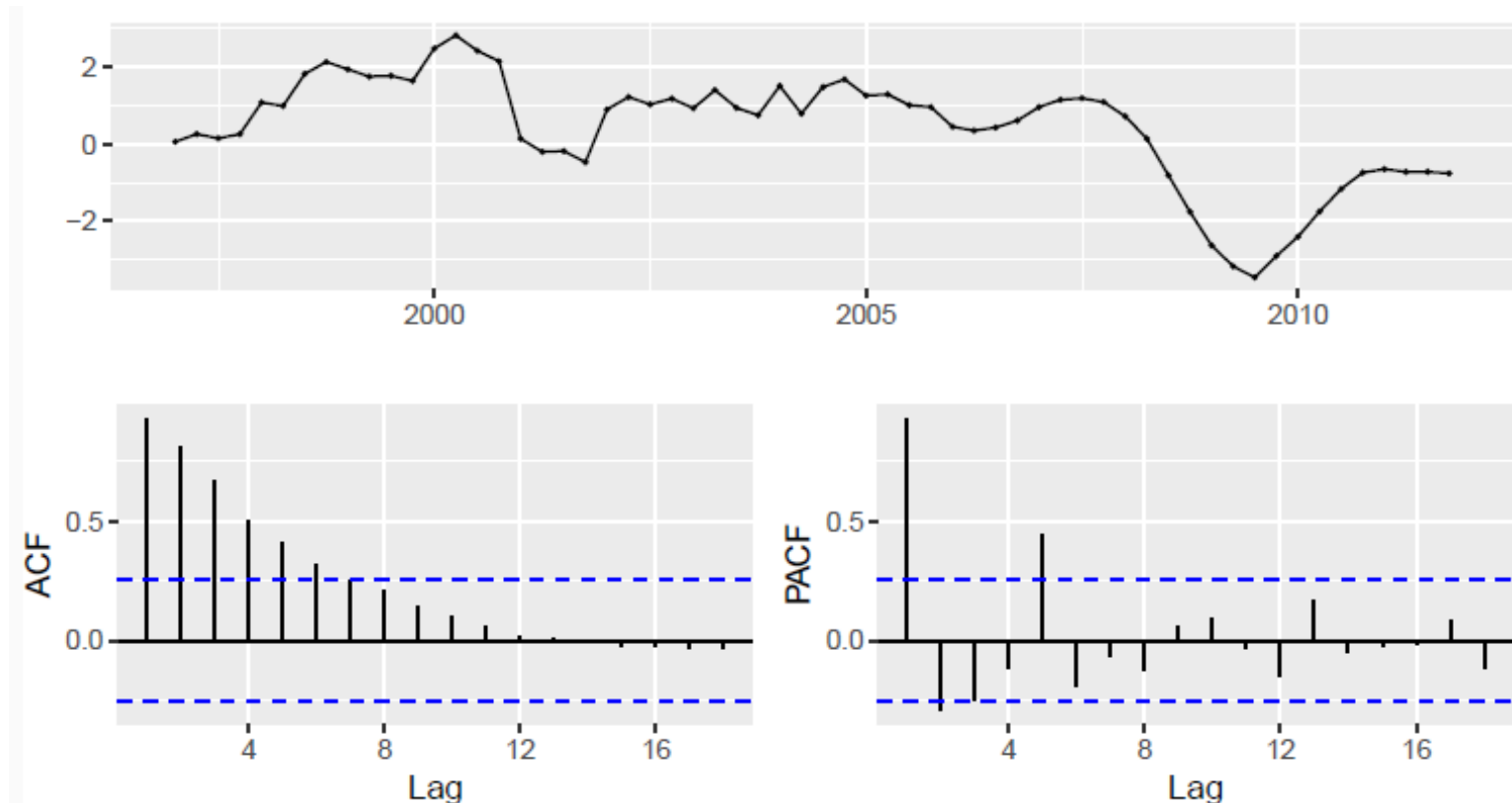
Seasonal ARIMA models

- ▶ Example: European quarterly retail trade index
 - ▶ (Index: 2005=1000)



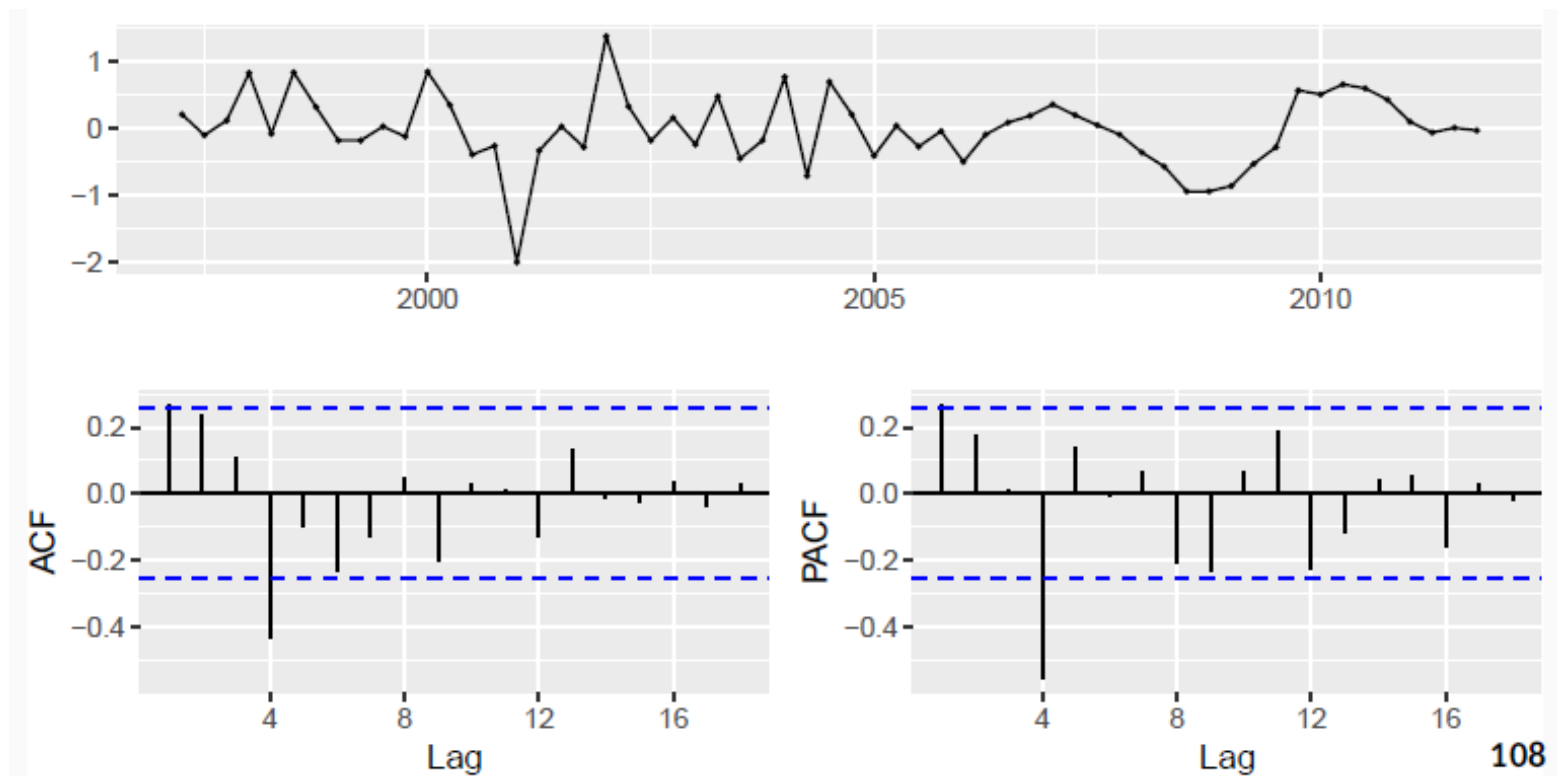
Seasonal ARIMA models

- ▶ **Example: European quarterly retail trade index**
 - ▶ Non-stationary with some seasonality
 - ▶ Let's first take a seasonal difference, i.e. $(1-B^4)y_t$



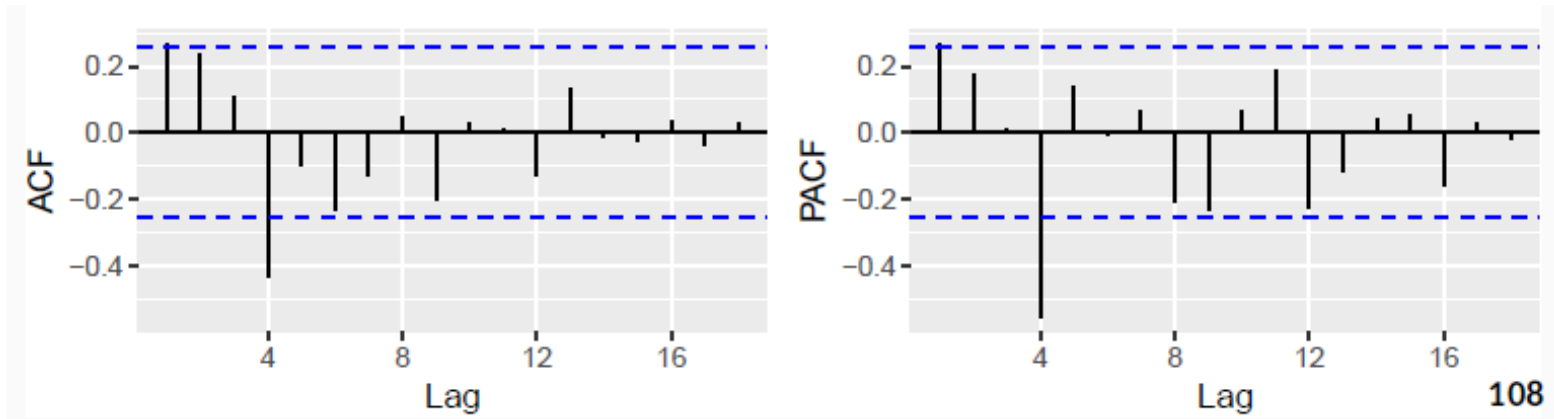
Seasonal ARIMA models

- ▶ **Example: European quarterly retail trade index**
 - ▶ Still non-stationary, so take another first difference, i.e. $(1-B)(1-B^4)y_t$



Seasonal ARIMA models

► Example: European quarterly retail trade index

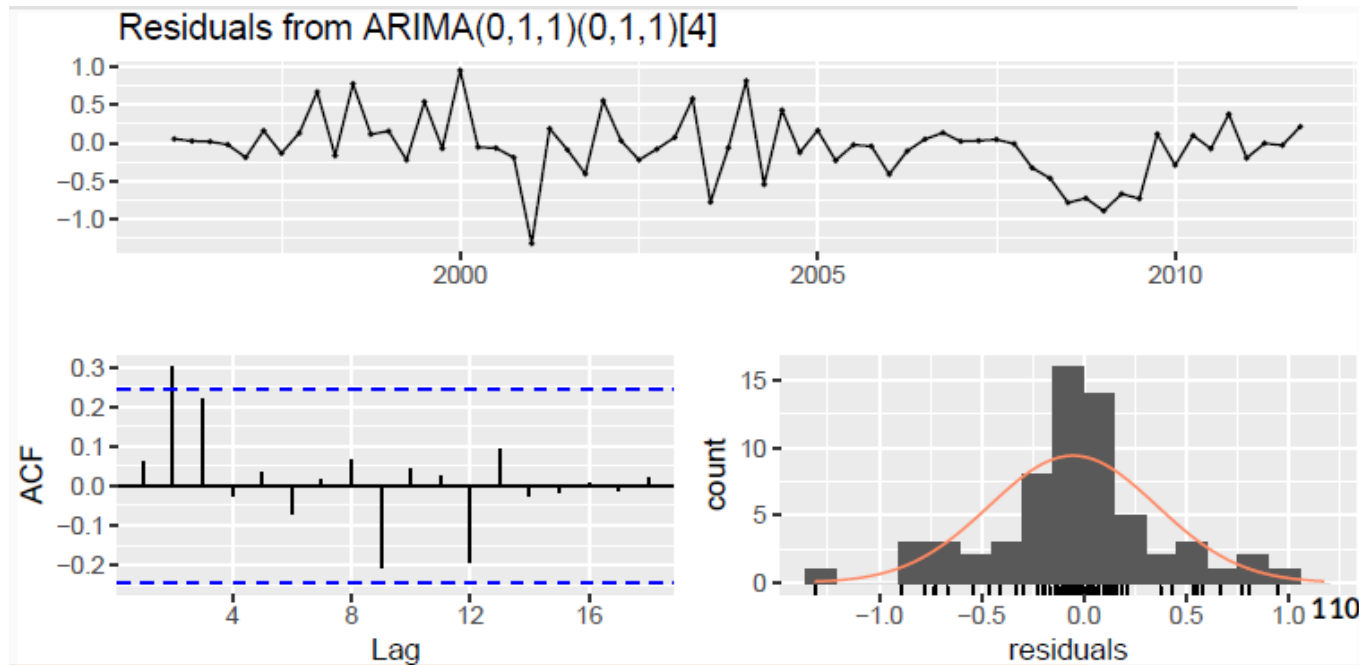


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- The significant spike at lag 1 in the ACF suggests a non-seasonal MA(1) component,
- The significant spike at lag 4 in the ACF suggests a seasonal MA(1) component.
- Thus start with $\text{ARIMA}(0,1,1)(0,1,1)_4$ (alternatively, you could select $\text{ARIMA}(1,1,0)(1,1,0)_4$)

Seasonal ARIMA models

- ▶ Example: European quarterly retail trade index
- ▶ Check the residuals from $ARIMA(0,1,1)(0,1,1)_4$ model



Seasonal ARIMA models

- ▶ Null hypothesis (residuals are not correlated) cannot be rejected at 5% level

```
##  
##  Ljung-Box  test  
##  
## data:  Residuals from ARIMA(0,1,1)(0,1,1)[4]  
## Q* = 10.654, df = 6, p-value = 0.09968  
##  
## Model df: 2.    Total lags used: 8
```

Seasonal ARIMA models

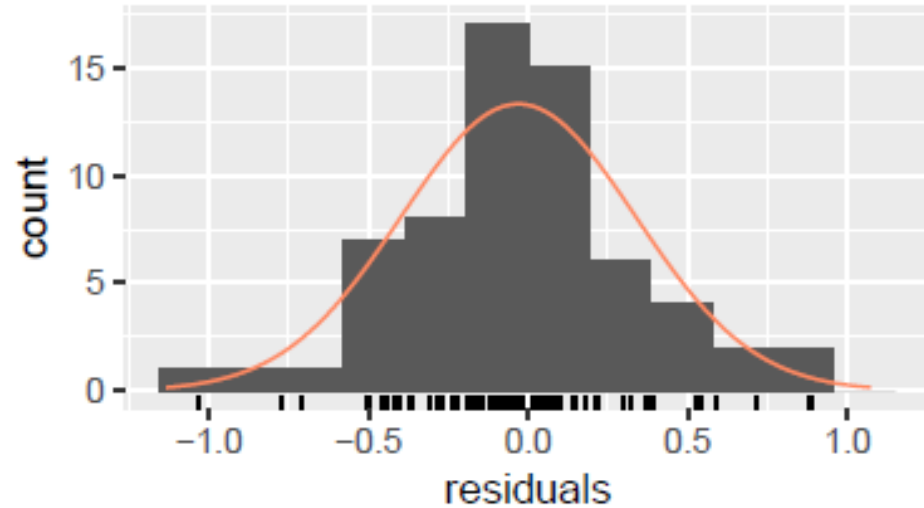
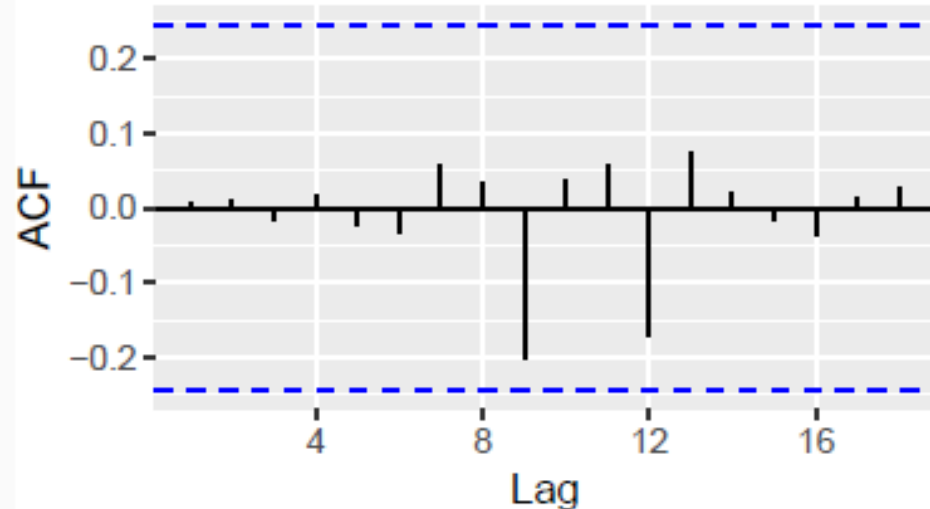
- ▶ ACF and PACF of residuals show significant spikes at lag 2, and maybe lag 3.
 - ▶ AICc of $\text{ARIMA}(0,1,2)(0,1,1)_4$ model is 74.27.
 - ▶ AICc of $\text{ARIMA}(0,1,3)(0,1,1)_4$ model is 68.39.

Seasonal ARIMA models

```
## Series: euretail
## ARIMA(0,1,3)(0,1,1)[4]
##
## Coefficients:
##          ma1      ma2      ma3      sma1
##      0.2630  0.3694  0.4200 -0.6636
## s.e.  0.1237  0.1255  0.1294  0.1545
##
## sigma^2 estimated as 0.156:  log likelihood=-28.63
## AIC=67.26    AICc=68.39    BIC=77.65
```

Seasonal ARIMA models

Residuals from ARIMA(0,1,3)(0,1,1)[4]



Seasonal ARIMA models

```
##  
##   Ljung-Box test  
##  
## data:  Residuals from ARIMA(0,1,3)(0,1,1)[4]  
## Q* = 0.51128, df = 4, p-value = 0.9724  
##  
## Model df: 4.    Total lags used: 8
```

Seasonal ARIMA models

- ▶ Example: European quarterly retail trade index
- ▶ Forecasts for the next 3 years:

