

# Non-Stationary Time Series - SARIMA (Contd.)

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# Outline

## 1 SARIMA

- Specifying the Order
  - Example 1
  - Example 2
  - Example 3
  - Example 4
  - Example 5
  - Example 6
  - General Guidelines

## 2 Real Datasets

- Air Passengers
- Electricity Production

# Specifying the Order - ACF/PACF

SAR(1) with  $s=12$ .

- Example 1: Consider a SARIMA  $(0, 0, 0) \times (1, 0, 0)_{12}$  model

$$\begin{aligned} X_t &= 0.5X_{t-12} + W_t \implies (1 - 0.5B^{12})X_t = W_t \\ \implies \underbrace{\Phi_1(B^{12})}_{\text{1 seasonal lag dep.}} X_t &= W_t \end{aligned}$$

- Use the **ARMAacf()** function to calculate theoretical ACF and PACF for the model

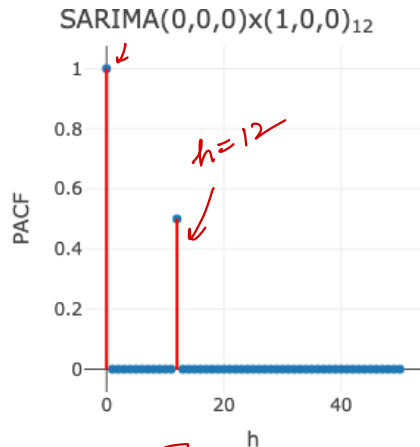
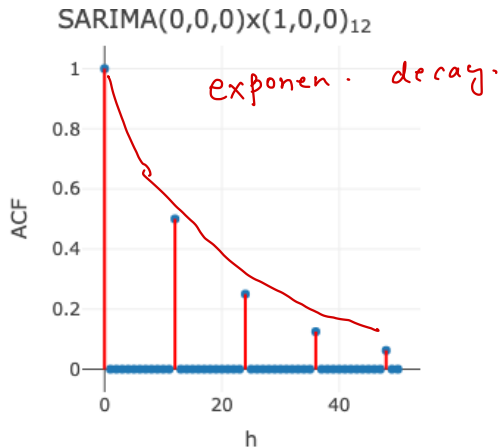
$\downarrow$   $\downarrow$

```
sar1<- ARMAacf(ar = c(rep(0,11), 0.5), lag.max=50) #ACF  
sar1_p <- ARMAacf(ar = c(rep(0,11), 0.5), lag.max=50,  
                  pacf=T) #PACF
```

$(\phi, \theta) \times (P, Q)$   $X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots + 0.5 X_{t-12} + W_t$

# Example 1

SAR(1) -



$$X_t = \phi X_{t-12} + w_t$$

# Specifying the Order - ACF/PACF

$sma(1), s = 4.$

- Example 2: Consider a SARIMA  $(0, 0, 0) \times (0, 0, 1)_4$  model

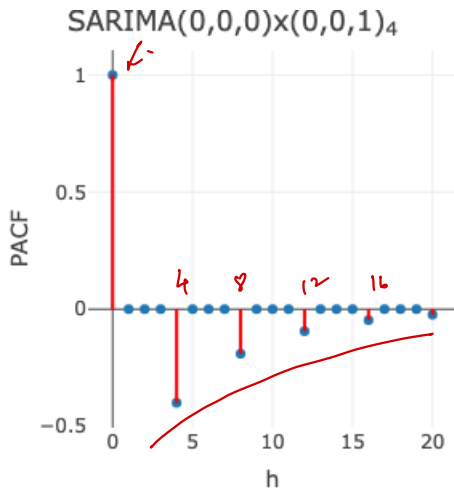
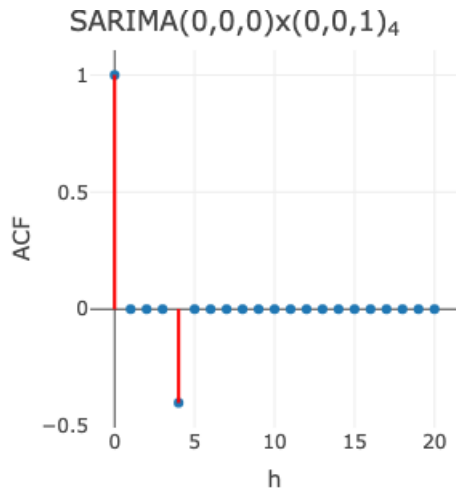
$$X_t = W_t - 0.5W_{t-4} = \underbrace{(1 - 0.5B^4)}_{\text{SAR}} W_t = \underbrace{\Theta_1(B^4)}_{\text{SAR}} W_t$$

- Use the **ARMAacf()** function to calculate theoretical ACF and PACF for the model

$w_{t-1}, w_{t-2}, w_{t-3}$        $w_{t-4}$

```
sma1 <- ARMAacf(ma = c(rep(0, 3), -0.5), lag.max=20) #ACF
sma1_p <- ARMAacf(ma = c(rep(0, 3), -0.5), lag.max=20,
                  pacf=T) #PACF
```

## Example 2 $X_t = w_t - 0.5 w_{t-4}$



# Specifying the Order - ACF/PACF

*SMA(2), s = 4.*

- Example 3: Consider a SARIMA (0, 0, 0) × (0, 0, 2)<sub>4</sub> model

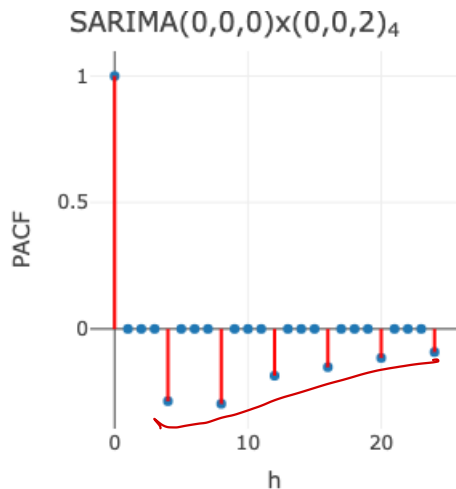
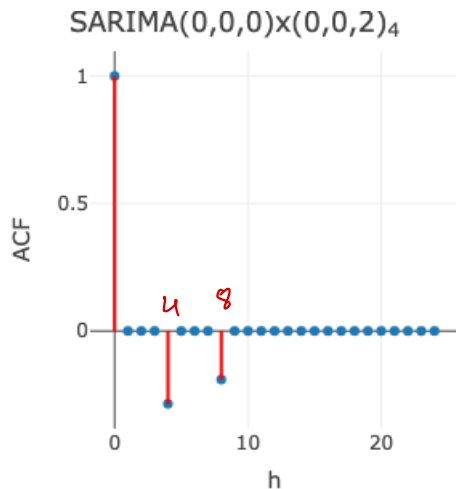
$$X_t = \underbrace{W_t}_{1-3} - 0.5 \underbrace{W_{t-4}}_{4} - 0.25 \underbrace{W_{t-8}}_{5-7} = (1 - 0.5B^4 - 0.25B^8)W_t = \Theta_2(B^4)W_t$$

- Use the **ARMAacf()** function to calculate theoretical ACF and PACF for the model

*1-3                      4                      5-7                      8*  
sma2 <- ARMAacf(ma = c(rep(0, 3), -0.5, rep(0, 3), -0.25),  
lag.max=24) #ACF

sma2\_p <- ARMAacf(ma = c(rep(0, 3), -0.5, rep(0, 3), -0.25),  
lag.max=24, pacf=T) #PACF

# Example 3





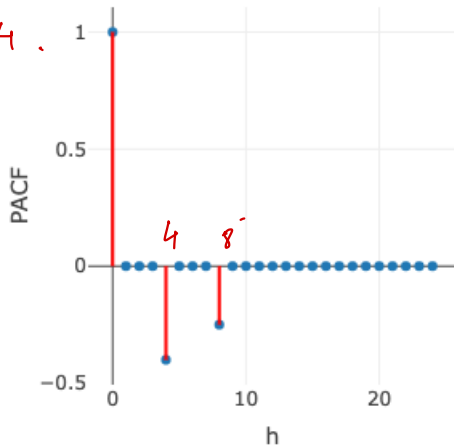
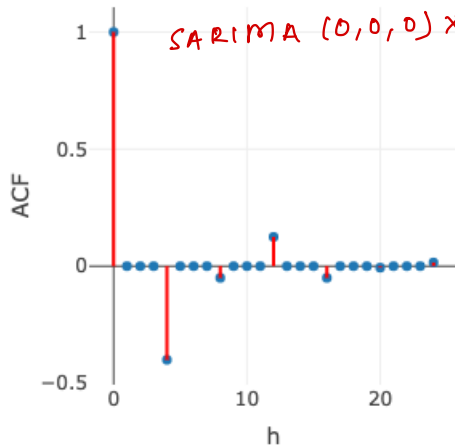
# Guess the order - I

SAR (2)

exp. decay

$$X_t = \phi_1 X_{t-4} + \phi_2 X_{t-8} + w_t$$

SARIMA (0,0,0) x (2|0,0)<sub>4</sub>



# Specifying the Order - ACF/PACF

$$\phi = 1, p = 1, s = 12$$

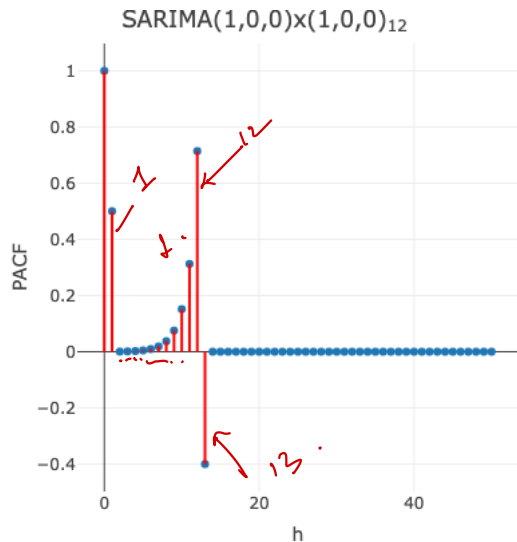
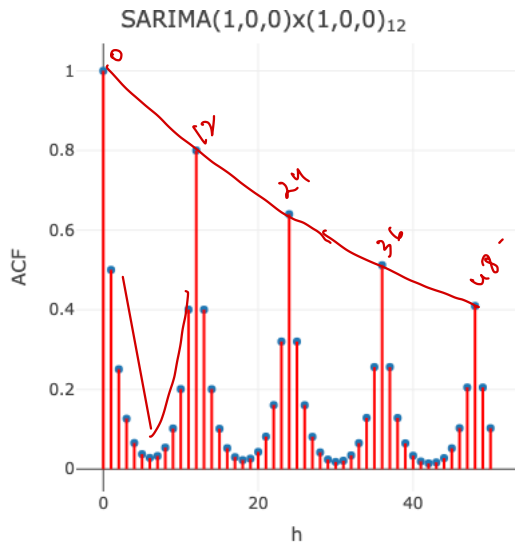
- Example 4: Consider a SARIMA  $(\underline{1}, 0, 0) \times (\underline{1}, 0, 0)_{12}$  model

$$\underline{X_t} = \underline{0.5X_{t-1}} + \underline{0.8X_{t-12}} - \underline{0.4X_{t-13}} + W_t \implies \phi(B) \phi_1(B^{12}) X_t = W_t$$

- Use the **ARMAacf()** function to calculate theoretical ACF and PACF for the model

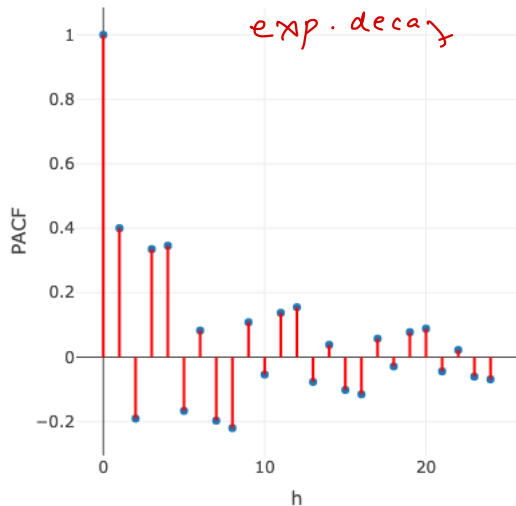
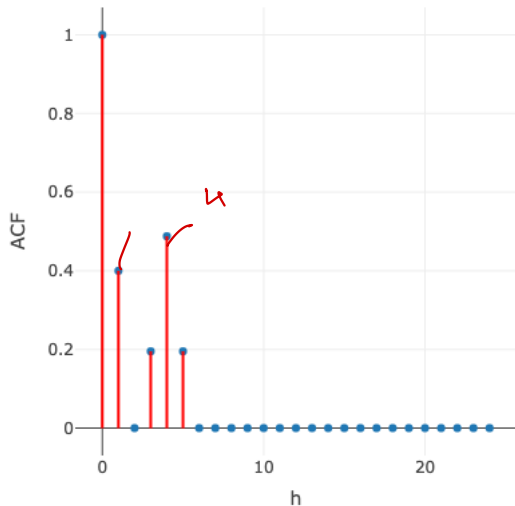
```
ar1_s <- ARMAacf(ar = c(10.5, 2-11rep(0, 10), 120.8, 13-0.5*0.8),
                  lag.max=50) #ACF
ar1_sp <- ARMAacf(ar = c(0.5, rep(0, 10), 0.8, -0.5*0.8),
                  lag.max=50, pacf=T) #PACF
```

# Example 4



## Guess the Order - II

SARIMA (0,0,1) × (0,0,1)<sub>4</sub>..



# Specifying the Order - ACF/PACF

AR(1), SMA(1)

S = 12

- Example 5: Consider a SARIMA (1, 0, 0) × (0, 0, 1)<sub>12</sub> model

$$\begin{aligned} X_t &= 0.8X_{t-1} + W_t - 0.5W_{t-12} \implies (1 - 0.8B)X_t = (1 - 0.5B^{12})W_t \\ &\implies \phi(B)X_t = \Theta_1(B^{12})W_t \end{aligned}$$

- Use the **ARMAacf()** function to calculate theoretical ACF and PACF for the model

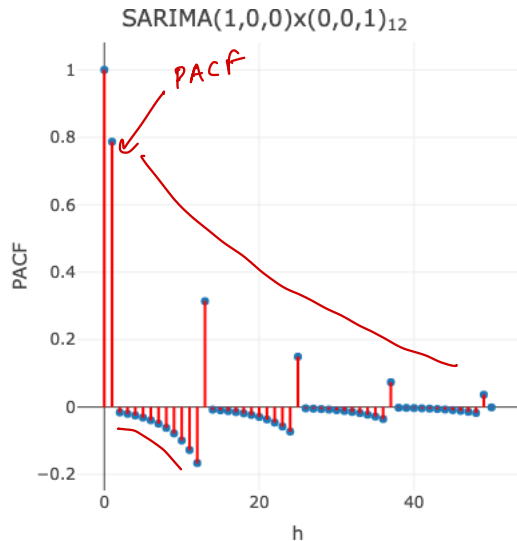
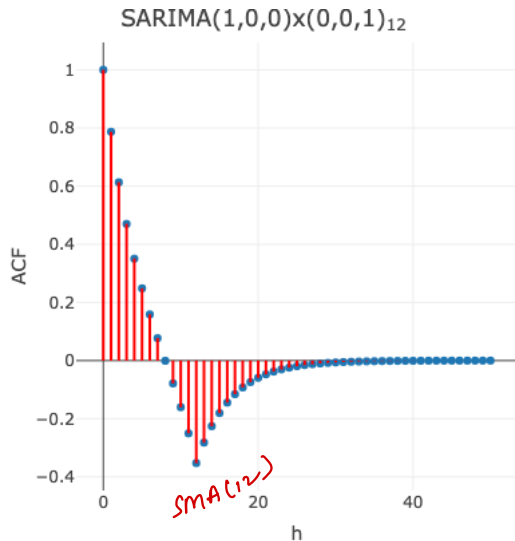
```
arσμα1 <- ARMAacf(ar = 0.8, ma = c(rep(0, 11), -0.5),  
lag.max = 50) #ACF
```

```
arσμα1_p <- ARMAacf(ar = 0.8, ma = c(rep(0, 11), -0.5),  
lag.max = 50, pacf=T) #PACF
```

## Example 5

AR(1) : exp. decay -  
MA -

AR(1) :



# Specifying the Order - ACF/PACF

- Example 6: Consider a SARIMA  $(1, 0, 1) \times (0, 0, 1)_{12}$  model

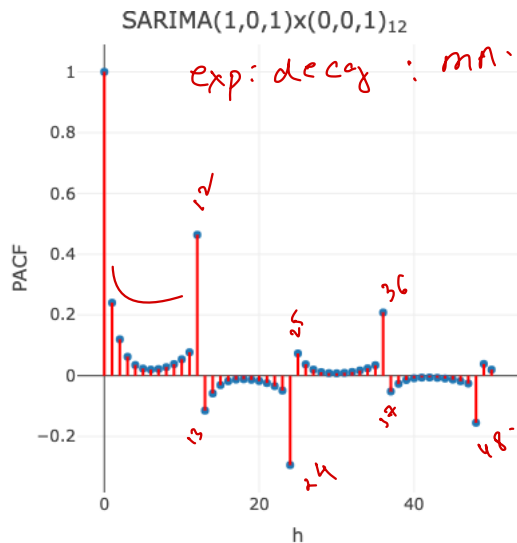
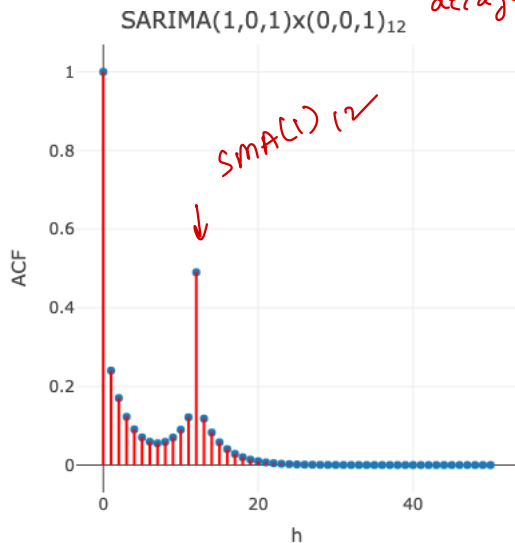
$$\begin{aligned} X_t &= 0.7X_{t-1} + W_t - 0.5W_{t-1} + 0.8W_{t-12} - 0.4W_{t-13} \\ &\Rightarrow (1 - 0.7B)X_t = (1 - 0.5B)(1 + 0.8B^{12})W_t \\ &\Rightarrow \phi(B)X_t = \theta(B)\Theta_1(B^{12})W_t \end{aligned}$$

- Use the **ARMAacf()** function to calculate theoretical ACF and PACF for the model

```
arsma2 <- ARMAacf(ar = 0.7, ma = c(-0.5, rep(0, 10), 0.8,
                                     -0.5*0.8), lag.max = 50) #ACF
arsma2_p <- ARMAacf(ar = 0.7, ma = c(-0.5, rep(0, 10), 0.8,
                                     -0.5*0.8), lag.max = 50, pacf=T) #PACF
```

# Example 6

exponential decay  $\rightarrow$  AR(1) - decay-





# Specifying the Order

- For seasonal AR(P) models, the ACF tends to tail off (decay toward zero) at lags  $ks$ , for  $k = 1, 2, \dots$ .
- For seasonal AR(P) models, the PACF tends to cut off (become zero) after lag  $Ps$ .
- For seasonal MA(Q) models, the ACF tends to cut off after lag  $Qs$ .
- For seasonal MA(Q) models, the PACF tends to tail off at lags  $ks$ .
- For seasonal ARMA(P;Q) models, both the ACF and the PACF tend to tail off at lags  $ks$ , so the ACF and PACF are not so useful for specifying the seasonal orders of the full SARMA model.

# Example - AirPassengers

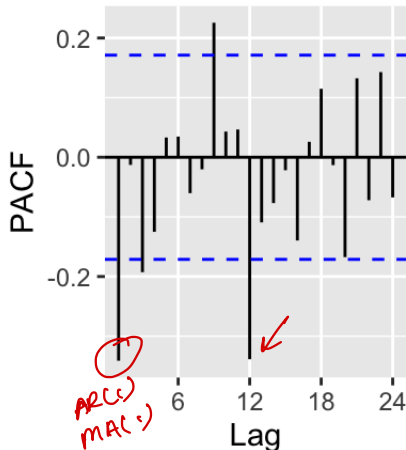
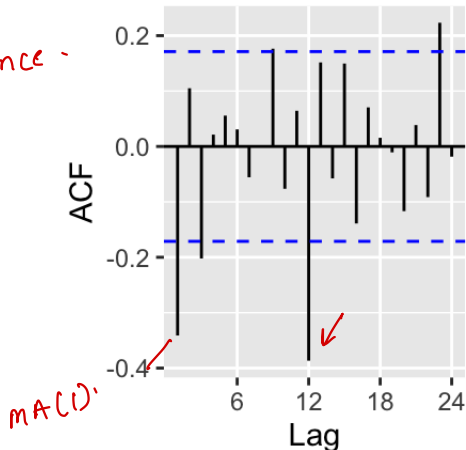
What we did earlier?

- Fit a quadratic trend plus seasonal means model to the log transformed time series (multiplicative).
- Analyze residuals - they were stationary but not white noise. Model suggestions for residuals:
  - ▶ auto.arima: MA(3)
  - ▶ armasubsets: AR(1) (we chose this!)
- We can now just using SARIMA to model the data thereby skipping the regression steps.
  - ▶ Let's try to figure out the order of the model by plotting ACF and PACF of the twice differenced log transformed series.

# Example - AirPassengers (ACF/PACF of Differenced Log Transformed Series)

seasonal : 1 lag ✓  
trend : 1 lag ✓

stabilizing  
the  
variance -



$$SARIMA(p, d, q) \times (P, D, Q)_s$$

$$d = 1$$

$$D = 1, \quad s = 12$$

$$q = 1, \quad Q = 1, \quad p + Q \leq 2$$

$$p = 0, 1, \quad \cancel{p} = 0, 1$$

# Example - AirPassengers

- R Code:

```
# Access AirPassengers data  
data("AirPassengers")  
auto.arima(log(AirPassengers))
```

- The model recommends a first order differencing along with a seasonal (lag 12) differencing.
- The suggested model is an MA(1) and seasonal MA(1).
- How do you interpret this?

Series: log(AirPassengers)  
ARIMA(0,1,1)(0,1,1)[12]

*p, d q, P, D Q S*

Coefficients:

	ma1	sma1
	-0.4018	-0.5569
s.e.	0.0896	0.0731

sigma^2 = 0.001371: log  
likelihood = 244.7  
AIC=-483.4 AICc=-483.21  
BIC=-474.77

$$X_t \rightarrow y_t = \log(X_t)$$

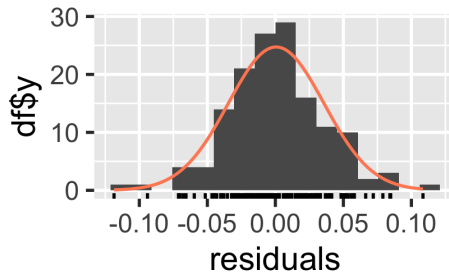
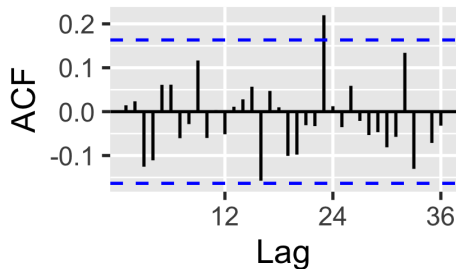
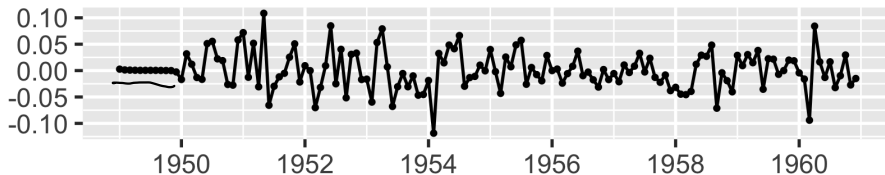
$$\underbrace{(1-B)}_{T.D} \underbrace{(1-B^{12})}_{S.D} y_t = \underbrace{(1-\textcircled{\pi}B^{12})}_{SMA(1)} \underbrace{(1-\theta B)}_{MA(1)} w_t$$

$$y_t - y_{t-1} - y_{t-12} + y_{t-13} = w_t - \theta w_{t-1} - \textcircled{\pi} w_{t-12} + \theta \textcircled{\pi} w_{t-13}$$

random shocks -

# Example - AirPassengers

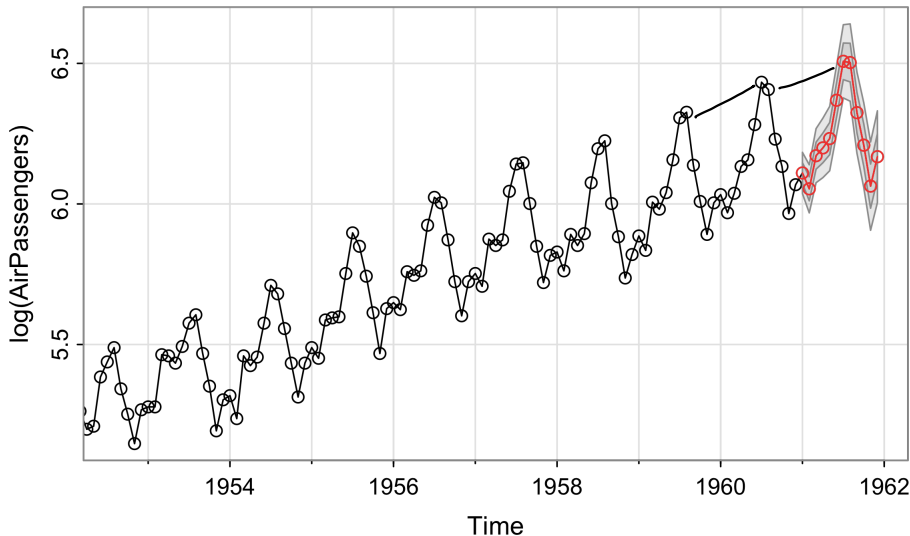
## Residuals



# Example - AirPassengers

Sarima for C

)





## Example - AirPassengers

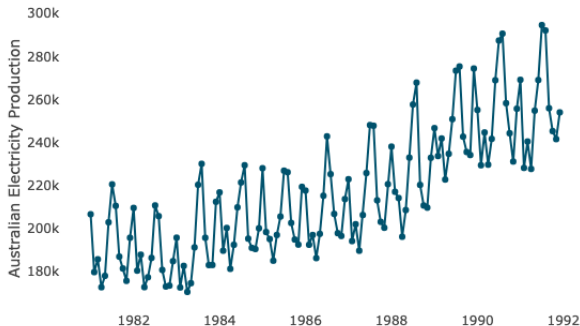
```
# Access the Air Passengers data
data("AirPassengers")
# Find the best model
auto.arima(log(AirPassengers))
# Fit the recommended model
fit <- arima(log(AirPassengers), order=c(0,1,1),
              seasonal = c(0,1,1))

# Analyze residuals
checkresiduals(fit$residuals)
# Forecast next 12 values
sarima.for(log(AirPassengers), n.ahead=12, p=0, d=1, q=1,
            P=0, D=1, Q=1, S=12)
```

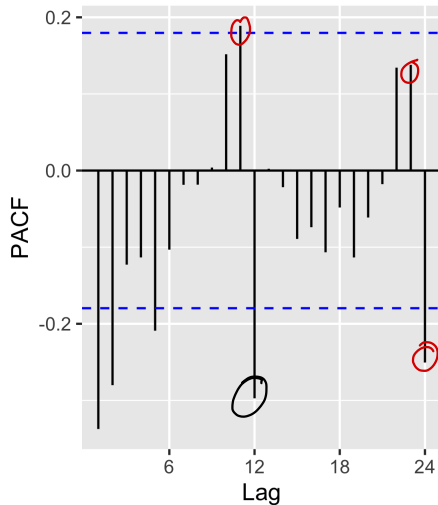
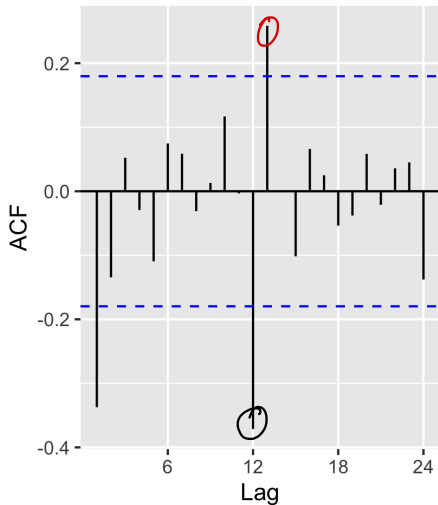
# Example - Electricity Production

SARIMA(L, d, 1) x L, 12

- Data on monthly electricity production in Australia is available in the **electricity** ts object in the **TSA** package.
- I am selecting a window from January 1981 to December 1991 for the analysis.



# Example - Electricity Production (Twice Differenced)



# Example - Electricity Production

```
auto.arima(elec, ic="aic")
```

Series: elec

ARIMA(1,1,1)(0,1,1)[12]

*d q D Q*

Coefficients:

	ar1	ma1	sma1
	0.3197	-0.7752	-0.8289
s.e.	0.1358	0.0862	0.1077

sigma^2 = 4.6e+07: log

likelihood = -1224.29

AIC=2456.58 AICc=2456.93

BIC=2467.7

```
auto.arima(elec, ic="bic")
```

Series: elec

ARIMA(0,1,1)(0,1,1)[12]

*d q D Q-*

Coefficients:

	ma1	sma1
	-0.5472	-0.8055
s.e.	0.1146	0.1013

sigma^2 = 48026429: log

likelihood = -1226.64

AIC=2459.27 AICc=2459.48

BIC=2467.61

# Example - Electricity Production

```
sarima.for(elec, p=1, d=1, q=1, P=0, D=1, Q=1, S=12, n.ahead = 12)
```

