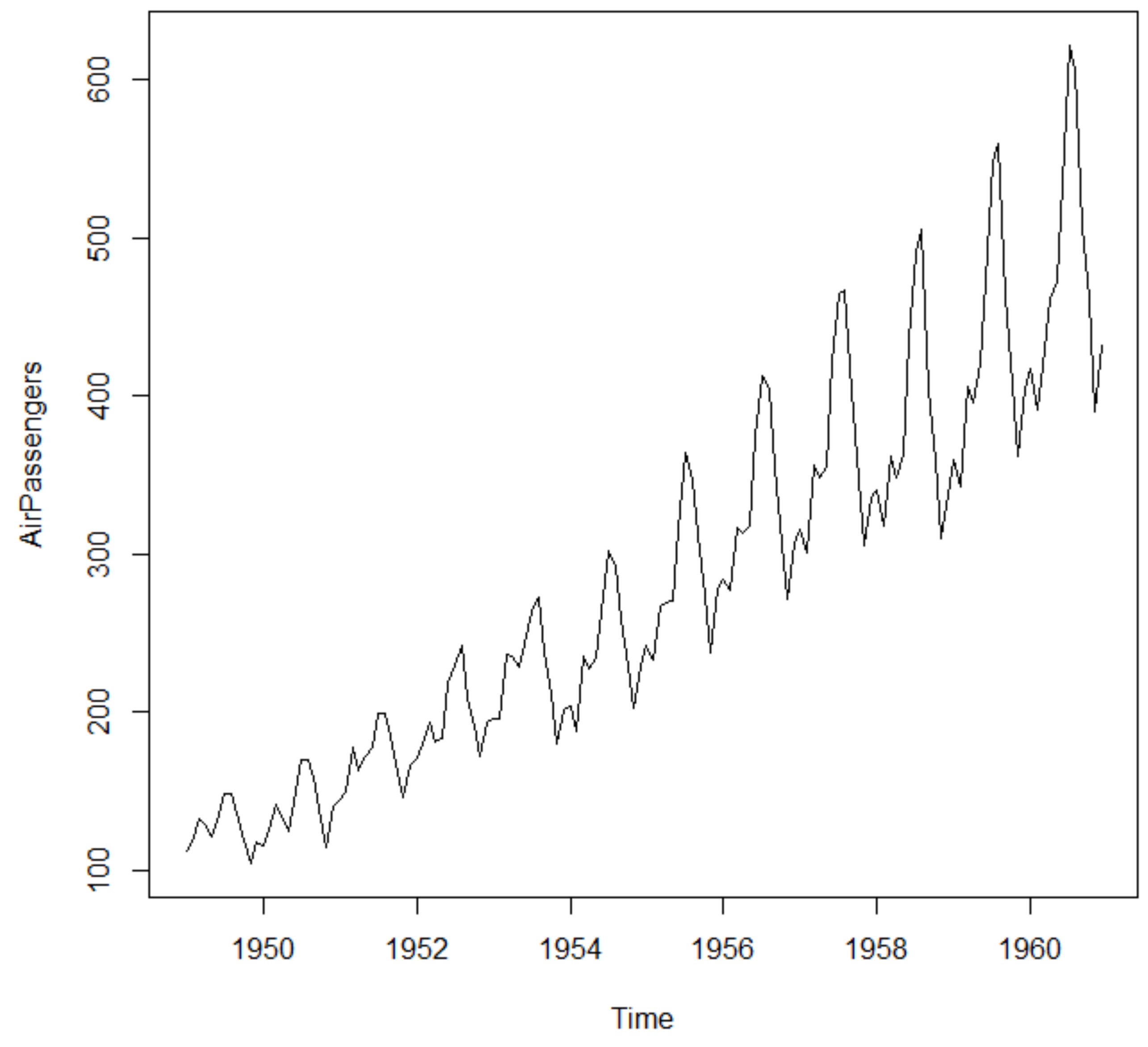
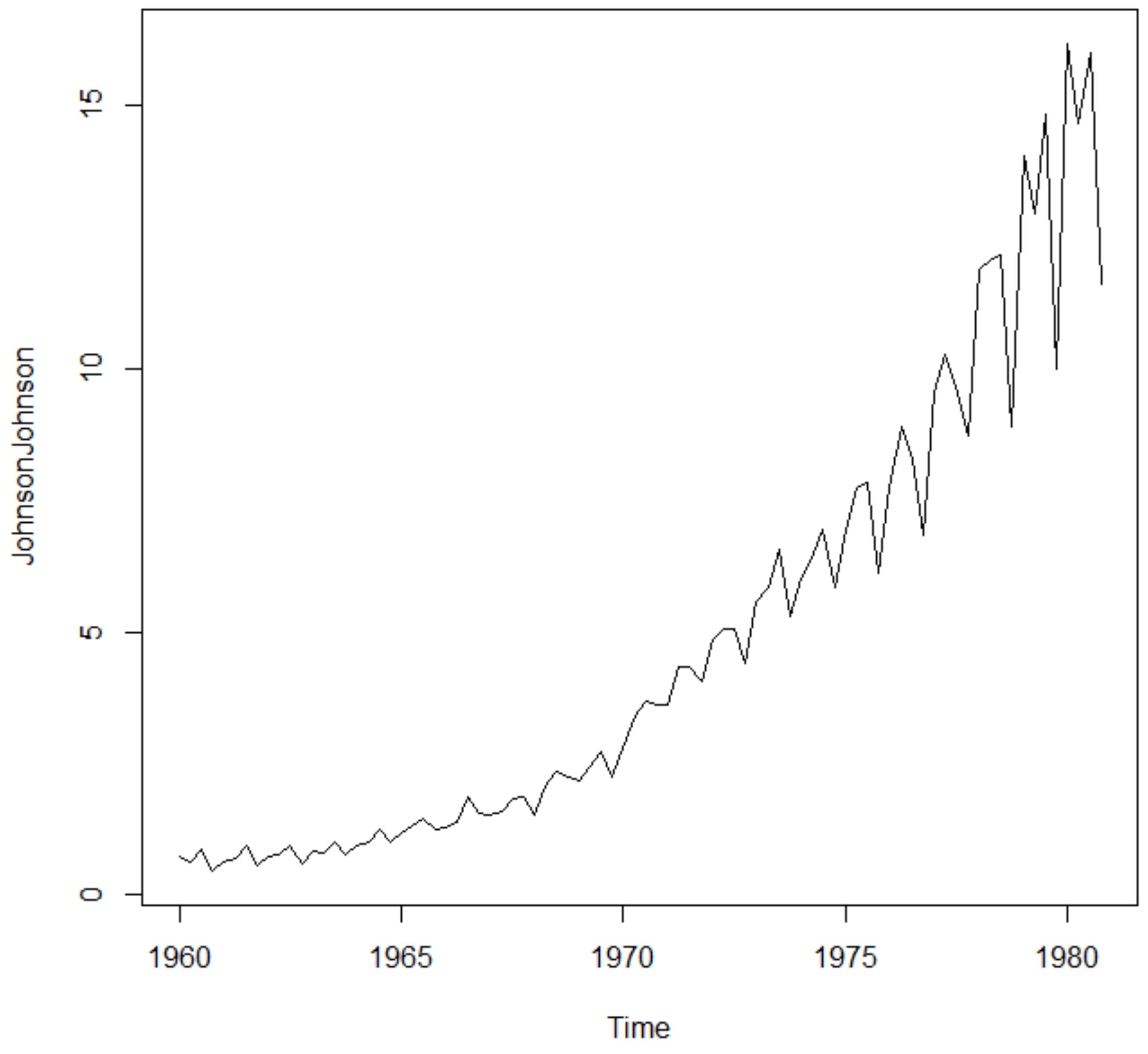
Pure Seasonal Models

Pure Seasonal Models

- Often collect data with a known seasonal component
- Air Passengers (1 cycle every $S = 12$ months)
- Johnson & Johnson Earnings (1 cycle every $S = 4$ quarters)

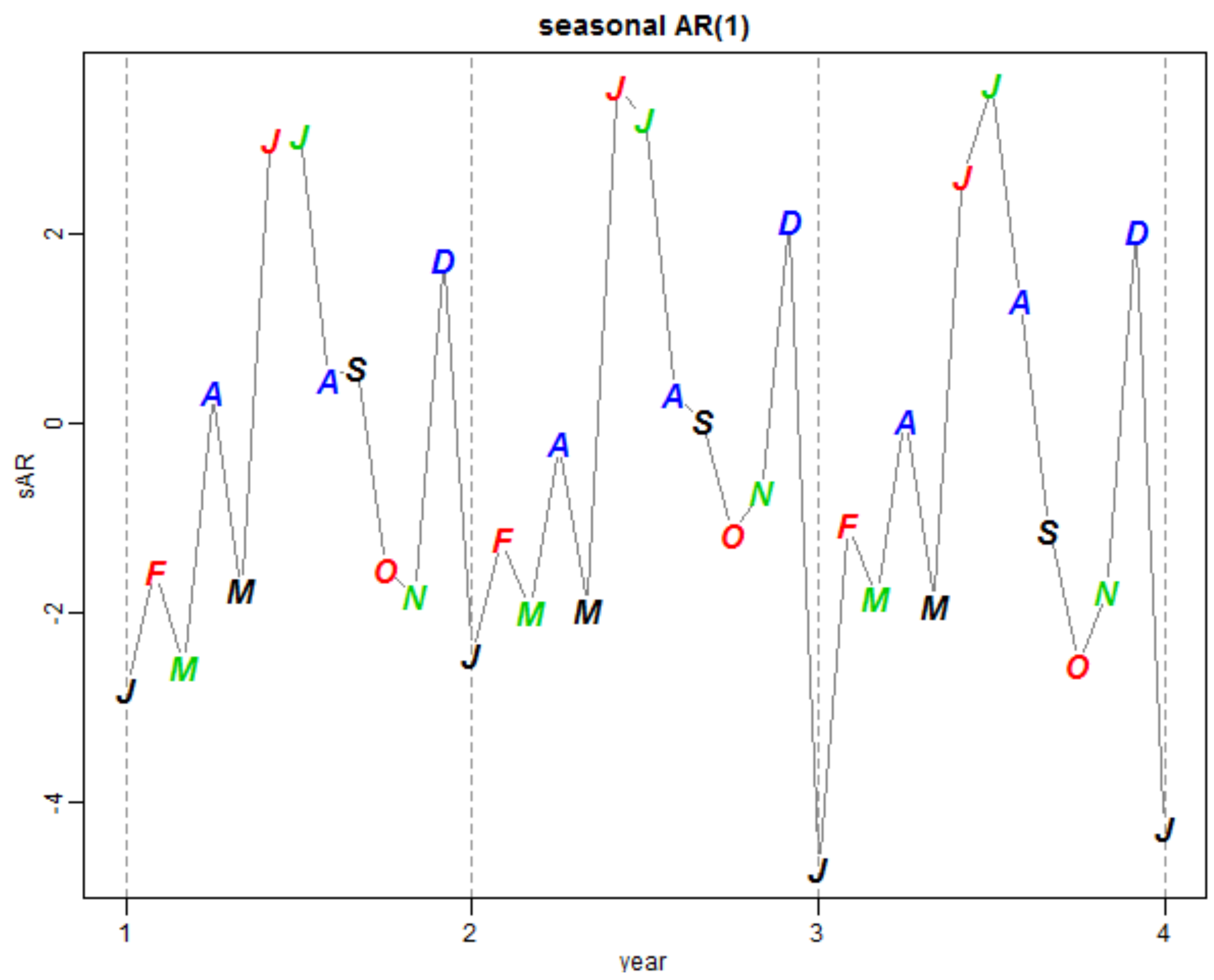




Pure Seasonal Models

- Consider pure seasonal models such as an SAR$(P = 1)_{S=12}$

$$X_t = \Phi X_{t-12} + W_t$$

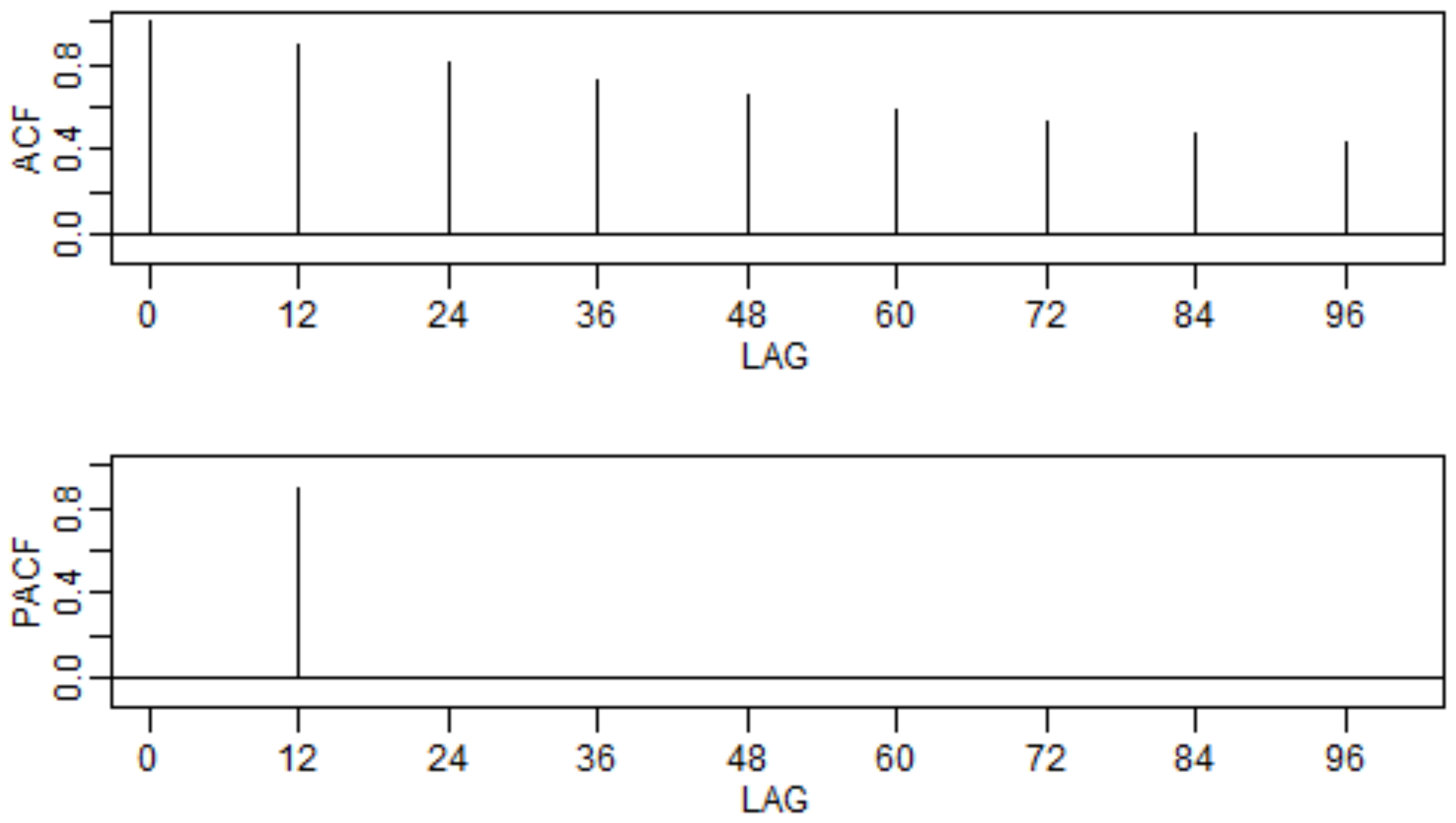


ACF and PACF of Pure Seasonal Models

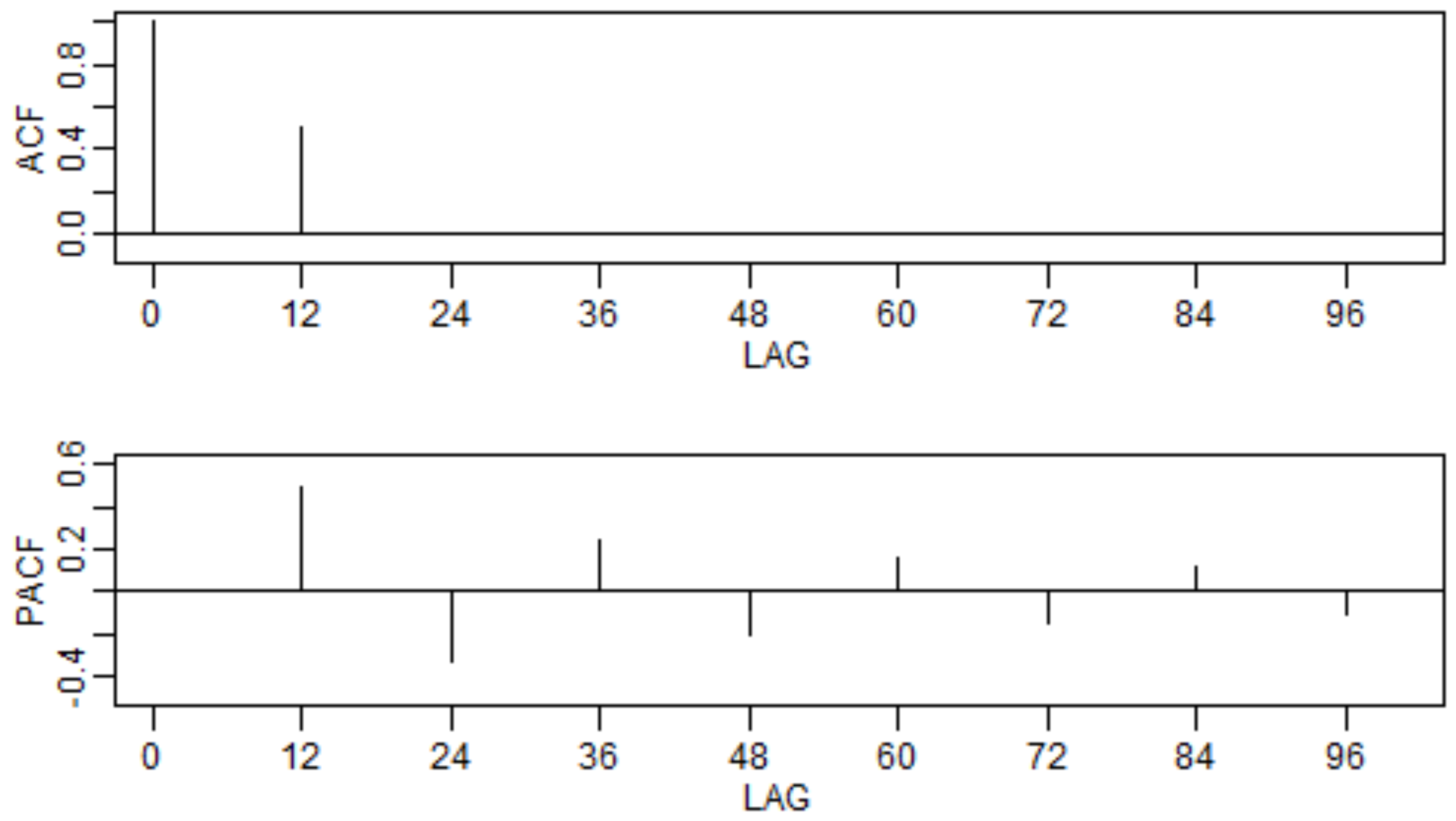
	$SAR(P)_S$	$SMA(Q)_S$	$SARMA(P, Q)_S$
ACF*	Tails off	Cuts off lag QS	Tails off
PACF*	Cuts off lag PS	Tails off	Tails off

* The values at the nonseasonal lags are zero

$SAR(1)_1$



$SMA(1)_1$



Let’s practice!

Mixed Seasonal Models

Mixed Seasonal Model

- Mixed model: SARIMA(p, d, q) x $(P, D, Q)_s$ model
- Consider a SARIMA(0, 0, 1) x $(1, 0, 0)_{12}$ model

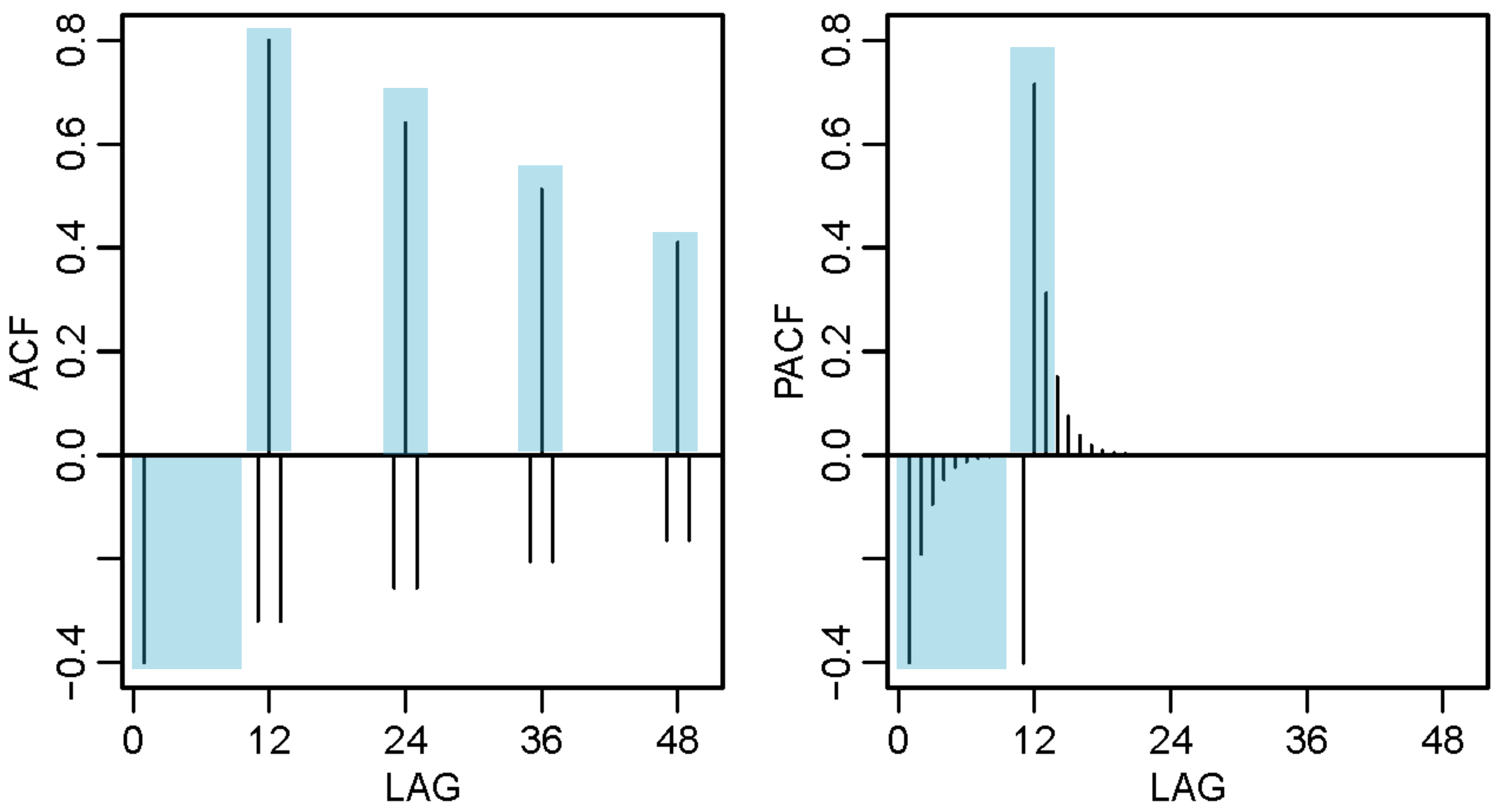
$$X_t = \Phi X_{t-12} + W_t + \theta W_{t-1}$$

- SAR(1): Value this month is related to last year's value X_{t-12}
- MA(1): This month's value related to last month's shock W_{t-1}

ACF and PACF of SARIMA(0,0,1) x (1,0,0) $_{S=12}$

- The ACF and PACF for this mixed model:

$$X_t = .8X_{t-12} + W_t - .5W_{t-1}$$



Seasonal

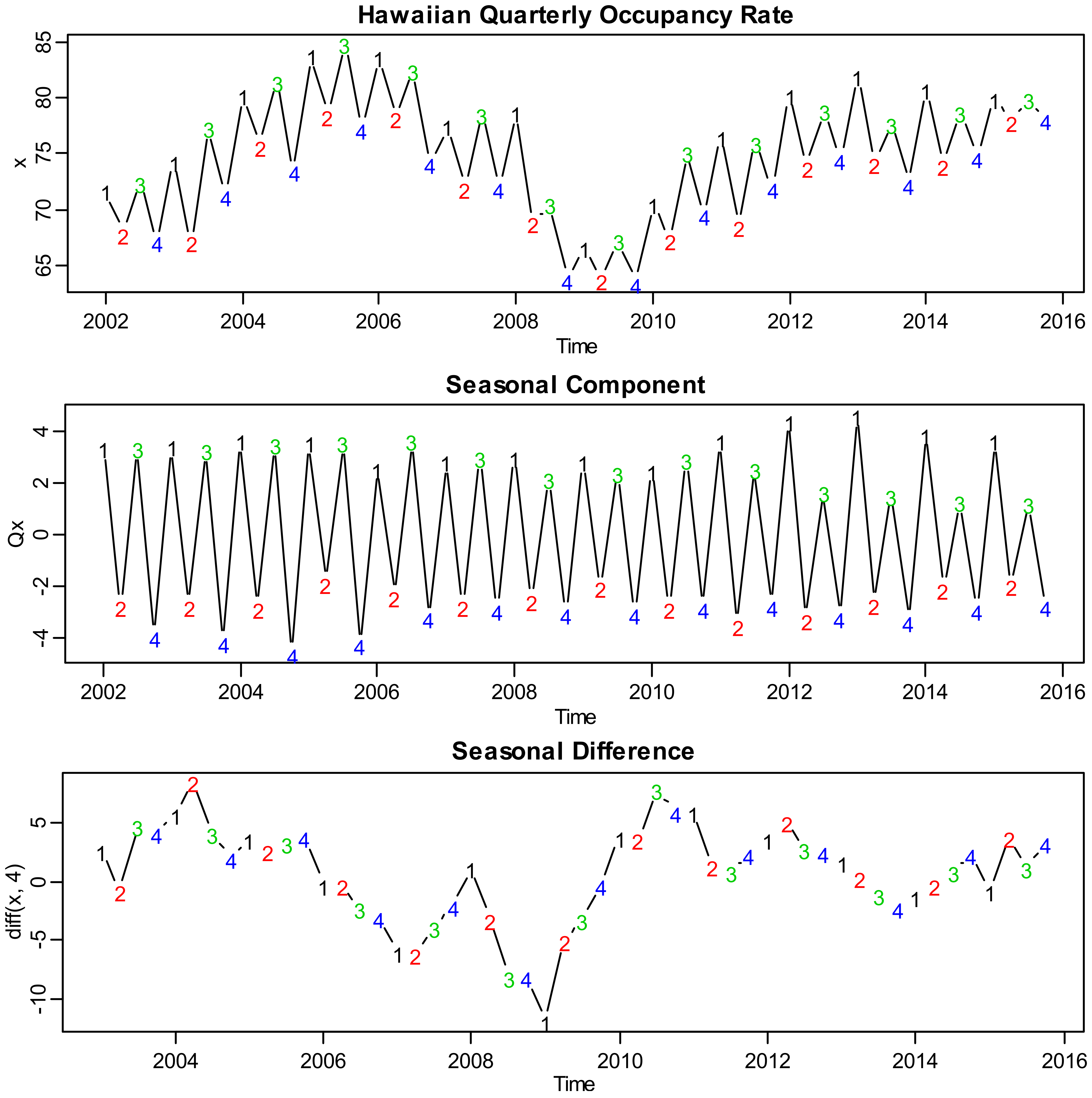
Non-seasonal

Seasonal Persistence

Quarterly Occupancy Rate:
% rooms filled

Seasonal Component:
this year vs. last year
Q1 ≈ Q1, Q2 ≈ Q2,
Q3 ≈ Q3, Q4 ≈ Q4

Remove seasonal persistence by a seasonal difference:
$X_t - X_{t-4}$ or $D = 1, S = 4$
for quarterly data



Air Passengers

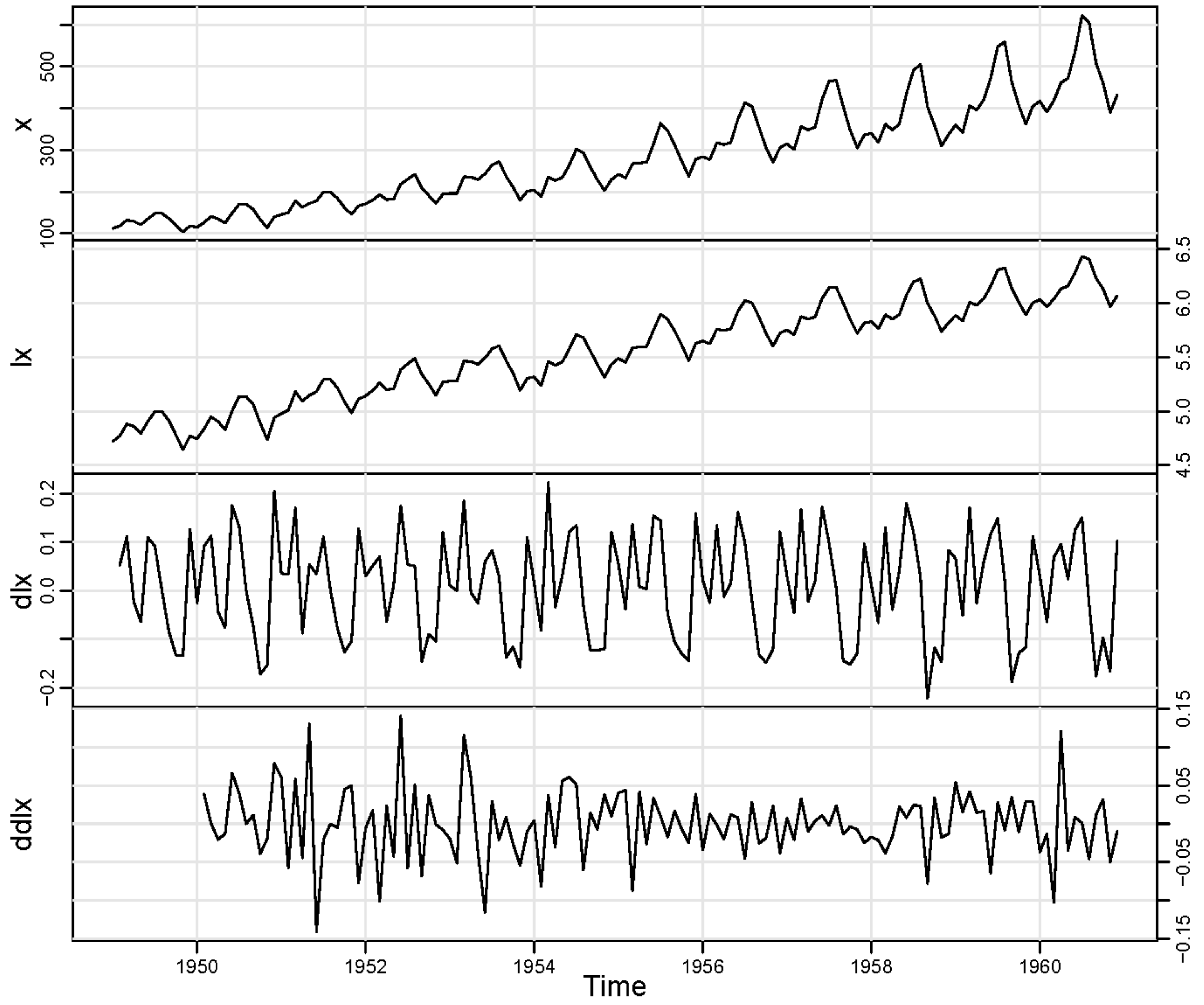
- Monthly totals of international airline passengers, 1949-1960

x: `AirPassengers`

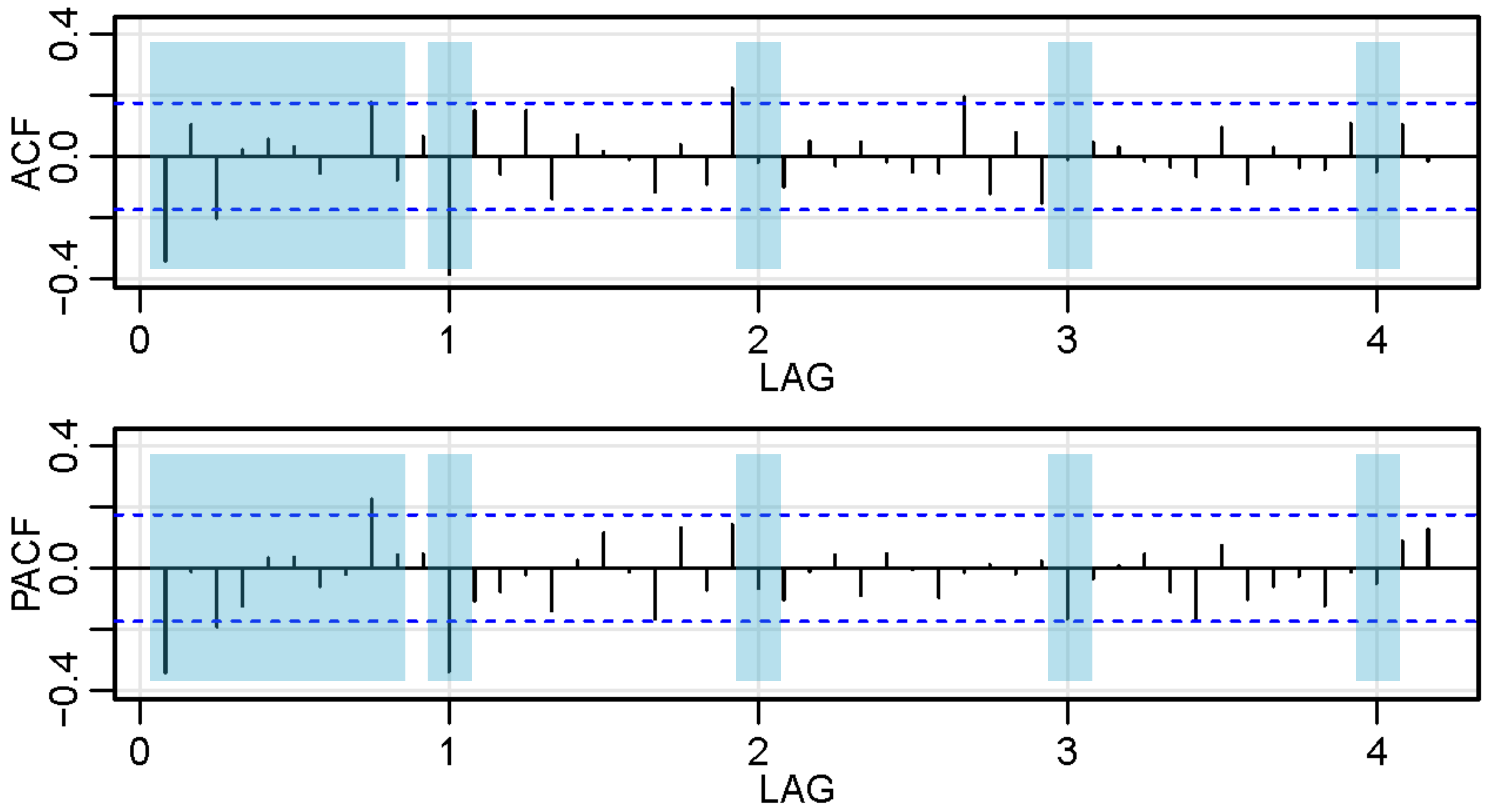
lx: `log(x)`

dlx: `diff(lx)`

ddlx: `diff(dlx, 12)`



Air Passengers: ACF and PACF of ddlx



- **Seasonal:** ACF cutting off at lag 1s (s = 12); PACF tailing off at lags 1s, 2s, 3s...
- **Non-Seasonal:** ACF and PACF both tailing off

Air Passengers

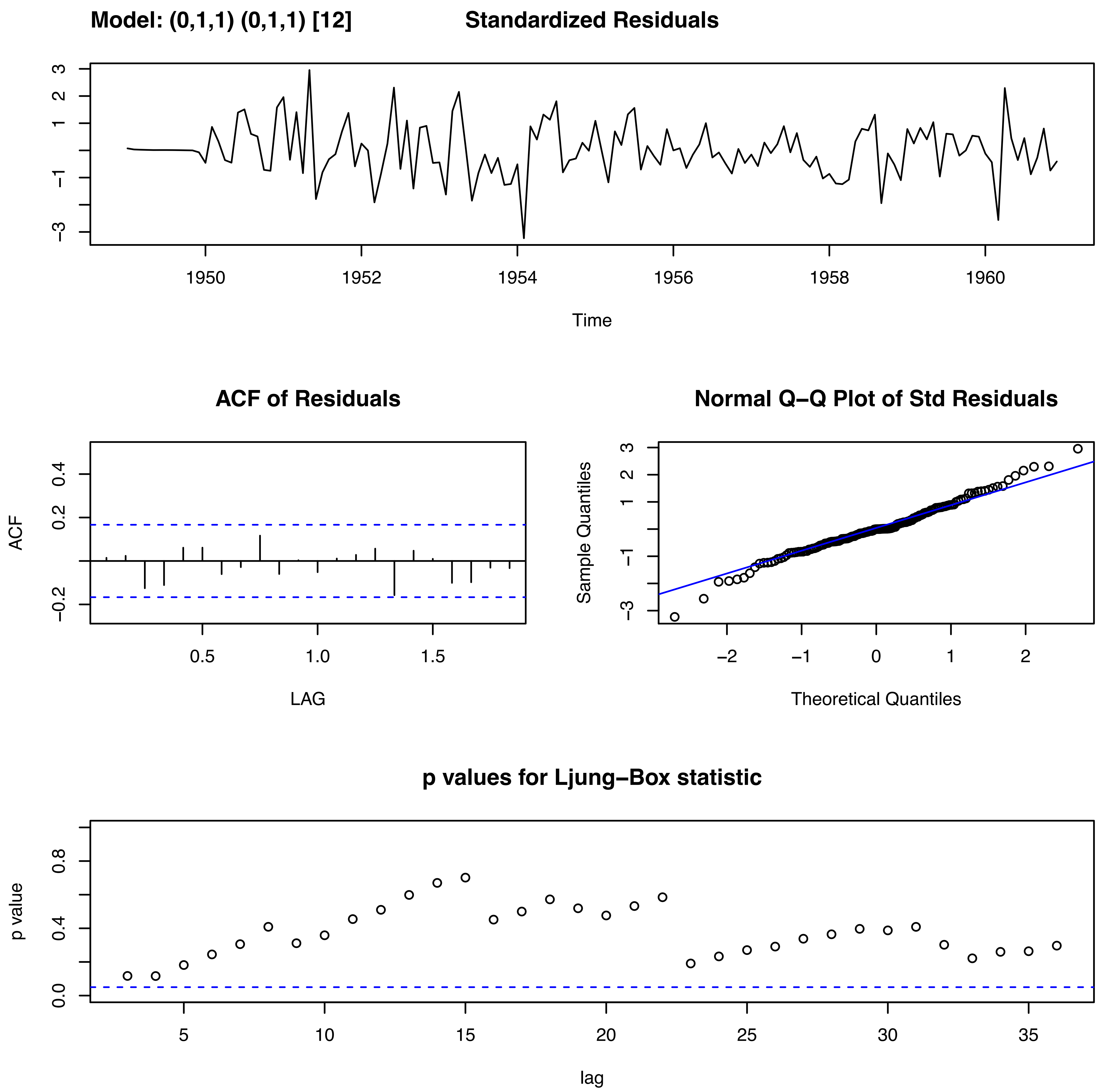
```
> airpass_fit1 <- sarima(log(AirPassengers), p = 1,
        d = 1, q = 1, P = 0,
        D = 1, Q = 1, S = 12)
> airpass_fit1$ttable

     Estimate     SE t.value p.value
ar1    0.1960 0.2475  0.7921  0.4296
ma1   -0.5784 0.2132 -2.7127  0.0075
sma1  -0.5643 0.0747 -7.5544  0.0000

> airpass_fit2 <- sarima(log(AirPassengers),
        0, 1, 1, 0, 1, 1, 12)
> airpass_fit2$ttable

     Estimate     SE t.value p.value
ma1   -0.4018 0.0896 -4.4825       0
sma1  -0.5569 0.0731 -7.6190       0
```

Air Passengers



Let's practice!

Forecasting Seasonal ARIMA

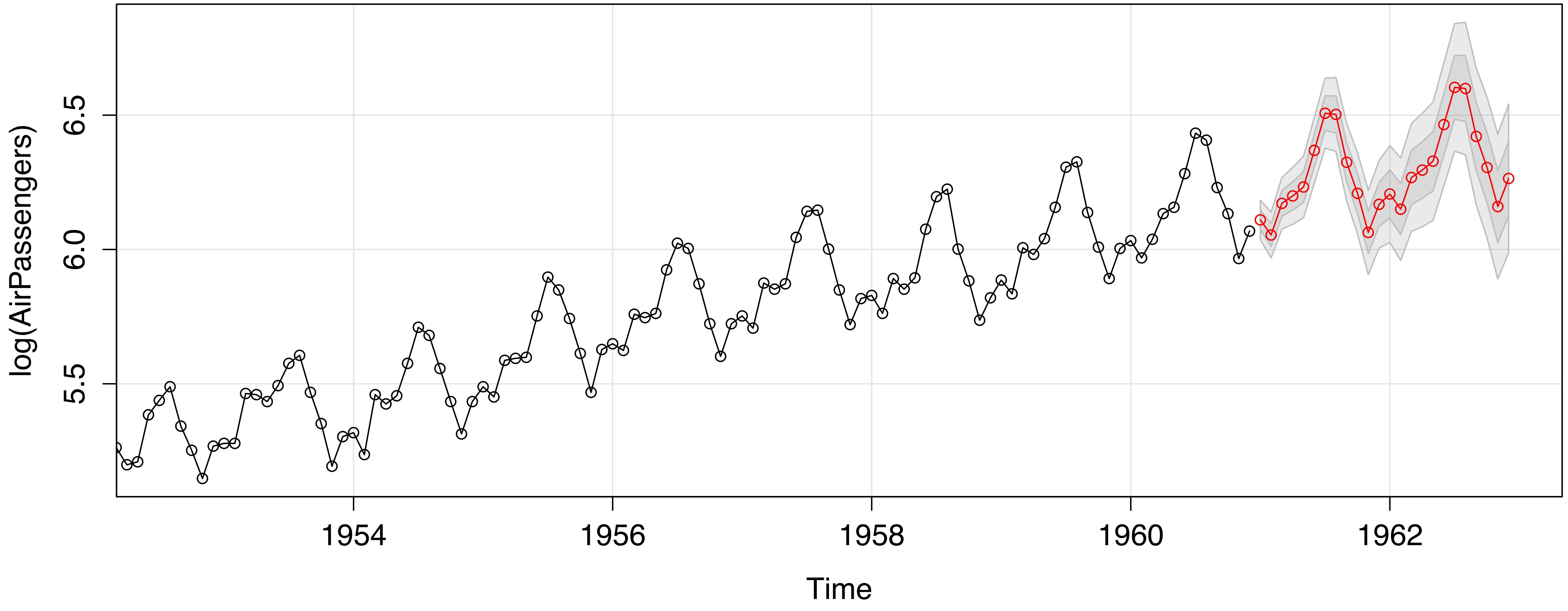
Forecasting ARIMA Processes

- Once model is chosen, forecasting is easy because the model describes how the dynamics of the time series behave over time
- Simply continue the model dynamics into the future
- In the `astsa` package, use `sarima.for()` for forecasting

Forecasting Air Passengers

- In the previous video, we decided that a SARIMA$(0,1,1)\times(0,1,1)_{12}$ model was appropriate

```
> sarima.for(log(AirPassengers), n.ahead = 24,
             0, 1, 1, 0, 1, 1, 12)
```



Let’s practice!

Congratulations!

What you've learned

- How to identify an ARMA model from data looking at ACF and PACF
- How to use integrated ARMA (ARIMA) models for nonstationary time series
- How to cope with seasonality

Don’t stop here!

- `astsa-package`
- Other DataCamp courses in Time Series Analysis

Thank you!