# ARIMA

Simulation and Fitting

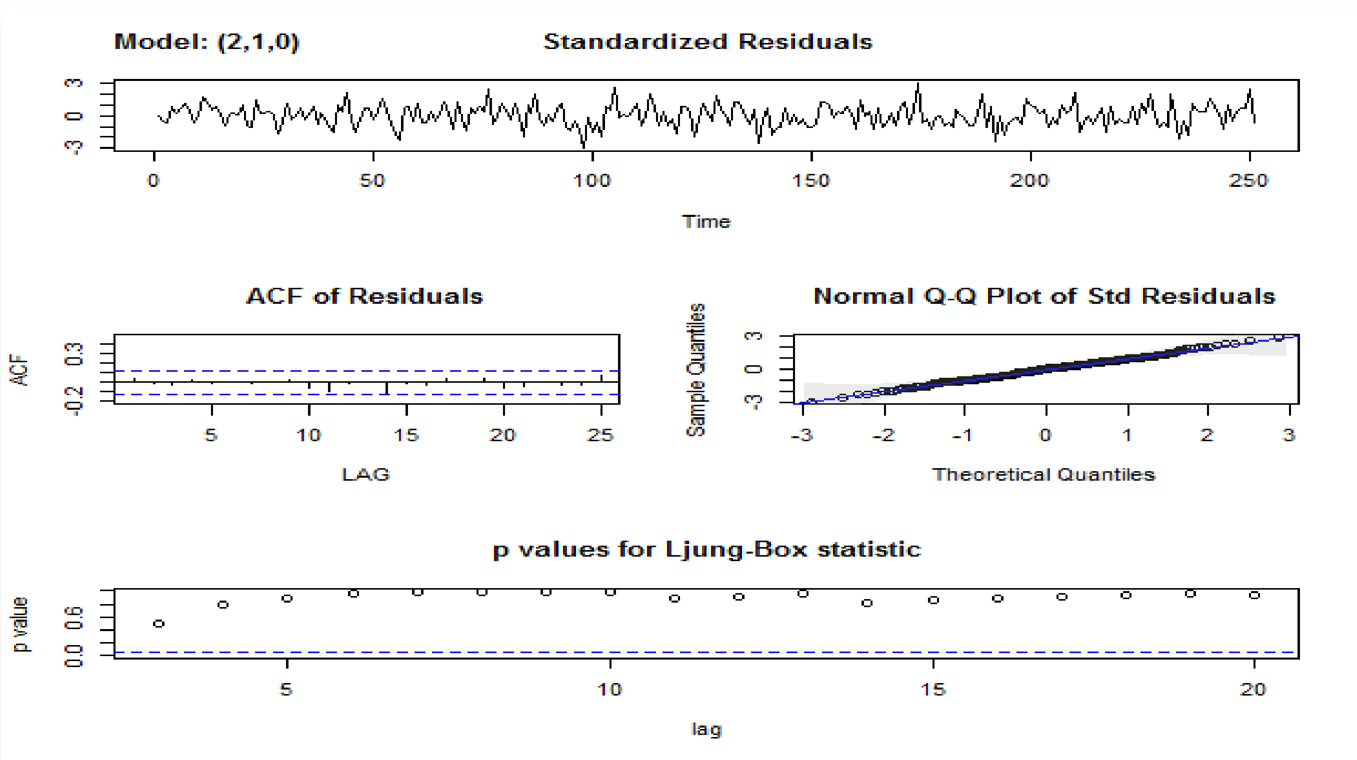
# Identifying ARIMA Model

- We can try differencing and then fitting the ARMA model
- If it fits after one or more differencing, then it can be ARIMA model

# Example: Simulated ARIMA

```r
library(astsa)
# Simulating ARIMA(2,1,0) model with drift 2
x <- arima.sim(model = list(order = c(2, 1, 0),
                         ar=c(1.5,-0.75)), n = 250, mean = 2)

x.fit <- sarima(x, p = 2, d = 1, q = 0)
```



Sane's STATS Academy of Statistics

# Example: Global mean land-ocean temperature deviations

```
> globtemp.fit <- sarima(globtemp,2,1,0,details = F)
> globtemp.fit$ttable
         Estimate     SE t.value p.value
ar1       -0.3027 0.0834 -3.6298  0.0004
ar2       -0.2678 0.0831 -3.2239  0.0016
constant   0.0073 0.0056  1.3047  0.1942
>
> globtemp.fit <- sarima(globtemp,3,1,0,details = F)
> globtemp.fit$ttable
         Estimate     SE t.value p.value
ar1       -0.3669 0.0842 -4.3592  0.0000
ar2       -0.3421 0.0849 -4.0319  0.0001
ar3       -0.2363 0.0838 -2.8186  0.0056
constant   0.0071 0.0044  1.6168  0.1083
>
> globtemp.fit <- sarima(globtemp,3,1,1,details = F)
> globtemp.fit$ttable
         Estimate     SE t.value p.value
ar1        0.2162 0.3897  0.5549  0.5799
ar2       -0.1546 0.1553 -0.9956  0.3213
ar3       -0.0344 0.1787 -0.1926  0.8475
ma1       -0.6007 0.3838 -1.5653  0.1199
constant   0.0071 0.0035  2.0114  0.0463
```

Fit

Overfit

# ARIMA – Automated Option

Package **forecast**

# Package **forecast**

- Package forecast by Rob Hyndman provides an automated function auto.arima() which identifies the optimal ARIMA fit
- It also provides a function named checkresiduals() which analyzes the residuals

# Function `auto.arima()`

Syntax :

auto.arima(y, …)

where y : a univariate time series

- All the other parameters like p, d, q etc. are taken based on the automated algorithms programed with this function
- Return type of this function is object of class ARIMA

# Function `checkresiduals()`

Syntax :

checkresiduals(ojbTS, …)

Where objTS : forecast object created from any time series modelling function

- Displays the result of Ljung-Box test which tests for white noise
- Small p-value of Ljung-Box test indicates the data probably are not white noise. In other words, larger the p-value there is more possibility of being a white noise
- Function also produces three diagnostic plots namely, line graph, ACF and histogram for examining the residuals

Sane's STATS Academy of Statistics

# Example 1: Global mean land-ocean temperature deviations

```
> library(forecast)
> fit <- auto.arima(globtemp)
> checkresiduals(fit)

        Ljung-Box test

data:  residuals
Q* = 8.7308, df = 6, p-value = 0.1893

Model df: 4.   Total lags used: 10
```

- P-value > 0.05 indicates that it is a white noise most probably

```
>      fit
Series: globtemp
ARIMA(3,1,0) with drift

Coefficients:
          ar1      ar2      ar3   drift
      -0.3669  -0.3421  -0.2363  0.0071
s.e.   0.0842   0.0849   0.0838  0.0044

sigma^2 estimated as 0.01003:  log likelihood=120.93
AIC=-231.85   AICc=-231.39   BIC=-217.32
```

# Example 2: International visitors to Australia

```
> fit <- auto.arima(austa)
> checkresiduals(fit)

        Ljung-Box test

data:  residuals
Q* = 3.2552, df = 8, p-value = 0.9173

Model df: 2.   Total lags used: 10
```

- P-value > 0.05 indicates that it is a white noise most probably

```
> fit
Series: austa
ARIMA(0,1,1) with drift

Coefficients:
         ma1   drift
      0.3006  0.1735
s.e.  0.1647  0.0390

sigma^2 estimated as 0.03376:  log likelihood=10.62
AIC=-15.24   AICc=-14.46   BIC=-10.57
```

# Seasonal ARIMA

Fitting

# Seasonal ARIMA

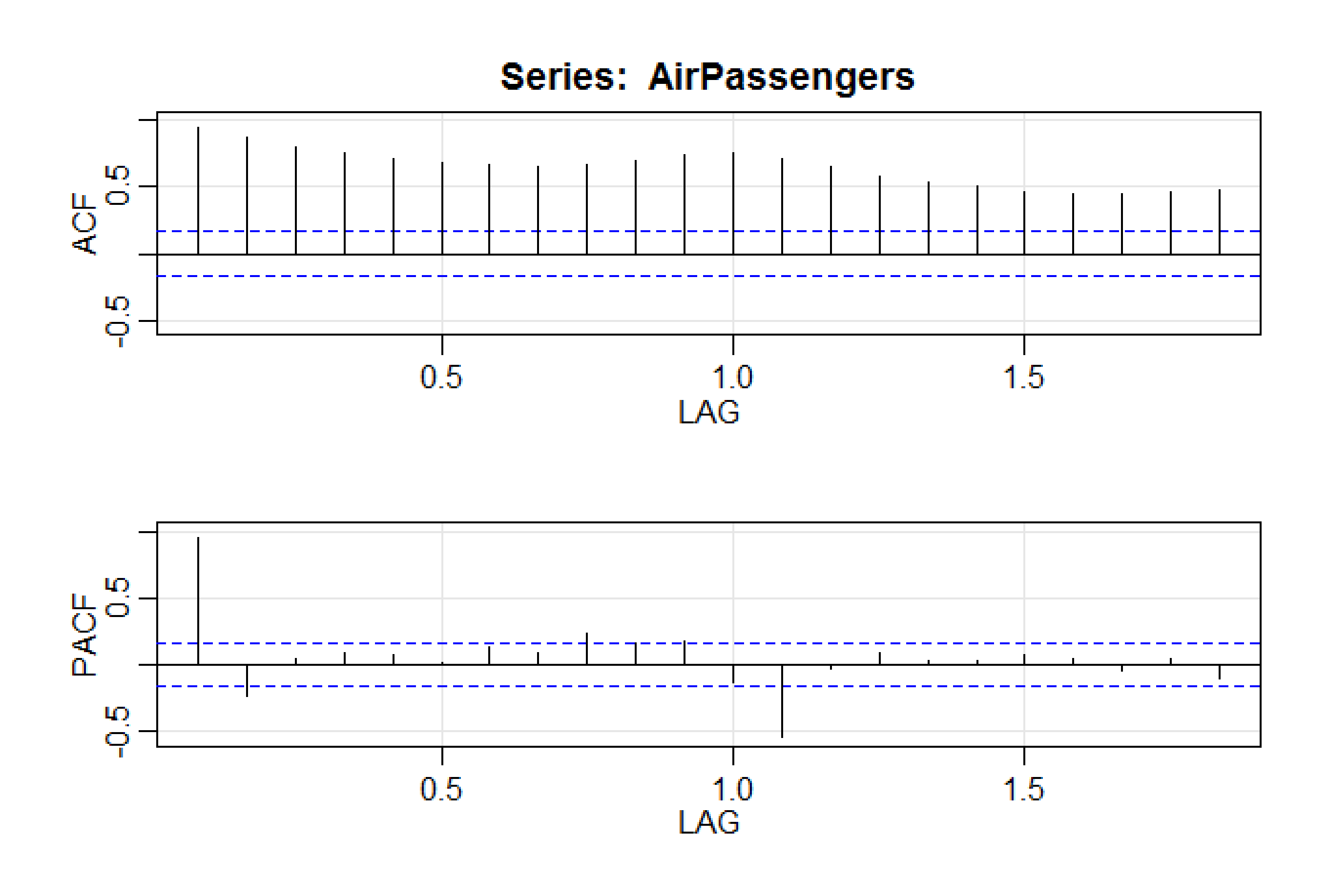
- It can be sometimes observed that the current values are influenced by some seasonal lag *s*
- There can some regular lags with which a pattern can be observed
- For seasonal ARIMA, we require four more parameters,
  - P : Seasonal AR order
  - D : Seasonal Difference
  - Q : Seasonal MA order
  - S : Seasonal period

# Thumb Rules for Identifying the Seasonal Models

- We can guess the SARMA models also with the help of ACF and PACF graphs
- Consider P = order of SAR , Q = order of SMA , S : Seasonal Period in the table below
- Also note that
  - “Tails off after g” means Starting to decrease at g
  - “Cuts off after g” means Disappears or becomes very small at g

| Graph | $AR(P)_S$ | MA(Q)S | $ARMA(P,Q)_S$ |
|---|---|---|---|
| ACF | Tails off after seasonal lags | Cuts off after lag QS | Tails off after seasonal lags |
| PACF | Cuts off after lag PS | Tails off after seasonal lags | Tails off after seasonal lags |

# Example: AirPassengers



# Fitting the Model to AirPassengers

```
> air.fit <- auto.arima(AirPassengers)
> air.fit
Series: AirPassengers
ARIMA(0,1,1)(0,1,0)[12]

Coefficients:
          ma1
      -0.3184
s.e.   0.0877

sigma^2 estimated as 138.3:  log likelihood=-508.32
AIC=1020.64   AICc=1020.73   BIC=1026.39
```

- Model identified here is ARIMA(0,1,1)(P=0,D=1,Q=0)S=12

# Forecasting

# Generating Forecasts

- Forecasts can be calculated based on the built model using various functions. But we are going to cover forecasting using
  - Function **`sarima.for()`** from package **astsa**
  - Function **`forecast()`** from package **forecast**

# Function `sarima.for()` from package **astsa**

## Syntax :

sarima.for(xdata, n.ahead, p, d, q, P = 0, D = 0, Q = 0, S = -1,…)

Where

xdata : Univariate time series

n.head : forecast horizon

p : AR order

d : difference order

q : MA order

P : Seasonal AR order

D : Seasonal Difference order

Q : Seasonal MA order

S : Seasonal period cycle