

# Forecasting: principles and practice

Rob J Hyndman

2.4 Non-seasonal ARIMA models

# Outline

- 1 Autoregressive models
- 2 Moving Average models
- 3 Non-seasonal ARIMA models
- 4 Estimation and order selection
- 5 ARIMA modelling in R
- 6 Lab session 15

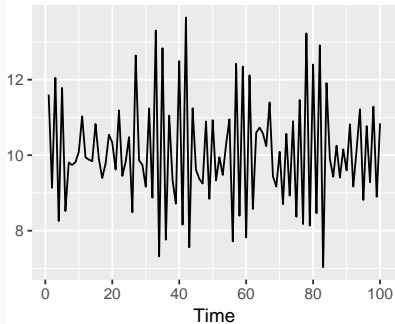
# Autoregressive models

## Autoregressive (AR) models:

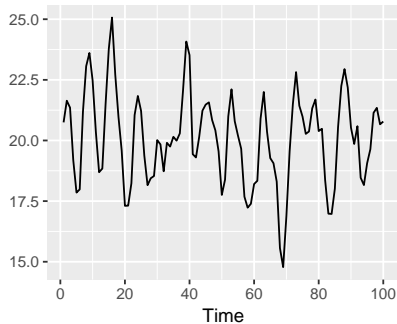
$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t,$$

where  $\varepsilon_t$  is white noise. This is a multiple regression with **lagged values** of  $y_t$  as predictors.

AR(1)



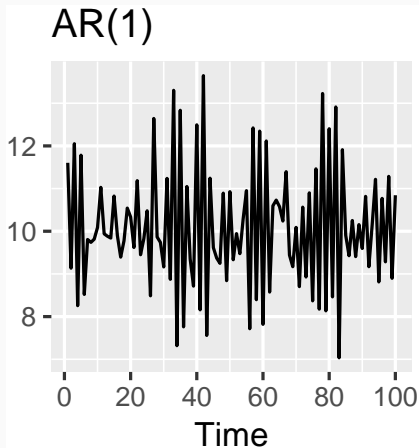
AR(2)



# AR(1) model

$$y_t = 2 - 0.8y_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$



# AR(1) model

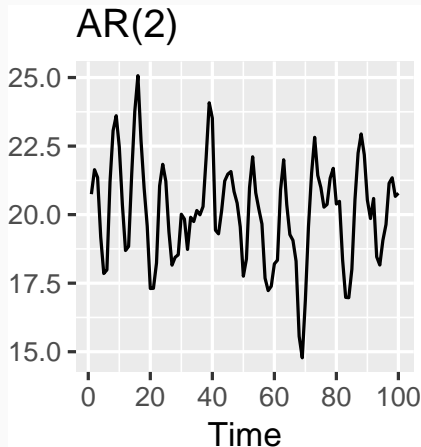
$$y_t = c + \phi_1 y_{t-1} + \varepsilon_t$$

- When  $\phi_1 = 0$ ,  $y_t$  is **equivalent to WN**
- When  $\phi_1 = 1$  and  $c = 0$ ,  $y_t$  is **equivalent to a RW**
- When  $\phi_1 = 1$  and  $c \neq 0$ ,  $y_t$  is **equivalent to a RW with drift**
- When  $\phi_1 < 0$ ,  $y_t$  tends to **oscillate between positive and negative values.**

# AR(2) model

$$y_t = 8 + 1.3y_{t-1} - 0.7y_{t-2} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$



# Stationarity conditions

We normally restrict autoregressive models to stationary data, and then some constraints on the values of the parameters are required.

## General condition for stationarity

Complex roots of  $1 - \phi_1 z - \phi_2 z^2 - \dots - \phi_p z^p$  lie outside the unit circle on the complex plane.

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- For  $p = 1$ :  $-1 < \phi_1 < 1$ .
- For  $p = 2$ :  
 $-1 < \phi_2 < 1$        $\phi_2 + \phi_1 < 1$        $\phi_2 - \phi_1 < 1$ .
- More complicated conditions hold for  $p \geq 3$ .



# Outline

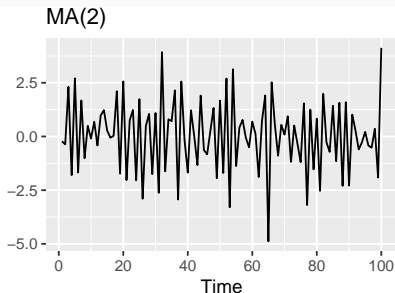
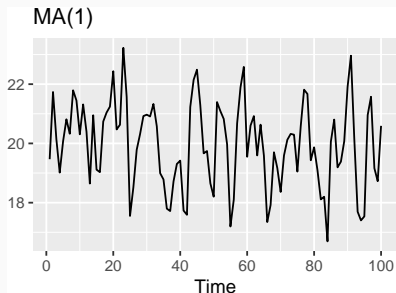
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# Moving Average (MA) models

## Moving Average (MA) models:

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q},$$

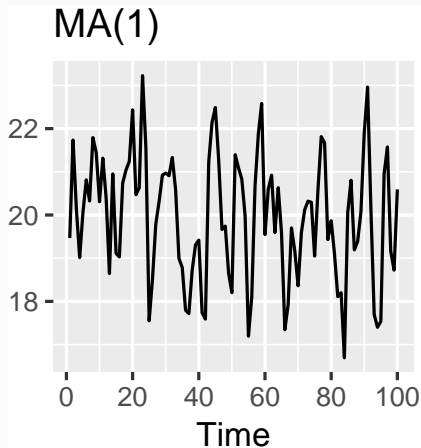
where  $\varepsilon_t$  is white noise. This is a multiple regression with **past errors** as predictors. *Don't confuse this with moving average smoothing!*



# MA(1) model

$$y_t = 20 + \varepsilon_t + 0.8\varepsilon_{t-1}$$

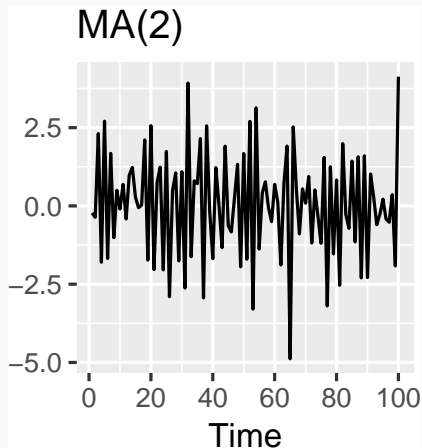
$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$



# MA(2) model

$$y_t = \varepsilon_t - \varepsilon_{t-1} + 0.8\varepsilon_{t-2}$$

$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$



# Invertibility

- Invertible models have property that distant past has negligible effect on forecasts. Requires constraints on MA parameters.

## General condition for invertibility

Complex roots of  $1 + \theta_1 z + \theta_2 z^2 + \dots + \theta_q z^q$  lie outside the unit circle on the complex plane.

# Invertibility

- Invertible models have property that distant past has negligible effect on forecasts. Requires constraints on MA parameters.

## General condition for invertibility

Complex roots of  $1 + \theta_1 z + \theta_2 z^2 + \dots + \theta_q z^q$  lie outside the unit circle on the complex plane.

- For  $q = 1$ :  $-1 < \theta_1 < 1$ .
- For  $q = 2$ :  
 $-1 < \theta_2 < 1$        $\theta_2 + \theta_1 > -1$        $\theta_1 - \theta_2 < 1$ .
- More complicated conditions hold for  $q \geq 3$ .

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# ARIMA models

## Autoregressive Moving Average models:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} \\ + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t.$$



# ARIMA models

## Autoregressive Moving Average models:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} \\ + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t.$$

- Predictors include both **lagged values of  $y_t$  and lagged errors.**
- Conditions on coefficients ensure stationarity.
- Conditions on coefficients ensure invertibility.

# ARIMA models

## Autoregressive Moving Average models:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} \\ + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t.$$

- Predictors include both **lagged values of  $y_t$  and lagged errors.**
- Conditions on coefficients ensure stationarity.
- Conditions on coefficients ensure invertibility.

## Autoregressive Integrated Moving Average models

- Combine ARMA model with **differencing.**
- $(1 - B)^d y_t$  follows an ARMA model.

# ARIMA models

## Autoregressive Integrated Moving Average models

### ARIMA( $p, d, q$ ) model

AR:  $p$  = order of the autoregressive part

I:  $d$  = degree of first differencing involved

MA:  $q$  = order of the moving average part.

- White noise model: ARIMA(0,0,0)
- Random walk: ARIMA(0,1,0) with no constant
- Random walk with drift: ARIMA(0,1,0) with const.
- AR( $p$ ): ARIMA( $p,0,0$ )
- MA( $q$ ): ARIMA(0,0, $q$ )

# Backshift notation for ARIMA

## ■ ARMA model:

$$y_t = c + \phi_1 B y_t + \dots + \phi_p B^p y_t + \varepsilon_t + \theta_1 B \varepsilon_t + \dots + \theta_q B^q \varepsilon_t$$

$$\text{or } (1 - \phi_1 B - \dots - \phi_p B^p) y_t = c + (1 + \theta_1 B + \dots + \theta_q B^q) \varepsilon_t$$

## ■ ARIMA(1,1,1) model:

$$\begin{array}{ccccc} (1 - \phi_1 B) & (1 - B) y_t & = & c + (1 + \theta_1 B) \varepsilon_t \\ \uparrow & \uparrow & & \uparrow \\ \text{AR(1)} & \text{First} & & \text{MA(1)} \\ & \text{difference} & & \end{array}$$

# Backshift notation for ARIMA

## ■ ARMA model:

$$y_t = c + \phi_1 B y_t + \dots + \phi_p B^p y_t + \varepsilon_t + \theta_1 B \varepsilon_t + \dots + \theta_q B^q \varepsilon_t$$

$$\text{or } (1 - \phi_1 B - \dots - \phi_p B^p) y_t = c + (1 + \theta_1 B + \dots + \theta_q B^q) \varepsilon_t$$

## ■ ARIMA(1,1,1) model:

$$(1 - \phi_1 B) (1 - B) y_t = c + (1 + \theta_1 B) \varepsilon_t$$



AR(1)



First



MA(1)

difference

Written out:

$$y_t = c + y_{t-1} + \phi_1 y_{t-1} - \phi_1 y_{t-2} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

# R model

## Intercept form

$$(1 - \phi_1 B - \dots - \phi_p B^p) y'_t = c + (1 + \theta_1 B + \dots + \theta_q B^q) \varepsilon_t$$

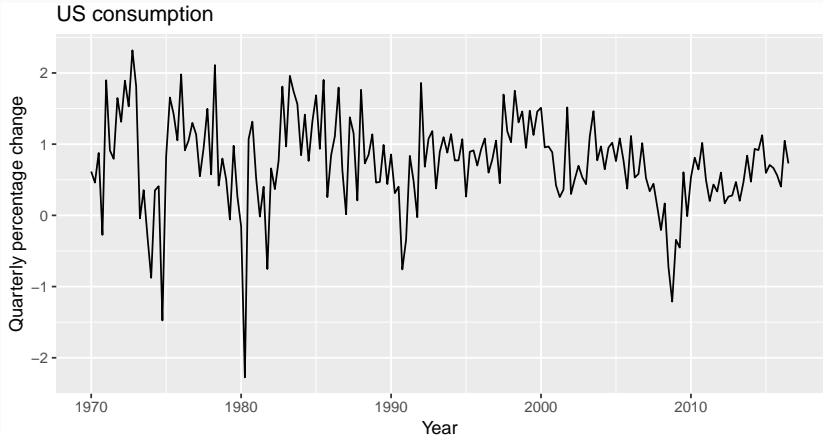
## Mean form

$$(1 - \phi_1 B - \dots - \phi_p B^p)(y'_t - \mu) = (1 + \theta_1 B + \dots + \theta_q B^q) \varepsilon_t$$

- $y'_t = (1 - B)^d y_t$
- $\mu$  is the mean of  $y'_t$ .
- $c = \mu(1 - \phi_1 - \dots - \phi_p)$ .
- R uses mean form.

# US personal consumption

```
autoplot(uschange[, "Consumption"]) +  
  xlab("Year") + ylab("Quarterly percentage change") +  
  ggtitle("US consumption")
```



# US personal consumption

```
(fit <- auto.arima(uschange[, "Consumption"]))
```

```
## Series: uschange[, "Consumption"]
## ARIMA(2,0,2) with non-zero mean
##
## Coefficients:
##          ar1      ar2      ma1      ma2      mean
##          1.391  -0.581  -1.180   0.558   0.746
## s.e.    0.255    0.208    0.238   0.140   0.084
##
## sigma^2 estimated as 0.351:  log likelihood=-165.1
## AIC=342.3   AICc=342.8   BIC=361.7
```



# US personal consumption

```
(fit <- auto.arima(uschange[, "Consumption"]))
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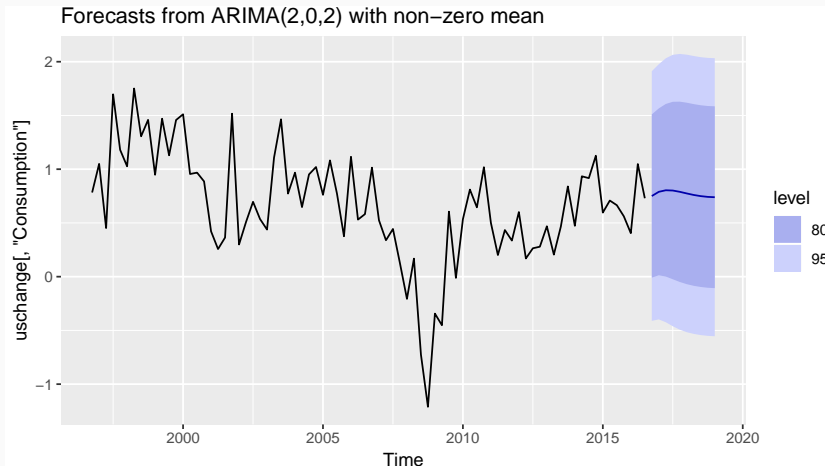
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```

## ARIMA(2,0,2) model:

$$y_t = c + 1.391y_{t-1} - 0.581y_{t-2} - 1.180\varepsilon_{t-1} + 0.558\varepsilon_{t-2} + \varepsilon_t,$$
  
where  $c = 0.746 \times (1 - 1.391 + 0.581) = 0.142$  and  $\varepsilon_t \sim N(0, 0.351)$ .

# US personal consumption

```
fit %>% forecast(h=10) %>% autoplot(include=80)
```



# Understanding ARIMA models

## Long-term forecasts

zero	$c = 0, d = 0$	
non-zero constant	$c = 0, d = 1$	$c \neq 0, d = 0$
linear	$c = 0, d = 2$	$c \neq 0, d = 1$
quadratic	$c = 0, d = 3$	$c \neq 0, d = 2$

## Forecast variance and $d$

- The higher the value of  $d$ , the more rapidly the prediction intervals increase in size.
- For  $d = 0$ , the long-term forecast standard deviation will go to the standard deviation of the historical data.

# Understanding ARIMA models

## Cyclic behaviour

- For cyclic forecasts,  $p \geq 2$  and some restrictions on coefficients are required.
- If  $p = 2$ , we need  $\phi_1^2 + 4\phi_2 < 0$ . Then average cycle of length

$$(2\pi) / \left[ \arccos(-\phi_1(1 - \phi_2)/(4\phi_2)) \right] .$$

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# Maximum likelihood estimation

Having identified the model order, we need to estimate the parameters  $c, \phi_1, \dots, \phi_p, \theta_1, \dots, \theta_q$ .

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Having identified the model order, we need to estimate the parameters  $c, \phi_1, \dots, \phi_p, \theta_1, \dots, \theta_q$ .

- MLE is very similar to least squares estimation obtained by minimizing

$$\sum_{t=1}^T e_t^2.$$

- The `Arima()` command allows CLS or MLE estimation.
- Non-linear optimization must be used in either case.
- Different software will give different estimates.

# Information criteria

## Akaike's Information Criterion (AIC):

$$\text{AIC} = -2 \log(L) + 2(p + q + k + 1),$$

where  $L$  is the likelihood of the data,

$k = 1$  if  $c \neq 0$  and  $k = 0$  if  $c = 0$ .



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## Corrected AIC:

$$\text{AICc} = \text{AIC} + \frac{2(p + q + k + 1)(p + q + k + 2)}{T - p - q - k - 2}.$$

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## Bayesian Information Criterion:

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## Bayesian Information Criterion:

$$\text{BIC} = \text{AIC} + \log(T)(p + q + k - 1).$$

Good models are obtained by minimizing either the AIC, AICc or BIC. My preference is to use the AICc.

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# How does auto.arima() work?

## A non-seasonal ARIMA process

$$\phi(B)(1 - B)^d y_t = c + \theta(B)\varepsilon_t$$

Need to select appropriate orders:  $p, q, d$

## Hyndman and Khandakar (JSS, 2008) algorithm:

- Select no. differences  $d$  and  $D$  via KPSS test and seasonal strength measure.
- Select  $p, q$  by minimising AICc.
- Use stepwise search to traverse model space.

# How does `auto.arima()` work?

**Step 1:** Select values of  $d$  and  $D$ .

**Step 2:** Select current model (with smallest AICc) from:

ARIMA(2,  $d$ , 2)

ARIMA(0,  $d$ , 0)

ARIMA(1,  $d$ , 0)

ARIMA(0,  $d$ , 1)

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ARIMA(1,  $d$ , 0)

ARIMA(0,  $d$ , 1)

**Step 3:** Consider variations of current model:

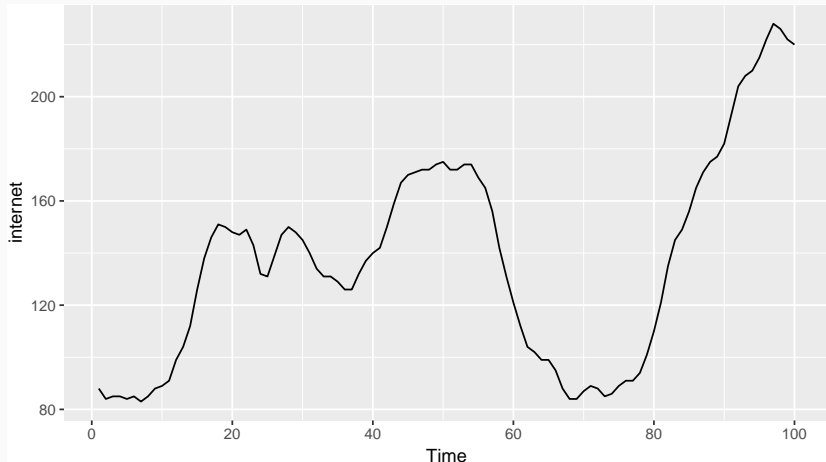
- vary one of  $p$ ,  $q$ , from current model by  $\pm 1$ ;
- $p$ ,  $q$  both vary from current model by  $\pm 1$ ;
- Include/exclude  $c$  from current model.

Model with lowest AICc becomes current model.

Repeat Step 3 until no lower AICc can be found.

# Choosing an ARIMA model

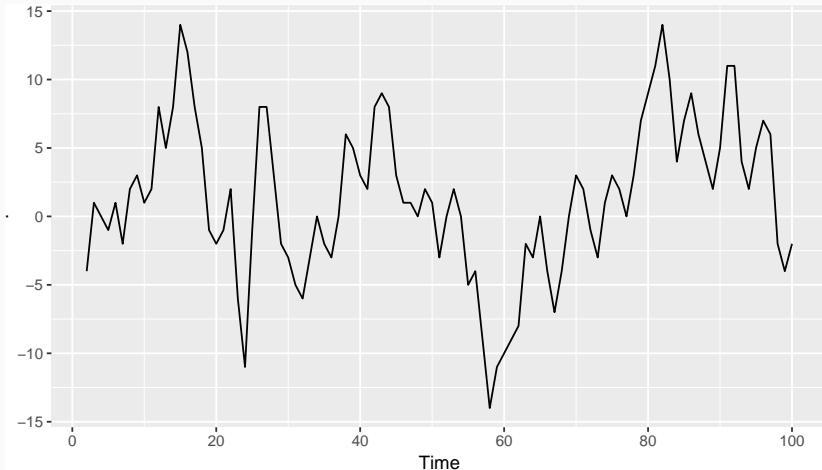
```
autoplot(internet)
```





# Choosing an ARIMA model

```
internet %>% diff() %>% autoplot()
```



# Choosing an ARIMA model

```
(fit <- auto.arima(internet))
```

```
## Series: internet
```

```
## ARIMA(1,1,1)
```

```
##
```

```
## Coefficients:
```

```
##          ar1      ma1
```

```
##          0.650   0.526
```

```
## s.e.    0.084   0.090
```

```
##
```

```
## sigma^2 estimated as 10:  log likelihood=-254.2
```

```
## AIC=514.3   AICc=514.5   BIC=522.1
```

# Choosing an ARIMA model

```
(fit <- auto.arima(internet, stepwise=FALSE,  
  approximation=FALSE))
```

```
## Series: internet
```

```
## ARIMA(3,1,0)
```

```
##
```

```
## Coefficients:
```

```
##          ar1      ar2      ar3
```

```
##          1.151  -0.661  0.341
```

```
## s.e.    0.095    0.135    0.094
```

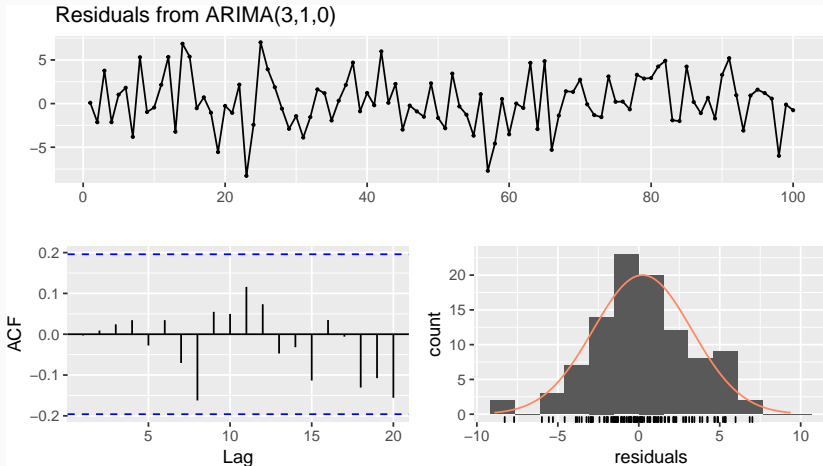
```
##
```

```
## sigma^2 estimated as 9.66:  log likelihood=-252
```

```
## AIC=512    AICc=512.4    BIC=522.4
```

# Choosing an ARIMA model

```
checkresiduals(fit, plot=TRUE)
```



# Choosing an ARIMA model

```
checkresiduals(fit, plot=FALSE)
```

```
##
```

```
##  Ljung-Box test
```

```
##
```

```
## data:  Residuals from ARIMA(3,1,0)
```

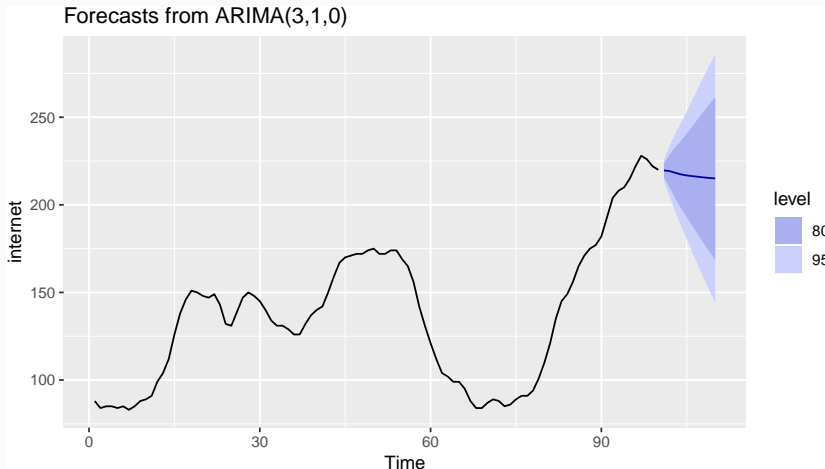
```
## Q* = 4.5, df = 7, p-value = 0.7
```

```
##
```

```
## Model df: 3.    Total lags used: 10
```

# Choosing an ARIMA model

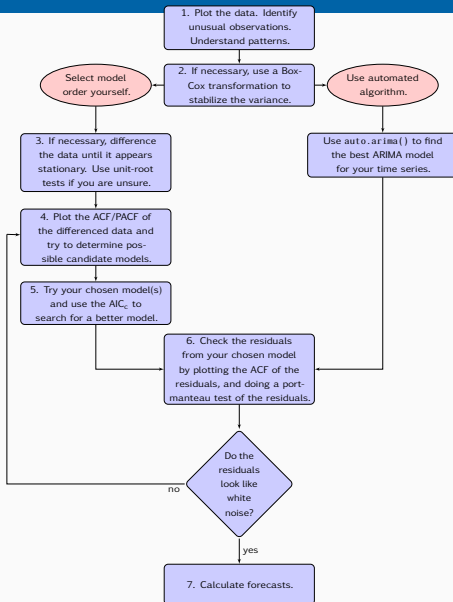
```
fit %>% forecast() %>% autoplot()
```



# Modelling procedure with `auto.arima`

- 1 Plot the data. Identify any unusual observations.
- 2 If necessary, transform the data (using a Box-Cox transformation) to stabilize the variance.
- 3 Use `auto.arima` to select a model.
- 4 Check the residuals from your chosen model by plotting the ACF of the residuals, and doing a portmanteau test of the residuals. If they do not look like white noise, try a modified model.
- 5 Once the residuals look like white noise, calculate forecasts.

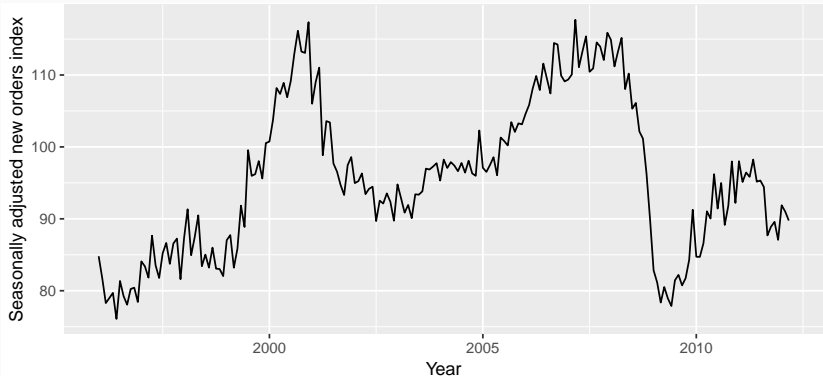
# Modelling procedure





# Seasonally adjusted electrical equipment

```
eeadj <- seasadj(stl(elecequip, s.window="periodic")  
autoplot(eeadj) + xlab("Year") +  
  ylab("Seasonally adjusted new orders index"))
```

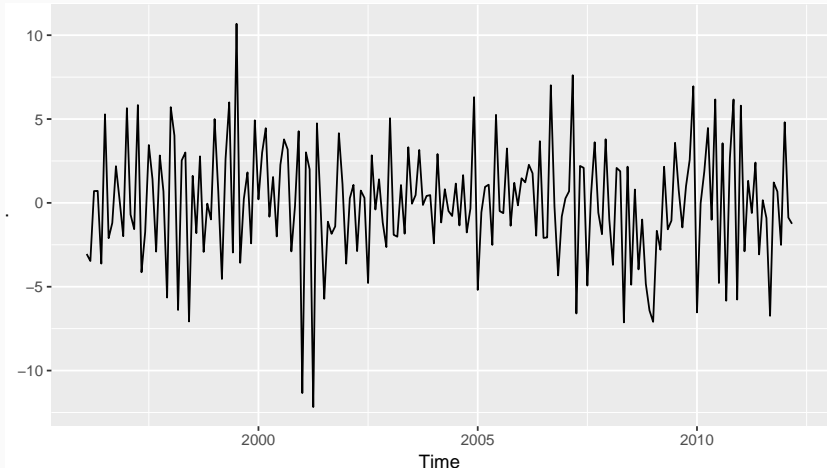


# Seasonally adjusted electrical equipment

- 1 Time plot shows sudden changes, particularly big drop in 2008/2009 due to global economic environment. Otherwise nothing unusual and no need for data adjustments.
- 2 No evidence of changing variance, so no Box-Cox transformation.
- 3 Data are clearly non-stationary, so we take first differences.

# Seasonally adjusted electrical equipment

```
eeadj %>% diff() %>% autoplot()
```



# Seasonally adjusted electrical equipment

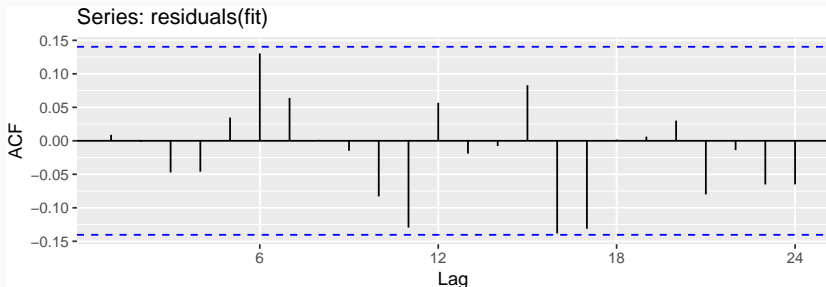
```
fit <- auto.arima(eeadj, stepwise=FALSE, approximation=FALSE)
summary(fit)
```

```
## Series: eeadj
## ARIMA(3,1,1)
##
## Coefficients:
##          ar1      ar2      ar3      ma1
##          0.004  0.092  0.370  -0.392
## s.e.    0.220  0.098  0.067   0.243
##
## sigma^2 estimated as 9.58:  log likelihood=-492.7
## AIC=995.4   AICc=995.7   BIC=1012
##
## Training set error measures:
##
##              ME  RMSE   MAE      MPE  MAPE   MASE
## Training set 0.03288 3.055 2.357 -0.00647 2.482 0.2884
##
##              ACF1
```

# Seasonally adjusted electrical equipment

- 6 ACF plot of residuals from ARIMA(3,1,1) model look like white noise.

```
ggAcf(residuals(fit))
```



# Seasonally adjusted electrical equipment

```
checkresiduals(fit, plot=FALSE)
```

```
##
```

```
##  Ljung-Box test
```

```
##
```

```
## data:  Residuals from ARIMA(3,1,1)
```

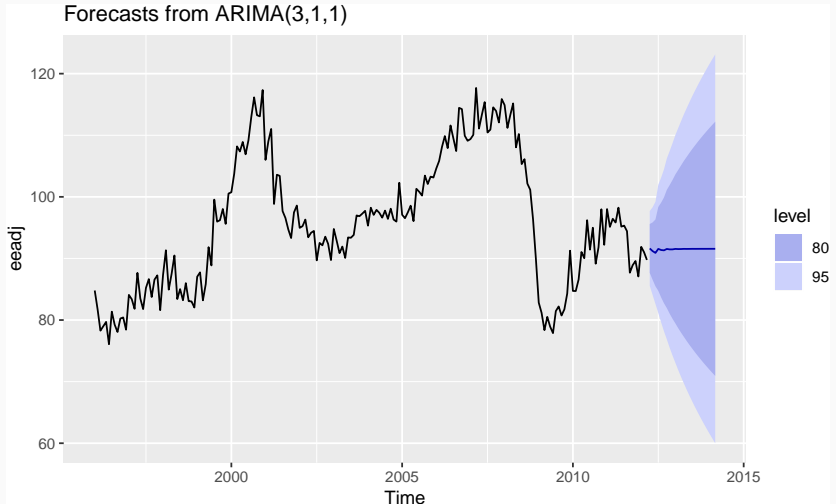
```
## Q* = 24, df = 20, p-value = 0.2
```

```
##
```

```
## Model df: 4.    Total lags used: 24
```

# Seasonally adjusted electrical equipment

```
fit %>% forecast() %>% autoplot()
```



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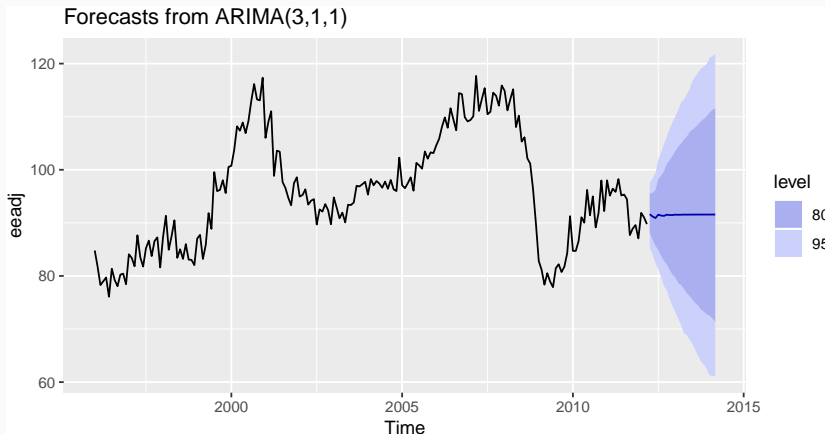
# Lab Session 15

# Prediction intervals

- Prediction intervals **increase in size with forecast horizon.**
- Calculations assume residuals are **uncorrelated** and **normally distributed.**
- Prediction intervals tend to be too narrow.
  - the uncertainty in the parameter estimates has not been accounted for.
  - the ARIMA model assumes historical patterns will not change during the forecast period.
  - the ARIMA model assumes uncorrelated future errors

# Bootstrapped prediction intervals

```
fit %>% forecast(bootstrap=TRUE) %>% autoplot()
```



- No assumption of normally distributed residuals.