



Tidy Time Series & Forecasting in R



8. ARIMA models

Outline

- 1 ARIMA models
- 2 Lab Session 13
- 3 Seasonal ARIMA models
- 4 Lab Session 14

Outline

- 1 ARIMA models
- 2 Lab Session 13
- 3 Seasonal ARIMA models
- 4 Lab Session 14

ARIMA models

AR: autoregressive (lagged observations as inputs)

I: integrated (differencing to make series stationary)

MA: moving average (lagged errors as inputs)

ARIMA models

AR: autoregressive (lagged observations as inputs)

I: integrated (differencing to make series stationary)

MA: moving average (lagged errors as inputs)

An ARIMA model is rarely interpretable in terms of visible data structures like trend and seasonality. But it can capture a huge range of time series patterns.

Stationarity

Definition

If $\{y_t\}$ is a stationary time series, then for all s , the distribution of (y_t, \dots, y_{t+s}) does not depend on t .

Stationarity

Definition

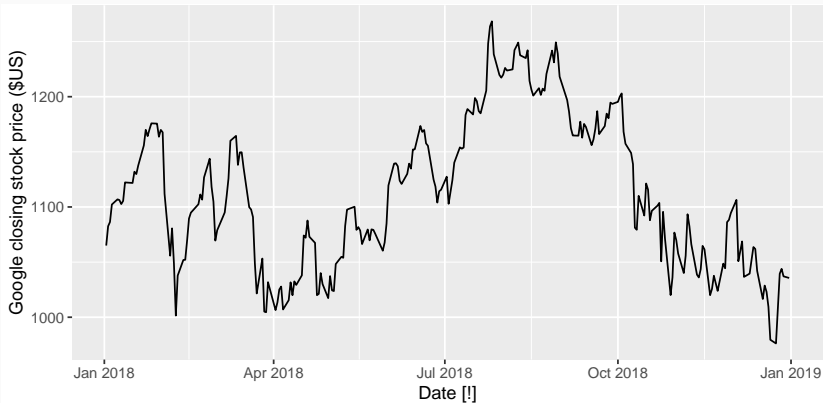
If $\{y_t\}$ is a stationary time series, then for all s , the distribution of (y_t, \dots, y_{t+s}) does not depend on t .

A **stationary series** is:

- roughly horizontal
- constant variance
- no patterns predictable in the long-term

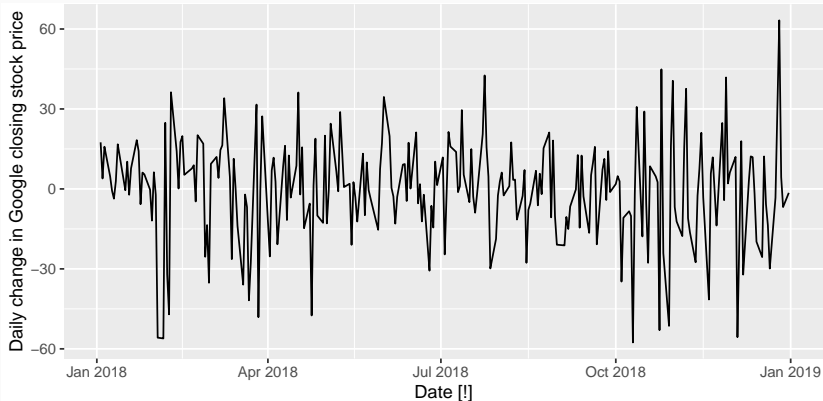
Stationary?

```
gafa_stock %>%  
  filter(Symbol == "GOOG", year(Date) == 2018) %>%  
  autoplot(Close) +  
    ylab("Google closing stock price ($US)")
```



Stationary?

```
gafa_stock %>%  
  filter(Symbol == "GOOG", year(Date) == 2018) %>%  
  autoplot(difference(Close)) +  
  ylab("Daily change in Google closing stock price")
```



Differencing

- Differencing helps to **stabilize the mean**.
- The differenced series is the *change* between each observation in the original series.
- Occasionally the differenced data will not appear stationary and it may be necessary to difference the data a second time.
- In practice, it is almost never necessary to go beyond second-order differences.

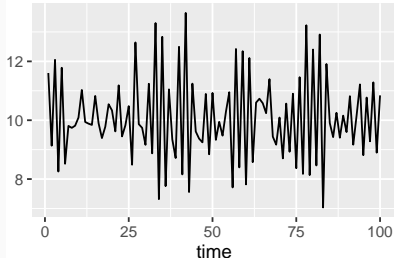
Autoregressive models

Autoregressive (AR) models:

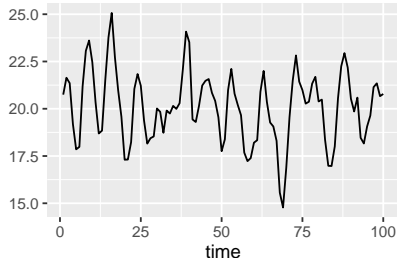
$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t,$$

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

AR(1)



AR(2)



- Cyclic behaviour is possible when $p \geq 2$.

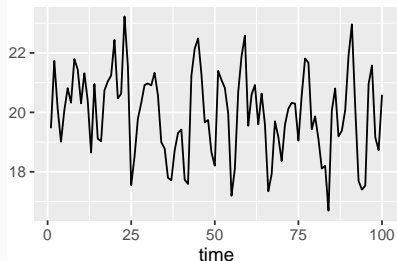
Moving Average (MA) models

Moving Average (MA) models:

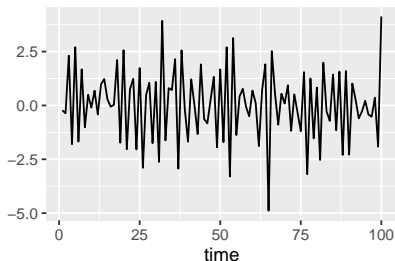
$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q},$$

where ε_t is white noise. This is a multiple regression with **lagged errors** as predictors. *Don't confuse this with moving average smoothing!*

MA(1)



MA(2)



ARIMA models

Autoregressive Moving Average models:

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

ARIMA models

Autoregressive Moving Average models:

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

- Predictors include both **lagged values of y_t** and **lagged errors**.

ARIMA models

Autoregressive Moving Average models:

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

- Predictors include both **lagged values of y_t** and **lagged errors**.

Autoregressive Integrated Moving Average models

- Combine ARMA model with **differencing**.
- d -differenced series follows an ARMA model.
- Need to choose p, d, q and whether or not to include c .

ARIMA 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)

Example: National populations

```
fit <- global_economy %>%  
  model(arima = ARIMA(Population))  
fit
```

```
## # A mable: 263 x 2  
## # Key:      Country [263]  
##   Country      arima  
##   <fct>        <model>  
## 1 Afghanistan <ARIMA(4,2,1)>  
## 2 Albania     <ARIMA(0,2,2)>  
## 3 Algeria     <ARIMA(2,2,2)>  
## 4 American Samoa <ARIMA(2,2,2)>  
## 5 Andorra     <ARIMA(2,1,2) w/ drift>  
## 6 Angola      <ARIMA(4,2,1)>  
## 7 Antigua and Barbuda <ARIMA(2,1,2) w/ drift>  
## 8 Arab World  <ARIMA(0,2,1)>
```

Example: National populations

```
fit %>% filter(Country=="Australia") %>% report()
```

```
## Series: Population
## Model: ARIMA(0,2,1)
##
## Coefficients:
##          ma1
##       -0.661
## s.e.    0.107
##
## sigma^2 estimated as 4.063e+09:  log likelihood=-699
## AIC=1401   AICc=1402   BIC=1405
```

Example: National populations

```
fit %>% filter(Country=="Australia") %>% report()
```

```
## Series: Population
```

```
## Model: ARIMA(0,2,1)
```

```
##
```

```
## Coefficients:
```

```
##          ma1
```

```
##        -0.661
```

```
## s.e.    0.107
```

```
##
```

```
## sigma^2 estimated as 4.063e+09:  log likelihood=-699
```

```
## AIC=1401   AICc=1402   BIC=1405
```

$$y_t = 2y_{t-1} - y_{t-2} - 0.7\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \sim \text{NID}(0, 4 \times 10^9)$$

Understanding ARIMA models

- If $c = 0$ and $d = 0$, the long-term forecasts will go to zero.
- If $c = 0$ and $d = 1$, the long-term forecasts will go to a non-zero constant.
- If $c = 0$ and $d = 2$, the long-term forecasts will follow a straight line.
- If $c \neq 0$ and $d = 0$, the long-term forecasts will go to the mean of the data.
- If $c \neq 0$ and $d = 1$, the long-term forecasts will follow a straight line.
- If $c \neq 0$ and $d = 2$, the long-term forecasts will follow a quadratic trend.

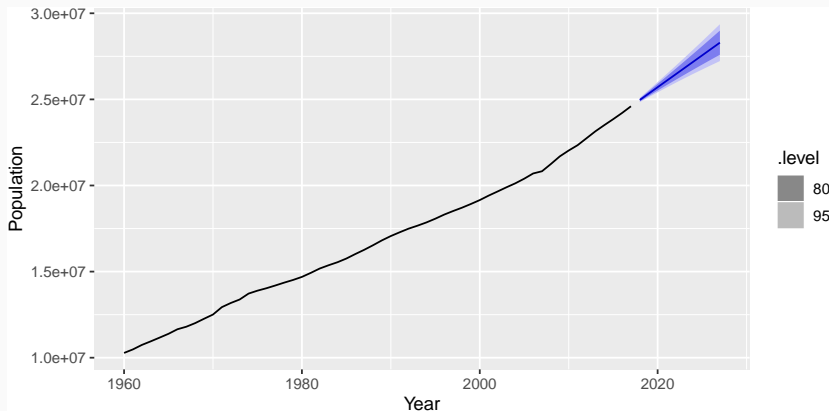
Understanding ARIMA models

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.

Example: National populations

```
fit %>% forecast(h=10) %>%  
  filter(Country=="Australia") %>%  
  autoplot(global_economy)
```



How does ARIMA() work?

Hyndman and Khandakar (JSS, 2008) algorithm:

- Select no. differences d via KPSS test.
- Select p, q and inclusion of c by minimising AICc.
- Use stepwise search to traverse model space.

How does ARIMA() work?

Hyndman and Khandakar (JSS, 2008) algorithm:

- Select no. differences d via KPSS test.
- Select p, q and inclusion of c by minimising AICc.
- Use stepwise search to traverse model space.

$$\text{AICc} = -2 \log(L) + 2(p+q+k+1) \left[1 + \frac{(p+q+k+2)}{T-p-q-k-2} \right].$$

where L is the maximised likelihood fitted to the *differenced* data, $k = 1$ if $c \neq 0$ and $k = 0$ otherwise.

How does ARIMA() work?

Hyndman and Khandakar (JSS, 2008) algorithm:

- Select no. differences d via KPSS test.
- Select p , q and inclusion of c by minimising AICc.
- Use stepwise search to traverse model space.

$$\text{AICc} = -2 \log(L) + 2(p+q+k+1) \left[1 + \frac{(p+q+k+2)}{T-p-q-k-2} \right].$$

where L is the maximised likelihood fitted to the *differenced* data, $k = 1$ if $c \neq 0$ and $k = 0$ otherwise.

Note: Can't compare AICc for different values of d .

How does ARIMA() work?

Step1: Select current model (with smallest AICc) from:

ARIMA(2, d , 2)

ARIMA(0, d , 0)

ARIMA(1, d , 0)

ARIMA(0, d , 1)

How does ARIMA() work?

Step1: Select current model (with smallest AICc) from:

ARIMA(2, d , 2)

ARIMA(0, d , 0)

ARIMA(1, d , 0)

ARIMA(0, d , 1)

Step 2: Consider variations of current model:

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

Model with lowest AICc becomes current model.

How does ARIMA() work?

Step1: Select current model (with smallest AICc) from:

ARIMA(2, d , 2)

ARIMA(0, d , 0)

ARIMA(1, d , 0)

ARIMA(0, d , 1)

Step 2: Consider variations of current model:

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

Model with lowest AICc becomes current model.

Repeat Step 2 until no lower AICc can be found.

Outline

- 1 ARIMA models
- 2 Lab Session 13
- 3 Seasonal ARIMA models
- 4 Lab Session 14

Lab Session 13

For the United States GDP data (from `global_economy`):

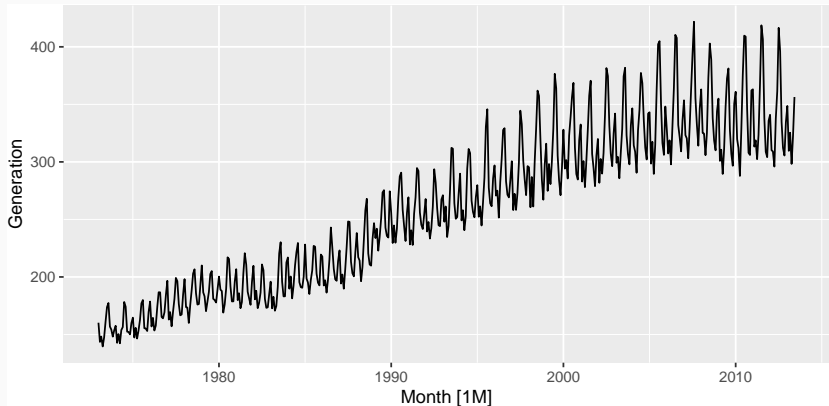
- Fit a suitable ARIMA model for the logged data.
- Produce forecasts of your fitted model. Do the forecasts look reasonable?

Outline

- 1 ARIMA models
- 2 Lab Session 13
- 3 Seasonal ARIMA models
- 4 Lab Session 14

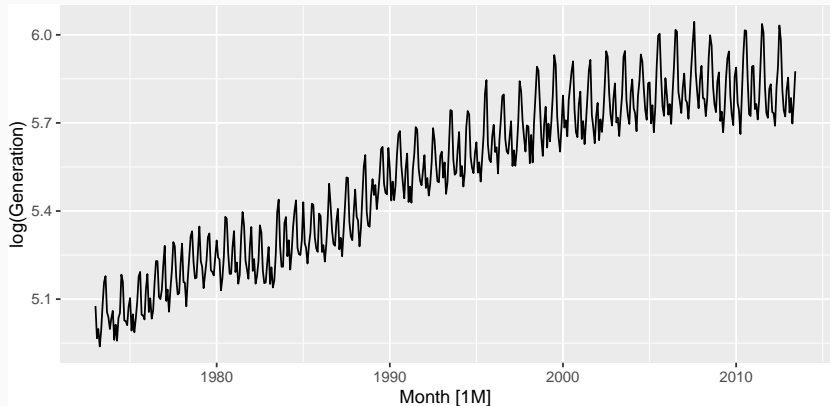
Electricity production

```
usmelec %>% autoplot(  
  Generation  
)
```



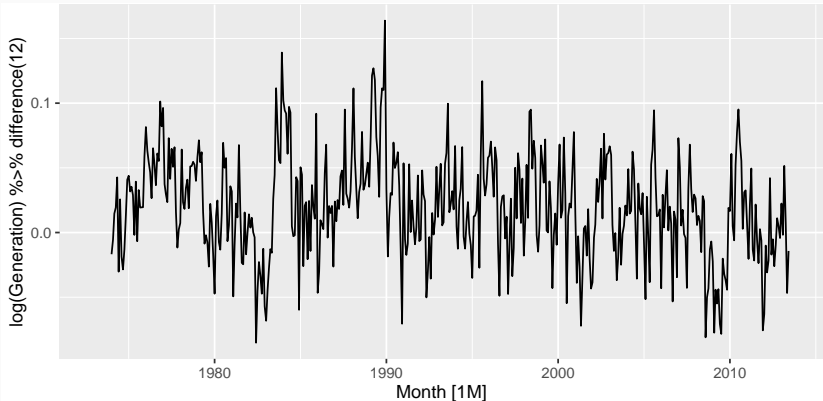
Electricity production

```
usmelec %>% autoplot(  
  log(Generation)  
)
```



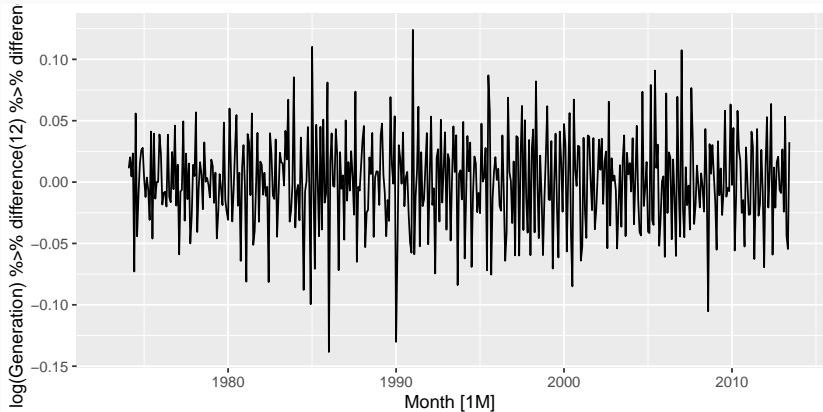
Electricity production

```
usmelec %>% autoplot(  
  log(Generation) %>% difference(12)  
)
```



Electricity production

```
usmelec %>% autoplot(  
  log(Generation) %>% difference(12) %>% difference()  
)
```



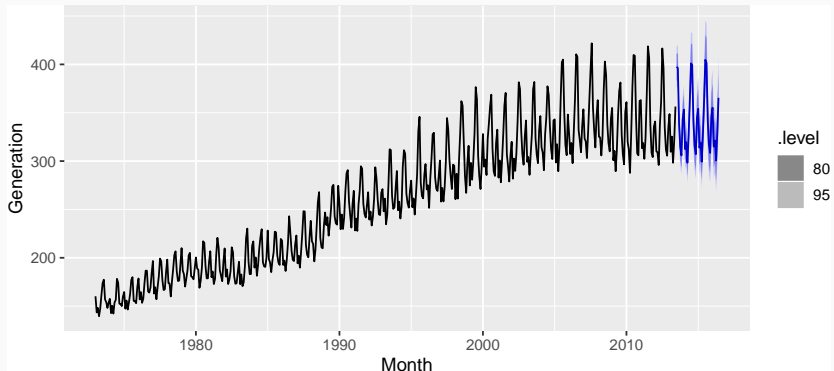
Example: US electricity production

```
usmelec %>%  
  model(arima = ARIMA(log(Generation))) %>%  
  report()
```

```
## Series: Generation  
## Model: ARIMA(1,1,1)(2,1,1)[12]  
## Transformation: log(.x)  
##  
## Coefficients:  
##          ar1          ma1          sar1          sar2          sma1  
##      0.4116   -0.8483    0.0100   -0.1017   -0.8204  
## s.e.  0.0617    0.0348    0.0561    0.0529    0.0357  
##  
## sigma^2 estimated as 0.0006841:  log likelihood=1047  
## AIC=-2082    AICc=-2082    BIC=-2057
```

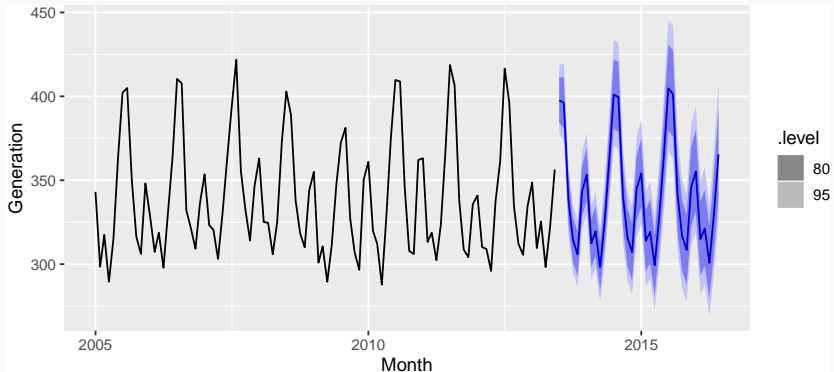
Example: US electricity production

```
usmelec %>%  
  model(arima = ARIMA(log(Generation))) %>%  
  forecast(h="3 years") %>%  
  autoplot(usmelec)
```



Example: US electricity production

```
usmelec %>%  
  model(arima = ARIMA(log(Generation))) %>%  
  forecast(h="3 years") %>%  
  autoplot(filter_index(usmelec, 2005 ~ .))
```



Seasonal ARIMA models

ARIMA	$\underbrace{(p, d, q)}$	$\underbrace{(P, D, Q)_m}$
	↑	↑
	Non-seasonal part of the model	Seasonal part of of the model

- m = number of observations per year.
- d first differences, D seasonal differences
- p AR lags, q MA lags
- P seasonal AR lags, Q seasonal MA lags

Seasonal and non-seasonal terms combine multiplicatively

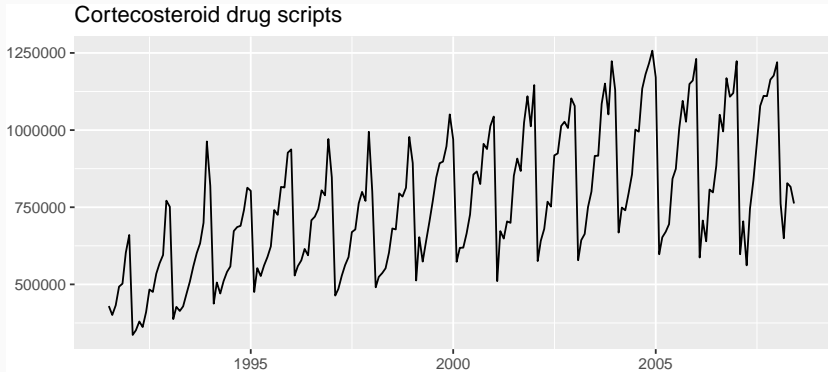
Common ARIMA models

The US Census Bureau uses the following models most often:

ARIMA(0,1,1)(0,1,1) _m	with log transformation
ARIMA(0,1,2)(0,1,1) _m	with log transformation
ARIMA(2,1,0)(0,1,1) _m	with log transformation
ARIMA(0,2,2)(0,1,1) _m	with log transformation
ARIMA(2,1,2)(0,1,1) _m	with no transformation

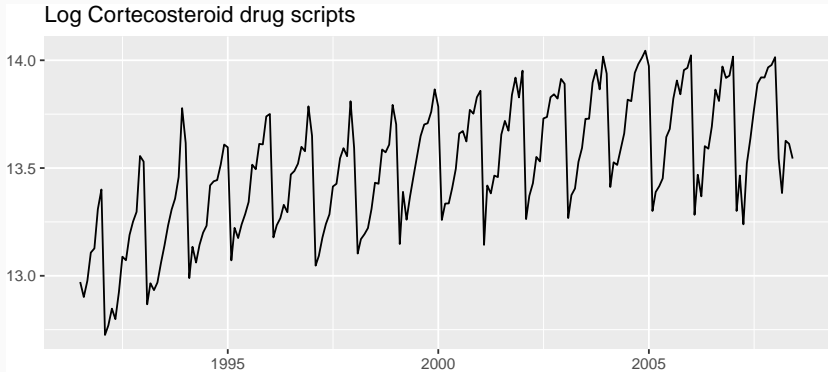
Corticosteroid drug sales

```
h02 <- PBS %>% filter(ATC2 == "H02") %>%  
  summarise(Cost = sum(Cost))  
h02 %>% autoplot(Cost) +  
  xlab("Year") + ylab("") +  
  ggtitle("Corticosteroid drug scripts")
```



Corticosteroid drug sales

```
h02 <- PBS %>% filter(ATC2 == "H02") %>%  
  summarise(Cost = sum(Cost))  
h02 %>% autoplot(log(Cost)) +  
  xlab("Year") + ylab("") +  
  ggtitle("Log Corticosteroid drug scripts")
```



Corticosteroid drug sales

```
fit <- h02 %>%  
  model(auto = ARIMA(log(Cost)))  
report(fit)
```

```
## Series: Cost  
## Model: ARIMA(2,1,0)(0,1,1)[12]  
## Transformation: log(.x)  
##  
## Coefficients:  
##          ar1      ar2      sma1  
##      -0.8491  -0.4207  -0.6401  
## s.e.   0.0712   0.0714   0.0694  
##  
## sigma^2 estimated as 0.004399:  log likelihood=245  
## AIC=-483   AICc=-483   BIC=-470
```

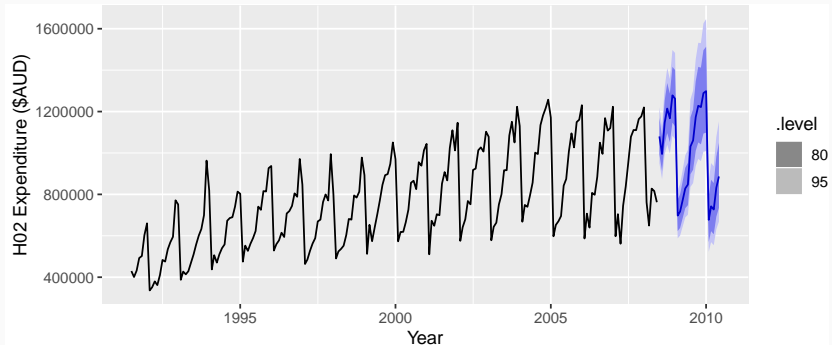
Corticosteroid drug sales

```
fit <- h02 %>%  
  model(best = ARIMA(log(Cost), stepwise = FALSE,  
    approximation = FALSE,  
    order_constraint = p + q + P + Q <= 9))  
report(fit)
```

```
## Series: Cost  
## Model: ARIMA(4,1,1)(2,1,2)[12]  
## Transformation: log(.x)  
##  
## Coefficients:  
##          ar1      ar2      ar3      ar4      ma1      sar1      sar2  
##      -0.0426  0.210   0.202  -0.227  -0.742   0.621  -0.383  
## s.e.   0.2167  0.181   0.114   0.081   0.207   0.242   0.118  
##          sma1     sma2  
##      -1.202   0.496  
## s.e.   0.249   0.214  
##  
## sigma^2 estimated as 0.004061:  log likelihood=254  
## AIC=-489   AICc=-487   BIC=-456
```

Corticosteroid drug sales

```
fit %>% forecast %>% autoplot(h02) +  
  ylab("H02 Expenditure ($AUD)") + xlab("Year")
```



Outline

- 1 ARIMA models
- 2 Lab Session 13
- 3 Seasonal ARIMA models
- 4 Lab Session 14

Lab Session 14

For the Australian tourism data (from `tourism`):

- Fit a suitable ARIMA model for all data.
- Produce forecasts of your fitted models.
- Check the forecasts for the “Snowy Mountains” and “Melbourne” regions. Do they look reasonable?