

Class 2: Moving averages and ARMA

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PRESS RECORD

Learning outcomes

- ▶ Recognise and understand the basic theory behind $MA(1)$ and $MA(q)$ models
- ▶ Understand the basic $ARMA(p,q)$ formulation
- ▶ Know the basics of using the forecast package
- ▶ Understand the limitations of ARMA forecasting

Reminder: The most important slide in the course

Almost all of time series is based on two ideas:

1. Base your future predictions on previous values of the data
2. **Base your future predictions on how wrong you were in your past predictions**

Reminder: AR models

- ▶ An Autoregressive (AR) model works by making the current data point dependent on the previous value, dampened by a parameter
- ▶ The usual likelihood used is:

$$y_t \sim N(\alpha + \beta y_{t-1}, \sigma^2)$$

- ▶ β is usually constrained (naturally via the data) to lie between -1 and 1. Outside that range the process blows up
- ▶ The sample PACF is often a good way of diagnosing if an AR model might be appropriate

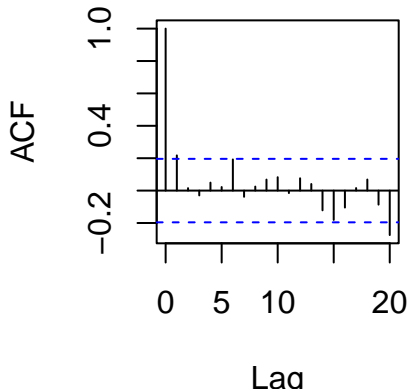
Intro to Moving Average Models

- ▶ Moving Average (MA) models are similar to AR models but they depend on the previous residual of the series rather than the value itself
- ▶ The previous residual is made up of how well we forecasted the last value of the series
- ▶ If the previous residual was large (i.e. our forecast was bad) then we want to make a big change to the next prediction
- ▶ If the previous residual was small (i.e. our forecast was good) then we might not want to make much of a change

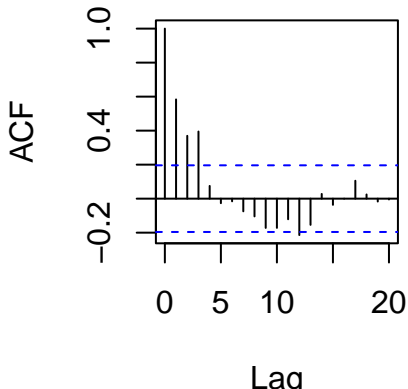
Moving average models and the ACF/PACF

- ▶ Recall that the sample partial autocorrelation function (PACF) can be used to diagnose whether an AR model is appropriate (and also suggest the order p)
- ▶ For the MA model, it is the sample autocorrelation function (ACF) that helps determine the order of the model

MA(1)



MA(4)



Example 1: MA(1)

- ▶ The MA(1) model is defined as:

$$y_t = \alpha + \theta\epsilon_{t-1} + \epsilon_t$$

where $\epsilon_t \sim N(0, \sigma^2)$ as usual

- ▶ Parameter α represents the overall mean, whilst θ controls the amount of weight placed on previous residuals
- ▶ Like the AR model the values of θ are not expected to be outside $(-1, 1)$, and negative values can sometimes be physically unrealistic
- ▶ The likelihood version of the model is:

$$y_t \sim N(\alpha + \theta\epsilon_{t-1}, \sigma^2)$$

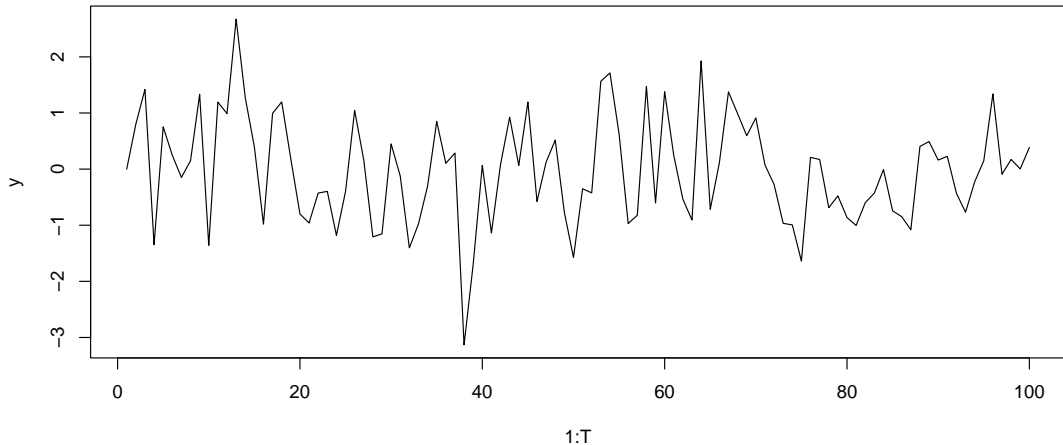
Simulating from the MA(1) process

Below is some simple code to simulate from an MA(1) process. Note that the first values of y and ϵ need to be initialised

```
T = 100 # Number of observations
sigma = 1 # Residual sd
alpha = 0 # Mean
theta = runif(1) # Choose a positive value
y = eps = rep(NA,T)
y[1] = alpha
eps[1] = 0
for(t in 2:T) {
  y[t] = rnorm(1, mean = alpha + theta * eps[t-1],
              sd = sigma)
  eps[t] = y[t] - alpha - theta * eps[t-1]
}
```


Time series plot

```
plot(1:T,y,type='l')
```



Fitting MA(1) models

- We can fit an MA(1) model with the forecast package like before

```
Arima(y, order = c(0, 0, 1))
```

```
## Series: y
## ARIMA(0,0,1) with non-zero mean
##
## Coefficients:
##           ma1      mean
##          0.2118 -0.0325
## s.e.  0.0924   0.1120
##
## sigma^2 estimated as 0.8747:  log likelihood=-134.21
## AIC=274.43   AICc=274.68   BIC=282.24
```

Extending to MA(q)

- ▶ As with the AR(p) process we can extend this model to have the current value of y depending on more than one previous residual
- ▶ The model becomes an MA(q) model with:

$$y_t \sim N(\alpha + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \dots + \theta_q\epsilon_{t-q}, \sigma^2)$$

- ▶ The parameters are as before, except there are now q values of θ .
- ▶ Usually when estimated they will decrease with q ; the older residuals matter less

Fitting an MA(q) model

```
Arima(y, order = c(0, 0, 3))
```

```
## Series: y
## ARIMA(0,0,3) with non-zero mean
##
## Coefficients:
##          ma1      ma2      ma3      mean
##          0.2269  0.0170 -0.0413 -0.0338
## s.e.    0.1005  0.0981  0.0876  0.1111
##
## sigma^2 estimated as 0.8897:  log likelihood=-134.04
## AIC=278.07   AICc=278.71   BIC=291.1
```

- Compare the AIC of this model with the previous MA(1) version

Forecasting an MA value

- ▶ You can create a one step ahead forecast for an MA(1) model by:

$$\hat{y}_{t+1} = \hat{\alpha} + \hat{\theta}\epsilon_t$$

- ▶ Forecasts of more than one step ahead will be pretty boring, as every future prediction of $\hat{\epsilon}_t$ will be 0
- ▶ Thus MA(q) models are only really informative if you are forecasting q steps ahead

Combining AR and MA into ARMA

- ▶ There is no reason why we have to use just AR or MA on their own
- ▶ It's possible to combine them together, for example:

$$y_t = \alpha + \beta y_{t-1} + \theta \epsilon_{t-1} + \epsilon_t$$

This is an *Autoregressive Moving Average* (ARMA) model

- ▶ It's often written as ARMA(p, q) where p is the number of AR terms (here 1) and q the number of MA terms (here also 1)
- ▶ ARMA models can deal with a very wide variety of flexible time series behaviour, though they remain stationary
- ▶ The likelihood format is:

$$y_t \sim N(\alpha + \beta y_{t-1} + \theta \epsilon_{t-1}, \sigma^2)$$

Fitting an ARMA(1, 1) model

```
Arima(y, order = c(1, 0, 1))
```

```
## Series: y
## ARIMA(1,0,1) with non-zero mean
##
## Coefficients:
##          ar1      ma1      mean
##      0.1119  0.1085 -0.0323
## s.e.  0.3743  0.3703  0.1153
##
## sigma^2 estimated as 0.8829:  log likelihood=-134.17
## AIC=276.33   AICc=276.76   BIC=286.76
```

- Compare again with previous models

The general ARMA(p, q) framework

- ▶ The general equation for an ARMA(p, q) model is:

$$y_t = \alpha + \sum_{i=1}^p \beta_i y_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j} + \epsilon_t$$

- ▶ The values of β and θ have to be tightly controlled to get a series that is stationary, though this is only really a problem if we want to simulate the time series
- ▶ Occasionally you will run into problems with Arima because it doesn't use maximum likelihood (by default) to fit the models. It uses something faster and more approximate instead

Predicting the future with ARMA

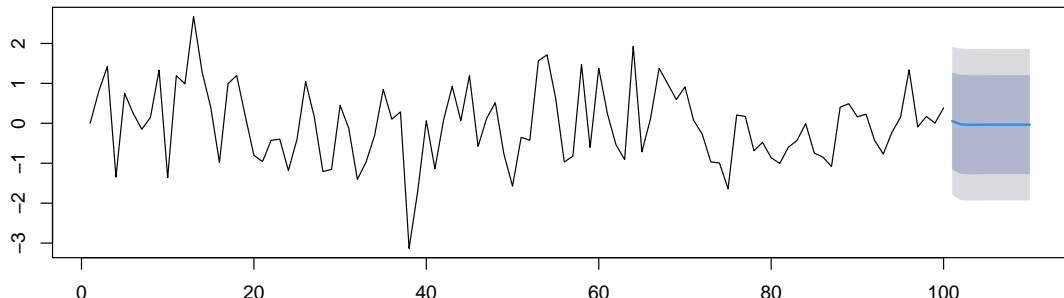
- ▶ The forecast package contains methods to predict into the future
- ▶ First create a model (here ARMA(2, 1))

```
my_model = Arima(y, order = c(2, 0, 1))
```

- ▶ ...then forecast...

```
plot(forecast(my_model, h = 10))
```

Forecasts from ARIMA(2,0,1) with non-zero mean



A real-world example

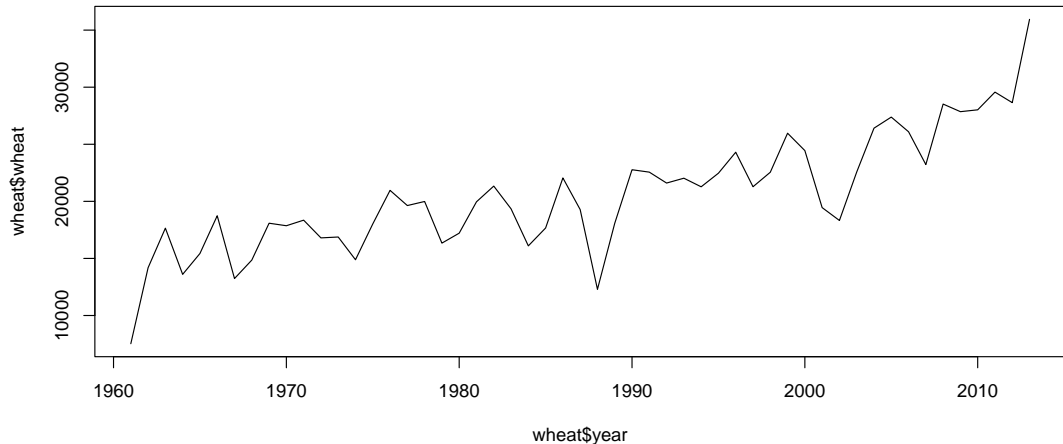
Steps in a time series analysis

1. Plot the data and the ACF/PACF
2. Decide if the data look stationary or not. If not, perform a suitable transformation and return to 1
3. Guess at a suitable p and q for an ARMA(p , q) model
4. Fit the model
5. Try a few models around it by increasing/decreasing p and q and checking the AIC (or others)
6. Check the residuals
7. Forecast into the future

A real example: wheat data

- Let's follow the steps for the wheat data:

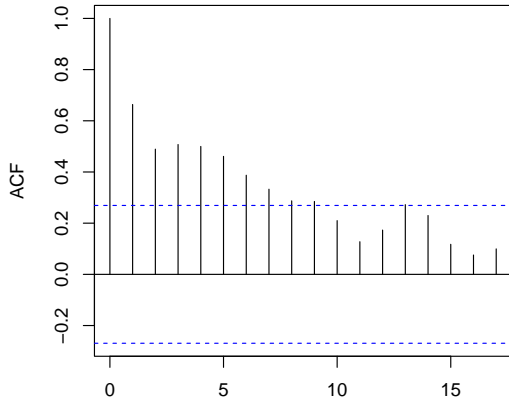
```
wheat = read.csv('../data/wheat.csv')  
plot(wheat$year, wheat$wheat, type = 'l')
```



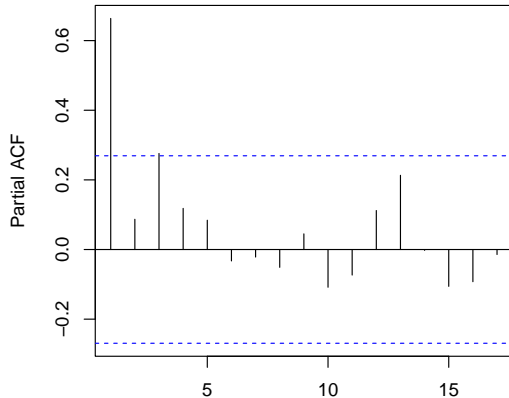
ACF and PACF

```
par(mfrow = c(1, 2))  
acf(wheat$wheat)  
pacf(wheat$wheat)
```

Series wheat\$wheat



Series wheat\$wheat



First model

```
Arima(wheat$wheat, order = c(1, 0, 0))
```

```
## Series: wheat$wheat
```

```
## ARIMA(1,0,0) with non-zero mean
```

```
##
```

```
## Coefficients:
```

```
##          ar1          mean
```

```
##          0.8972  20849.522
```

```
## s.e.    0.0826   3615.541
```

```
##
```

```
## sigma^2 estimated as 10079564:  log likelihood=-502.34
```

```
## AIC=1010.68   AICc=1011.17   BIC=1016.59
```

Next models

- ▶ Try AR(2), ARMA(1, 1), and ARMA(2, 1)

```
Arima(wheat$wheat, order = c(2, 0, 0))$aic
```

```
## [1] 1012.683
```

```
Arima(wheat$wheat, order = c(1, 0, 1))$aic
```

```
## [1] 1011.36
```

```
Arima(wheat$wheat, order = c(2, 0, 1))$aic
```

```
## [1] 1004.125
```

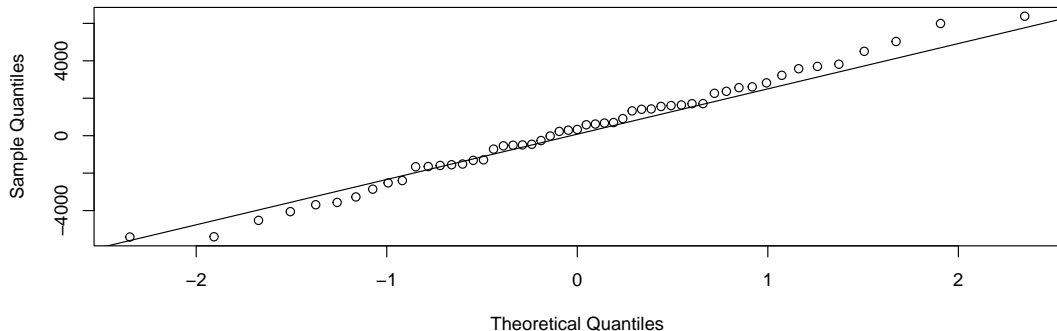
- ▶ Best one seems to be ARMA(2, 1). (could also try others)

Check residuals

- Check the residuals of this model

```
my_model_ARMA21 = Arima(wheat$wheat, order = c(2, 0, 1))  
qqnorm(my_model_ARMA21$residuals)  
qqline(my_model_ARMA21$residuals)
```

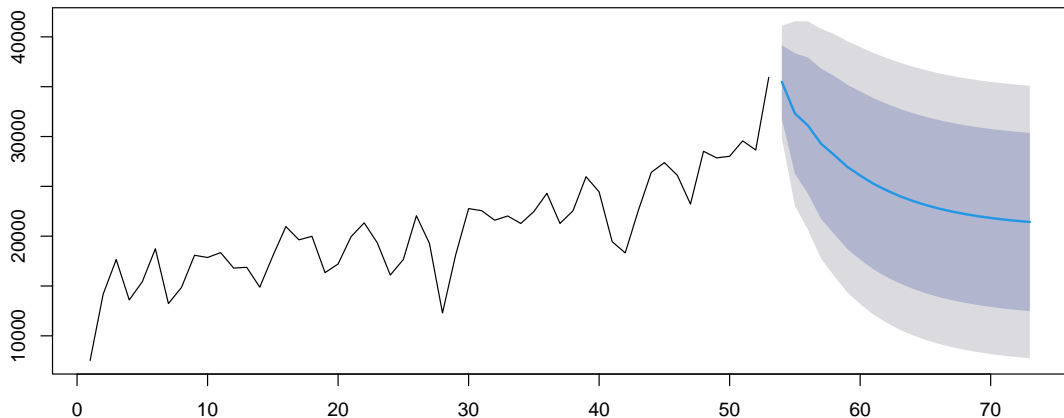
Normal Q-Q Plot



Forecast into the future

```
plot(forecast(my_model_ARMA21, h=20))
```

Forecasts from ARIMA(2,0,1) with non-zero mean



What happened to the forecasts here?

- ▶ Why did the series diverge rapidly away from what you might have expected?
- ▶ The answer is that we have fitted a *stationary model*, i.e. one with constant mean and variance
- ▶ The model will just slowly reverts back to that mean over time. The speed at which it reverts will depend on the amount of autocorrelation in the series
- ▶ The solution to this lies in better identification of the trend. See the next lecture!

Summary

- ▶ MA(q) models are used to create future forecasts based on the error in the previous forecasts
- ▶ ARMA models combine AR and MA ideas together
- ▶ The forecast package allows us to fit all of these models
- ▶ We need to be a bit careful with forecasts that assume stationarity - they will mean-revert