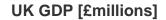
# Time Series - Assignment 1

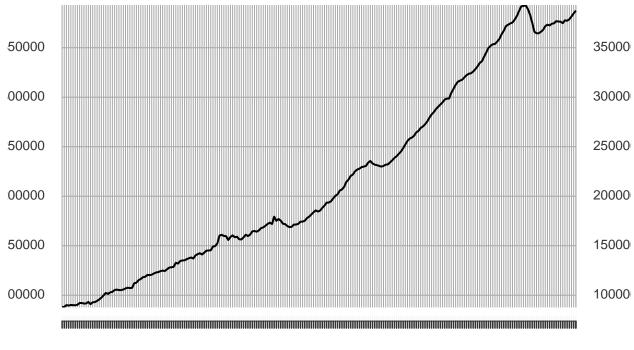
Damian Baeza 14 February 2018

#### Question 1

```
require(ggplot2)
## Loading required package: ggplot2
require(dplyr)
## Loading required package: dplyr
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
require(zoo)
## Loading required package: zoo
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##
       as.Date, as.Date.numeric
require(xts)
## Loading required package: xts
## Attaching package: 'xts'
## The following objects are masked from 'package:dplyr':
##
##
       first, last
load("UKGDP.RData")
yq <- paste(UKGDP$V1, UKGDP$V2)</pre>
df.yq <- cbind(UKGDP, as.yearqtr(yq))</pre>
df.xts <- xts(df.yq$V3, order.by = df.yq$`as.yearqtr(yq)`)</pre>
plot(df.xts, main = "UK GDP [£millions]")
```



#### 1955 Q1 / 2013 Q4



1955-Q1 1962-Q4 1970-Q3 1978-Q2 1986-Q1 1993-Q4 2001-Q3 2009-Q2

As can be observed on the above plot, the gross domestic product of the UK has an trend that varies according to t (the year). This implies that the UK GDP does not have a constant trend, therefore the expected value of  $X_t$  (UK GDP) is not constant. The aforementioned indicates that using an ARMA(p,q) model would not be appropriate.

#### Question 2

```
ARIMA1.Order <- c(0, 1, 1)

ARIMA2.Order <- c(1, 1, 0)

ARIMA3.Order <- c(1, 1, 1)

ARIMA1 <- arima(x = df.xts, order = ARIMA1.Order)

ARIMA2 <- arima(x = df.xts, order = ARIMA2.Order)

ARIMA3 <- arima(x = df.xts, order = ARIMA3.Order)

AICs <- c(ARIMA1$aic, ARIMA2$aic, ARIMA3$aic)

AIC.Probs <- exp((min(AICs) - AICs)/2)
```

#### (a) Model selection

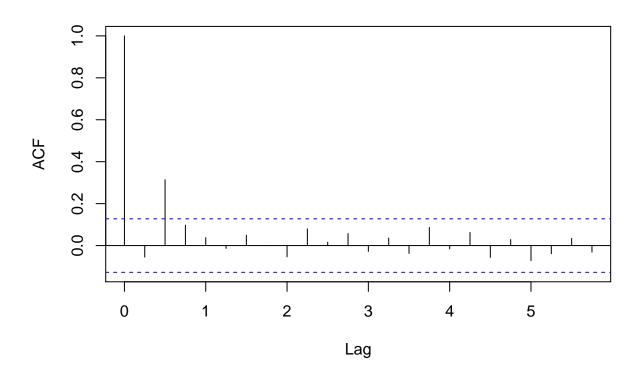
The ARIMA(1,1,1) model presents the lowest AIC value and further to that fact, the ARIMA(0,1,1) and ARIMA(1,1,0) models are  $2.261 \cdot 10^{-13}$  and  $1.707 \cdot 10^{-5}$  times as probable as the ARIMA(1,1,1) model to

minimise the information loss.

The correlograms of the residuals are depicted in the following plots.

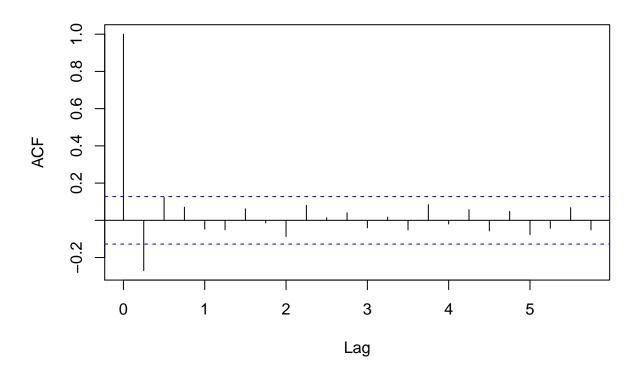
```
# Correlogram of ARIMA(0,1,1) model
acf(ARIMA1$residuals)
```

### Series ARIMA1\$residuals



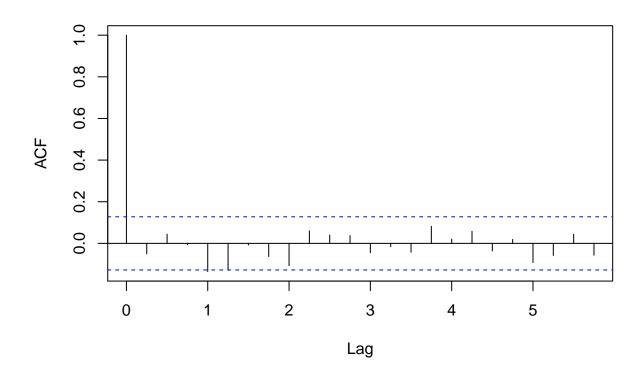
# Correlogram of ARIMA(1,1,0) model
acf(ARIMA2\$residuals)

## Series ARIMA2\$residuals



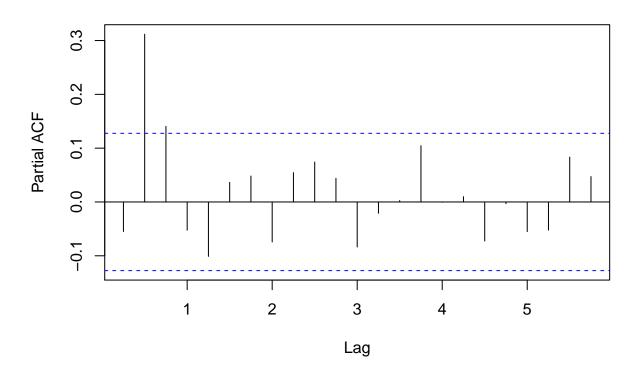
# Correlogram of ARIMA(1,1,1) model
acf(ARIMA3\$residuals)

## Series ARIMA3\$residuals



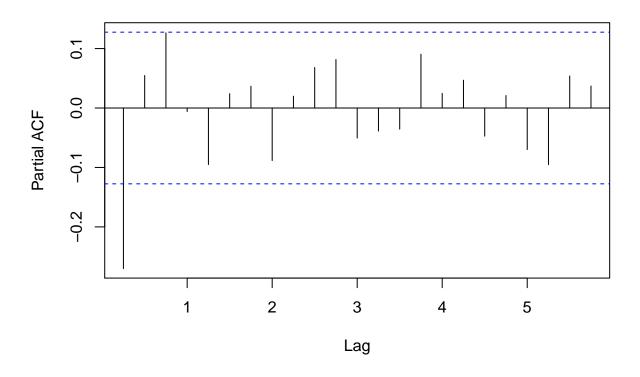
# PACF of ARIMA(0,1,1) model
pacf(ARIMA1\$residuals)

## Series ARIMA1\$residuals



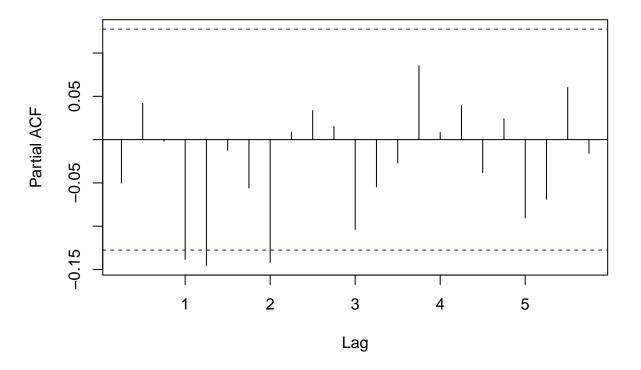
# PACF of ARIMA(1,1,0) model
pacf(ARIMA2\$residuals)

# Series ARIMA2\$residuals



# PACF of ARIMA(1,1,1) model
pacf(ARIMA3\$residuals)

#### Series ARIMA3\$residuals



From the above correlograms it is possible to visualize that the residuals are uncorrelated for the ARIMA(1,1,1) model. This indicates that the estimated residuals are white noise.

### (b) Chosen model

The fitted  $\operatorname{ARIMA}(1,1,1)$  model can be written as follows:

$$X_t = \alpha_1 X_{t-1} + Z_t - \theta_1 Z_{t-1}$$