PSet1

March 3, 2020

1 PROBLEM SET 1 - PART 4

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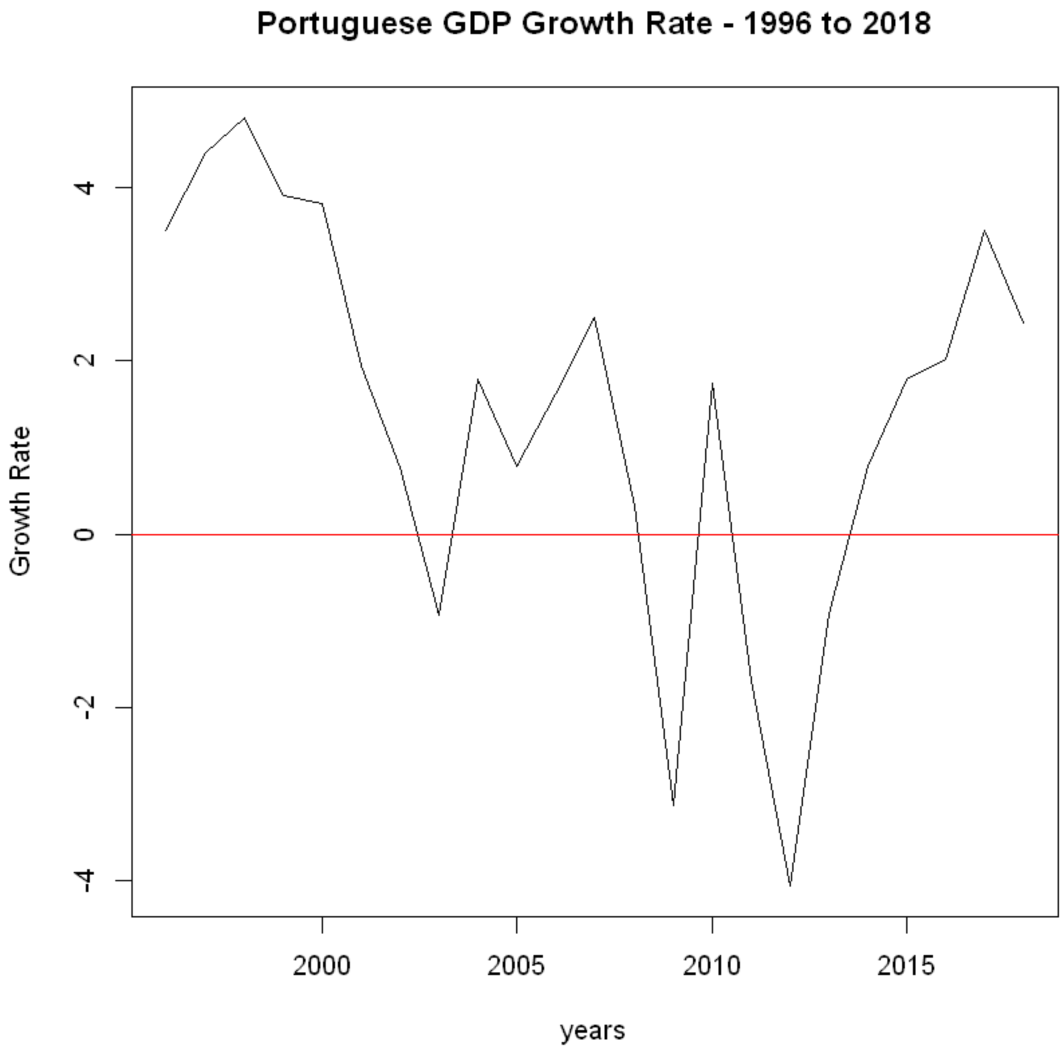
2 a)

[20]:
```
library(quantmod)

getSymbols("NAEXKP01PTA657S", src= "FRED")
GDP_growth = ts(as.vector(NAEXKP01PTA657S), start = 1996, deltat=1)
plot(GDP_growth,main="Portuguese GDP Growth Rate - 1996 to 2018", xlab="years",␣
↪ylab="Growth Rate")
abline(h=0, col="red")
```

'NAEXKP01PTA657S'



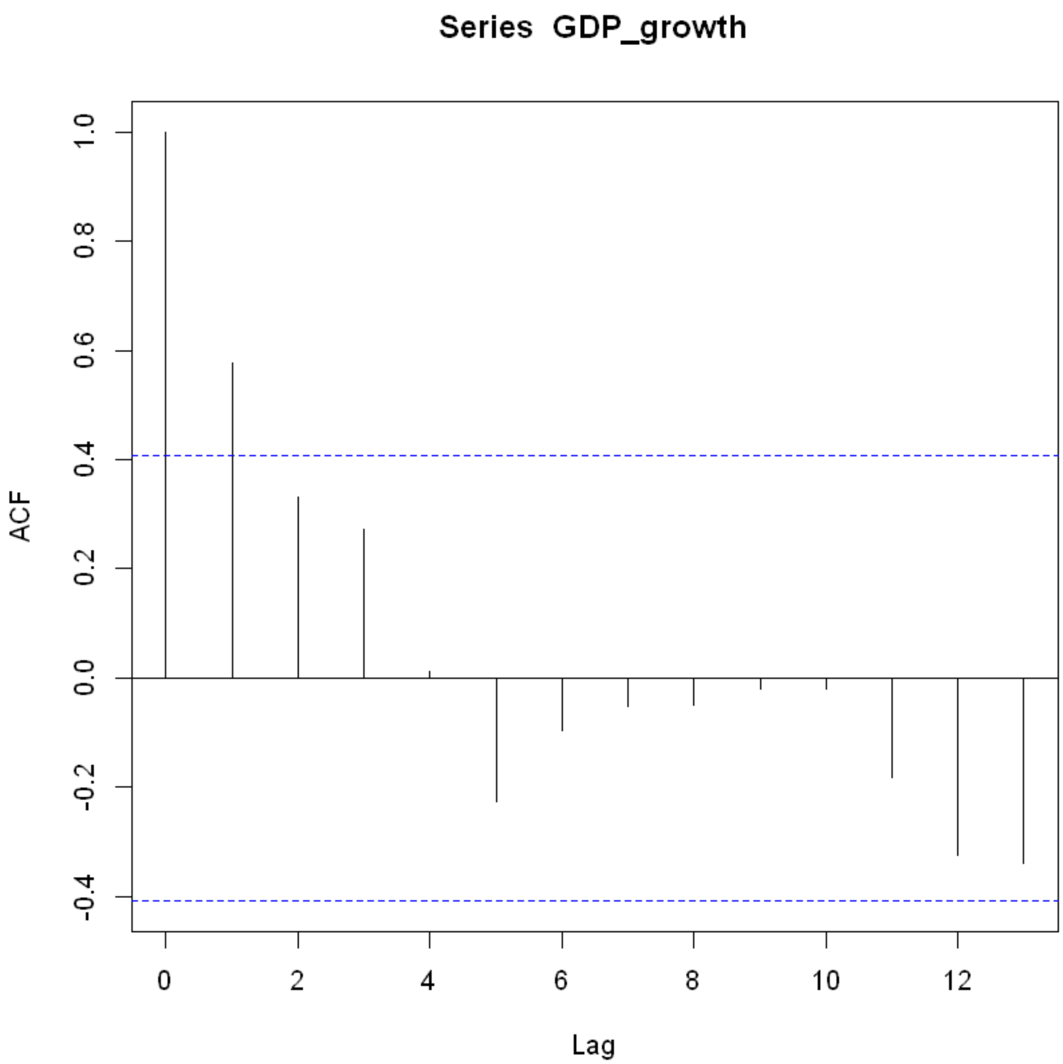
The time series does appear to be stationary, as it revolves around a mean of (seemingly) 0. However, being sure just by looking at a plot is unwise. This is just a first approximation. Further testing would need to be done to conclude with certainty.

3 b)

To do this, we follow the Box-Jenkins methodology.

Step 1 - Stationarity

[21]:
```
acf(GDP_growth)
```



The series looks stationary, as there is a decay in autocorrelation. It starts to pick up again after the 10th lag, but it is still "within boundaries" - within our confidence interval. So, I conclude the series to look stationary.

Step 2 - ARMA Identification

Since we are attempting to identify an ARMA model, we can't resort to ACF or PACF - Information Criterias are the best tool. The use of AIC is preferred in small samples, and that is what I will use.

[22]:
```
AIC = matrix(nrow=8, ncol=8,dimnames=list(c(paste("p=",0:7)),(c(paste("q=",0:
↪7)))))

for(i in 1:nrow(AIC)) {
```

```
  for(j in 1:ncol(AIC)) {
    AIC[i, j] = arima(GDP_growth, order=c(i-1,0,j-1))$aic
  }
}


AIC


AIC == min(AIC)
```

```
Warning message in arima(GDP_growth, order = c(i - 1, 0, j - 1)):
"possible convergence problem: optim gave code = 1"Warning message in
arima(GDP_growth, order = c(i - 1, 0, j - 1)):
"possible convergence problem: optim gave code = 1"
```

	q= 0	q= 1	q= 2	q= 3	q= 4	q= 5	q= 6	q= 7
p= 0	106.88282	101.1851	102.4924	102.2526	101.2937	103.1562	105.0450	106.8340
p= 1	99.38727	101.3013	103.1819	102.9473	103.0645	104.0114	106.9995	106.2960
p= 2	101.33754	103.3088	104.9263	102.6937	105.0346	105.0242	107.9715	107.4865
p= 3	102.71758	104.3322	104.1788	106.0303	107.0331	106.3402	108.3383	109.4846
p= 4	103.02052	104.3580	104.0448	105.9807	106.5687	108.4797	109.1269	111.2207
p= 5	103.44346	104.9340	106.9126	108.8148	108.3502	110.3231	110.2968	113.0670
p= 6	104.84895	106.8212	106.1679	107.5368	109.4508	113.0488	115.0418	114.9552
p= 7	106.83414	108.8411	110.7859	109.4301	110.5694	112.3704	115.5965	116.7457

	q= 0	q= 1	q= 2	q= 3	q= 4	q= 5	q= 6	q= 7
p= 0	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
p= 1	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
p= 2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
p= 3	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
p= 4	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
p= 5	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
p= 6	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
p= 7	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

Following this strategy, we conclude for an ARMA(1,0) model - an AR(1) model. Just to be sure, I will run another way to check this below, using the auto.arima().

[23]:
```
library(forecast)
arima= auto.arima(GDP_growth)
arima
```

```
Series: GDP_growth
ARIMA(1,0,0) with zero mean

Coefficients:
         ar1
      0.7002
```

```
s.e.  0.1494

sigma^2 estimated as 3.834:  log likelihood=-47.92
AIC=99.83   AICc=100.43   BIC=102.11
```

This method equals the same results as the previous one. So, I conclude with certainty that the series is stationary and ARMA(1,0,0), which is the same as AR(1).

4 c)

[24]:
```
arma1= arima(GDP_growth, order=c(1,0,0))
arma1
```

```
Call:
arima(x = GDP_growth, order = c(1, 0, 0))

Coefficients:
         ar1  intercept
      0.5815     1.5514
s.e.  0.1651     0.8657

sigma^2 estimated as 3.335:  log likelihood = -46.69,  aic = 99.39
```

The model we are presented with can be written roughly like this: y_t= 1.5514 + 0.5815y_{t-1}+ ϵ_t

(Note: apologies for my less than good LaTeX expertise)

Since we are looking at an AR(1) model, it is pretty easy to conclude the estimated model is stable just looking ath the coefficient for ar1. It is 0.5815, and the condition for stability is that this parameter is | |<1. |0.5815| <1, so the model is stable. It does not have an explosive growth.

5 d)

To check the model, we use the Ljung-Box test.

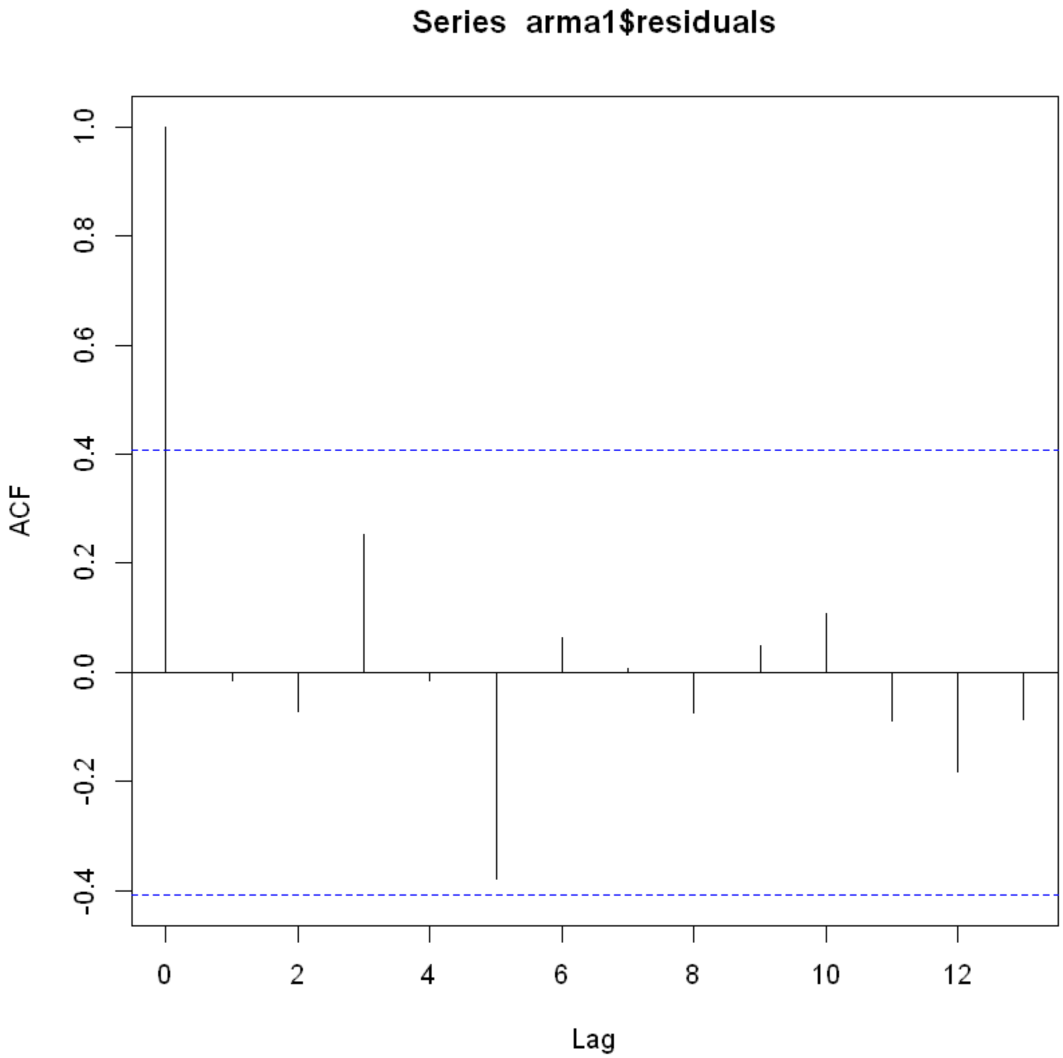
For this test, the hypothesis are as follows:

H_0: No serial correlation of the error terms H_1: Serial correlation of the error terms

[25]:
```
acf(arma1$residuals)
Box.test(arma1$residuals, lag=22, type='Ljung')
```

```
Box-Ljung test

data:  arma1$residuals
X-squared = 15.199, df = 22, p-value = 0.8535
```



The ACF does not show significant autocorrelation in the residuals for any lag length considered. The Ljung-Box test returns a p-value of 0.8535, meaning we do not reject the null hypothesis of no autocorrelation.

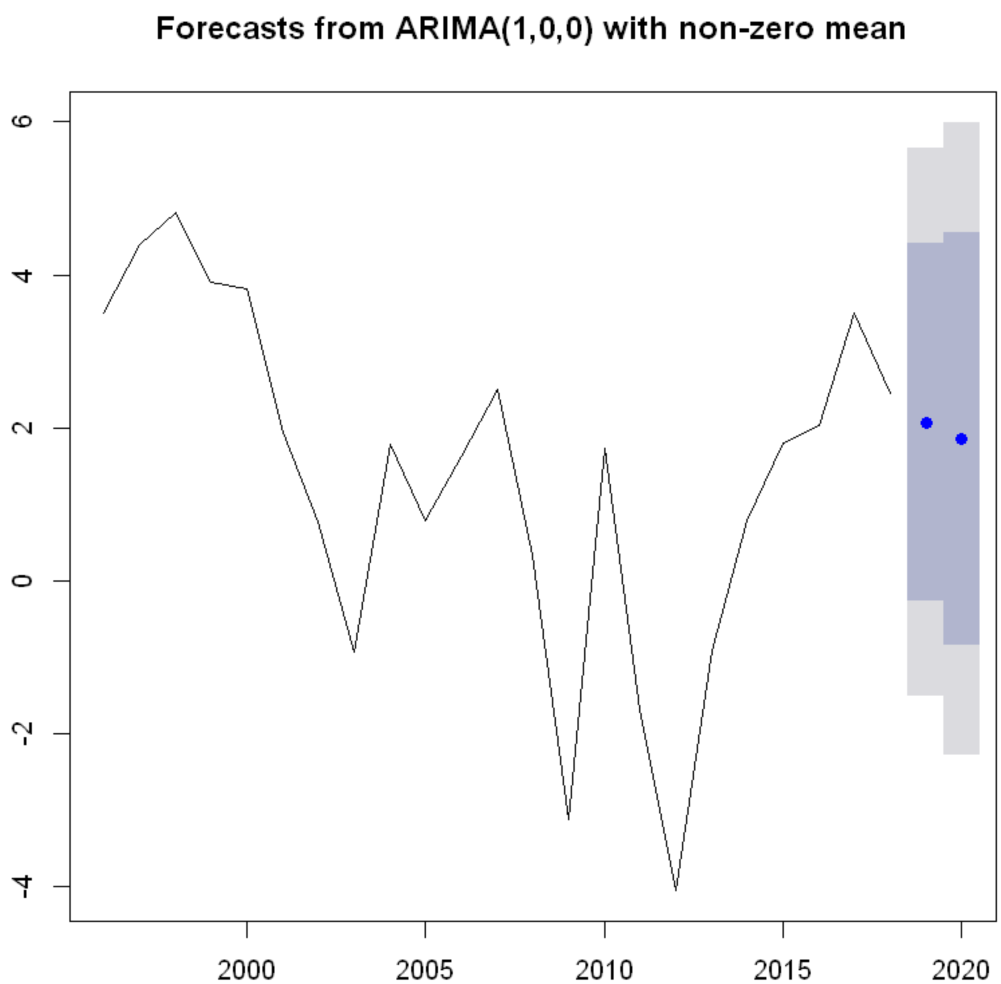
Given this, I conclude the model to be a valid model, properly estimated.

6 e)

[29]:
```
forecast(arma1, h=2)
plot(forecast(arma1, h=2))
```

```
     Point Forecast      Lo 80    Hi 80     Lo 95    Hi 95
2019       2.068844 -0.2715506 4.409238 -1.510481 5.648168
```

```
2020        1.852284 -0.8550293 4.559598 -2.288194 5.992763
```



(Note: This doesn't look good, graphically speaking, but I couldn't get it to look any nicer. But I did forecast 2019 and 2020.)

[30]:
```
forecast(arma1, h=2)
```

```
     Point Forecast       Lo 80    Hi 80     Lo 95    Hi 95
2019        2.068844 -0.2715506 4.409238 -1.510481 5.648168
2020        1.852284 -0.8550293 4.559598 -2.288194 5.992763
```

Bank of Portugal official Forecasts: 2019: 2.0% 2020: 1.7%

My forecast is better for 2019 than it is for 2020. However, forecasts are always better the closest we are to the period being forecasted - as can be seen by the smaller variance for the 2019 estimate.

Below I plot my forecasts with the predictions for 2019 and 2020 for a better graphical view.

[41]:
```
plot(forecast(arma1, h=2))
abline(h=2, col="red")
text(1998,2.4, "2019 BdP", col = "red")
abline(h=1.7, col="blue")
text(1998,1.4, "2020 BdP", col = "blue")
```