Trabalho 2

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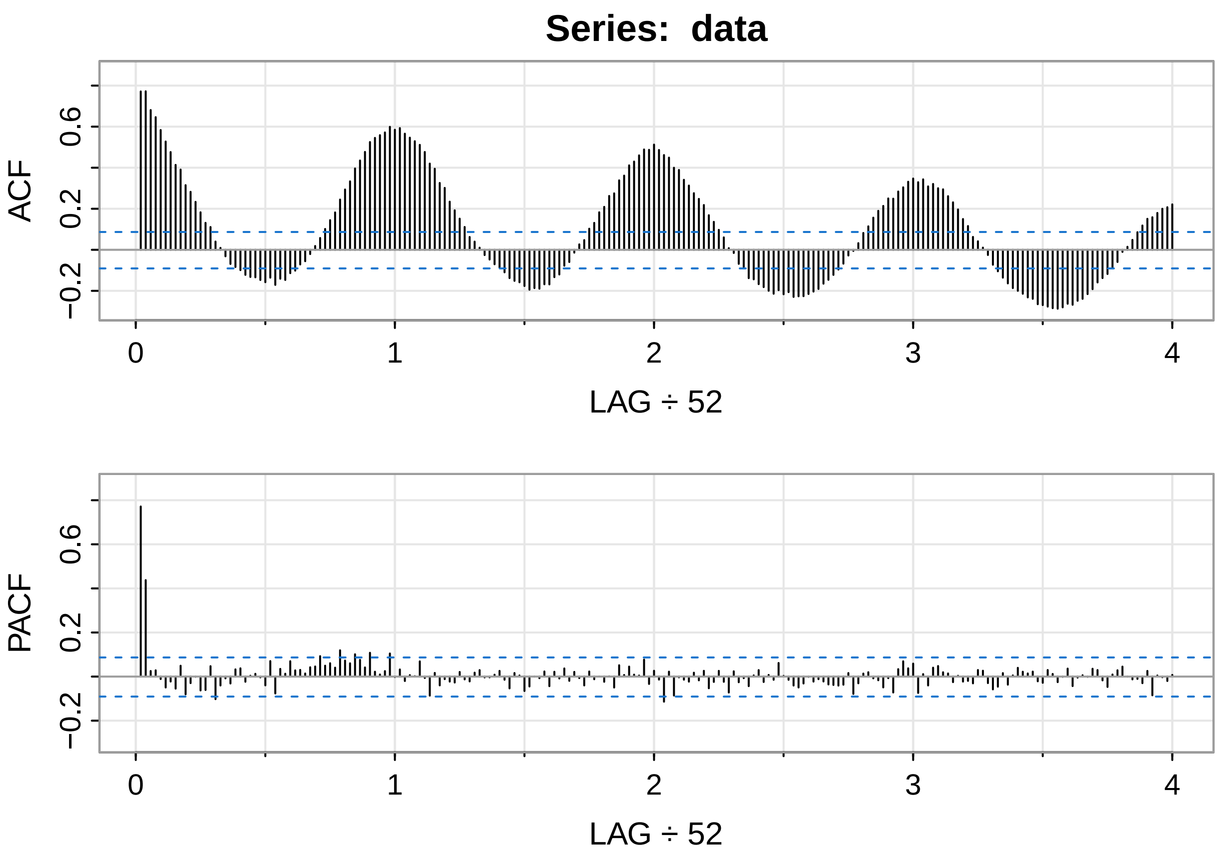
Questão 10

```
data <- cmort
acf2(data)
```




```
##      [,1] [,2] [,3] [,4]  [,5]  [,6]  [,7]  [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.77 0.77 0.68 0.65  0.58  0.53  0.48  0.41 0.39  0.32  0.28  0.23  0.18
## PACF 0.77 0.44 0.03 0.03 -0.01 -0.05 -0.02 -0.05 0.05 -0.08 -0.03  0.00 -0.06
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23] [,24] [,25]
## ACF   0.13  0.11  0.04  0.01 -0.03 -0.07 -0.08 -0.10 -0.12 -0.13 -0.13 -0.15
## PACF -0.06  0.05 -0.10 -0.04 -0.01 -0.03  0.03  0.04 -0.02  0.00  0.01  0.00
##      [,26] [,27] [,28] [,29] [,30] [,31] [,32] [,33] [,34] [,35] [,36] [,37]
```

```
## ACF  -0.16 -0.14 -0.17 -0.14 -0.15 -0.11 -0.10 -0.07 -0.06 -0.02  0.02  0.06
## PACF -0.04  0.07 -0.08  0.03  0.01  0.07  0.03  0.03  0.01  0.04  0.05  0.09
##       [,38] [,39] [,40] [,41] [,42] [,43] [,44] [,45] [,46] [,47] [,48] [,49]
## ACF   0.10  0.14  0.18  0.24  0.29  0.33   0.4  0.44  0.48  0.53  0.55  0.56
## PACF  0.05  0.06  0.04  0.12  0.07  0.06   0.1  0.08  0.04  0.11  0.02  0.01
##       [,50] [,51] [,52] [,53] [,54] [,55] [,56] [,57] [,58] [,59] [,60] [,61]
## ACF   0.57   0.6  0.58  0.59  0.57  0.55  0.53  0.51  0.48  0.42  0.39  0.33
## PACF  0.02   0.1  0.00  0.03 -0.02  0.01  0.00  0.07 -0.01 -0.09  0.02 -0.04
##       [,62] [,63] [,64] [,65] [,66] [,67] [,68] [,69] [,70] [,71] [,72] [,73]
## ACF   0.30  0.23  0.19  0.15  0.11  0.06  0.04  0.01 -0.03 -0.05 -0.07 -0.09
## PACF -0.01 -0.02 -0.03  0.02 -0.01 -0.02  0.02  0.03  0.00  0.00  0.01  0.03
##       [,74] [,75] [,76] [,77] [,78] [,79] [,80] [,81] [,82] [,83] [,84] [,85]
## ACF  -0.11 -0.14 -0.15 -0.16 -0.18 -0.19 -0.19 -0.19 -0.17 -0.17 -0.13 -0.12
## PACF -0.01 -0.05  0.02  0.00 -0.07 -0.04  0.00 -0.01  0.02 -0.04  0.02 -0.01
##       [,86] [,87] [,88] [,89] [,90] [,91] [,92] [,93] [,94] [,95] [,96] [,97]
## ACF  -0.08 -0.06 -0.01  0.03  0.05  0.10  0.13  0.18  0.21  0.26  0.28  0.34
## PACF  0.04 -0.02  0.02 -0.01 -0.04  0.02 -0.01  0.00 -0.02  0.00 -0.05  0.05
##       [,98] [,99] [,100] [,101] [,102] [,103] [,104] [,105] [,106] [,107] [,108]
## ACF   0.36  0.41   0.43   0.46   0.49   0.49   0.51   0.49   0.46   0.45   0.40
## PACF  0.01  0.05   0.01   0.00   0.08  -0.03   0.03  -0.01  -0.11   0.02  -0.09
##       [,109] [,110] [,111] [,112] [,113] [,114] [,115] [,116] [,117] [,118]
## ACF     0.39   0.34   0.31   0.28   0.25   0.22   0.17   0.14   0.10   0.06
## PACF    0.00  -0.01  -0.02   0.02  -0.02   0.03  -0.05  -0.02   0.03  -0.02
##       [,119] [,120] [,121] [,122] [,123] [,124] [,125] [,126] [,127] [,128]
## ACF     0.01  -0.02  -0.07  -0.08  -0.14  -0.14  -0.17  -0.18  -0.20  -0.21
## PACF   -0.07   0.02  -0.03  -0.01  -0.04   0.01   0.03  -0.02   0.01  -0.01
##       [,129] [,130] [,131] [,132] [,133] [,134] [,135] [,136] [,137] [,138]
## ACF    -0.20  -0.22  -0.21  -0.23  -0.23  -0.23  -0.22  -0.20  -0.19  -0.17
## PACF    0.06   0.00  -0.01  -0.04  -0.05  -0.03   0.00  -0.02  -0.01  -0.02
##       [,139] [,140] [,141] [,142] [,143] [,144] [,145] [,146] [,147] [,148]
## ACF    -0.15  -0.12  -0.10  -0.07  -0.03  -0.01   0.03   0.08   0.11   0.16
## PACF   -0.04  -0.04  -0.04  -0.04   0.02  -0.08  -0.03   0.01   0.02  -0.01
##       [,149] [,150] [,151] [,152] [,153] [,154] [,155] [,156] [,157] [,158]
## ACF     0.19   0.21   0.25   0.25   0.28   0.30   0.33   0.35   0.33   0.34
## PACF   -0.02  -0.05  -0.01  -0.07   0.03   0.07   0.04   0.06  -0.07   0.01
##       [,159] [,160] [,161] [,162] [,163] [,164] [,165] [,166] [,167] [,168]
## ACF     0.31   0.32   0.30   0.29   0.26   0.23    0.2   0.15   0.12   0.06
## PACF   -0.04   0.04   0.05   0.02   0.01  -0.03    0.0  -0.02  -0.02  -0.03
##       [,169] [,170] [,171] [,172] [,173] [,174] [,175] [,176] [,177] [,178]
## ACF     0.04   0.01  -0.03  -0.07  -0.10  -0.14  -0.16  -0.19  -0.20  -0.21
## PACF    0.03   0.03  -0.03  -0.06  -0.05   0.02  -0.04   0.01   0.04   0.02
##       [,179] [,180] [,181] [,182] [,183] [,184] [,185] [,186] [,187] [,188]
## ACF    -0.23  -0.24  -0.27  -0.27  -0.28  -0.28  -0.29  -0.28  -0.26  -0.27
## PACF    0.01   0.02  -0.02  -0.03   0.03   0.01  -0.03   0.00   0.04  -0.04
##       [,189] [,190] [,191] [,192] [,193] [,194] [,195] [,196] [,197] [,198]
## ACF    -0.25  -0.24  -0.22  -0.19  -0.16  -0.14  -0.12  -0.09  -0.06  -0.01
## PACF    0.00   0.01   0.00   0.04   0.03  -0.02  -0.05   0.01   0.03   0.05
##       [,199] [,200] [,201] [,202] [,203] [,204] [,205] [,206] [,207] [,208]
## ACF     0.01   0.05   0.09   0.12   0.15   0.16   0.18    0.2   0.21   0.22
## PACF    0.00  -0.01  -0.01  -0.03   0.03  -0.08   0.00    0.0  -0.02   0.01
```

```r
#Utilizando a fórmula descrita no exemplo III.19
(regr <- ar.ols(data, order = 2, demean = F,intercept = F))
```

```
##
## Call:
## ar.ols(x = data, order.max = 2, demean = F, intercept = F)
##
## Coefficients:
##       1       2
## 0.4926  0.5054
##
## Order selected 2  sigma^2 estimated as  33.78
```

```r
#Semana 1
sem1 <- cmort[length(cmort)] * regr$ar[1] + cmort[length(cmort)-1] * regr$ar[2]

#Semana 2
sem2 <- sem1 * regr$ar[1] + cmort[length(cmort)] * regr$ar[2]

#Semana 3
sem3 <-  sem2 * regr$ar[1] + sem1 * regr$ar[2]

#Semana 4
sem4 <-  sem3 * regr$ar[1] + sem2 * regr$ar[2]


#Utilizando predict
data.frame("predict" = predict(regr, n.ahead = 4)$pred, "se" = predict(regr, n.ahead = 4)$se, "formula"
```

```
##    predict       se  formula
## 1 87.31378 5.811975 87.31378
## 2 86.22078 6.478879 86.22078
## 3 86.60416 7.802572 86.60416
## 4 86.24057 8.588367 86.24057
```

Questão 18

```r
#Regressão Yule - walker
(rec.yw = ar.yw(data, order=2))
```

```
##
## Call:
## ar.yw.default(x = data, order.max = 2)
##
## Coefficients:
##       1       2
## 0.4339  0.4376
##
## Order selected 2  sigma^2 estimated as  32.84
```

```r
(estimativas <- data.frame(OLS = c(regr$ar),
                  "Yule-Walker" = c(rec.yw$ar)))
```

```
##         OLS Yule.Walker
## 1 0.4926052   0.4339481
## 2 0.5054340   0.4375768
```

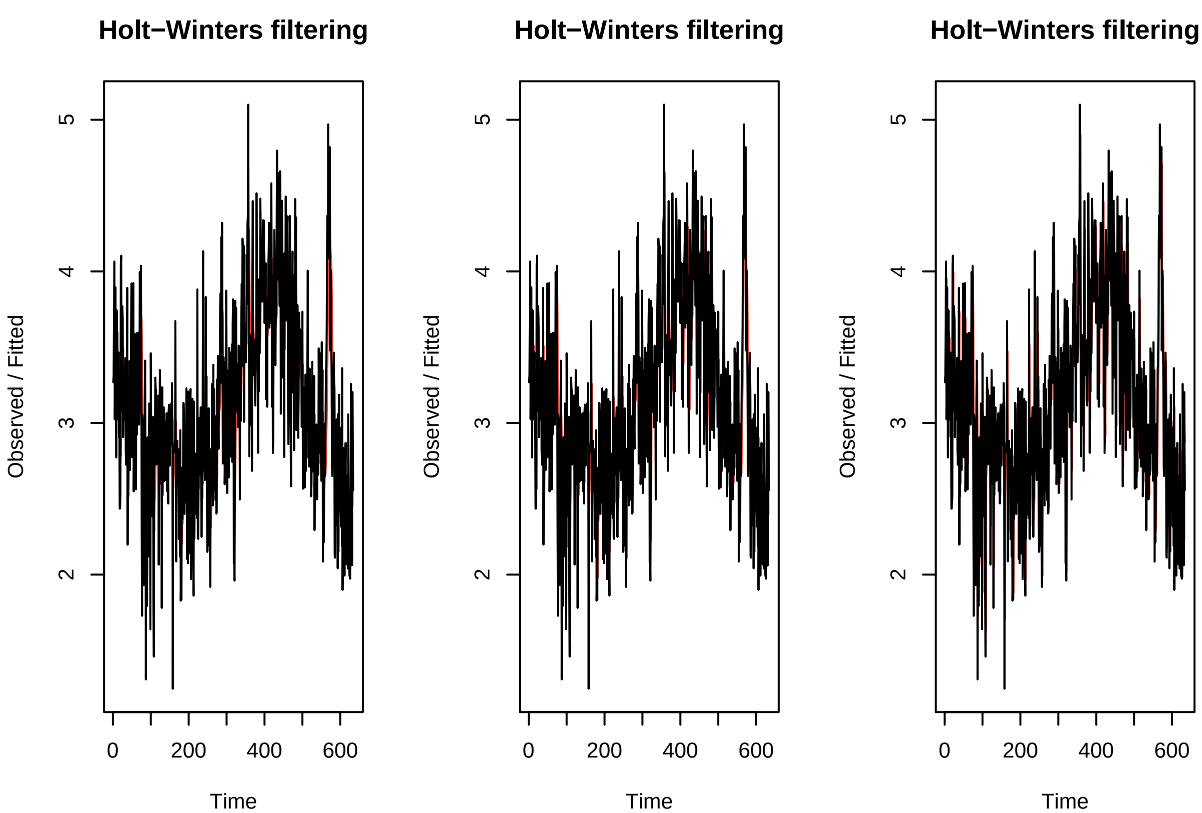
#Questão 30

```
data <- log(varve) #Salvando a transformações dos dados
#Ajustando com os diferentes Alphas
HW025 <- HoltWinters(data, alpha = 0.25, beta = FALSE, gamma = FALSE)
HW050 <- HoltWinters(data, alpha = 0.50, beta = FALSE, gamma = FALSE)
HW075 <- HoltWinters(data, alpha = 0.75, beta = FALSE, gamma = FALSE)
```

```
data.frame("0.25" = HW025$coefficients,
                 "0.50" = HW050$coefficients,
                 "0.75" = HW075$coefficients)
```

```
##      X0.25    X0.50    X0.75
## a 2.659031 2.688861 2.635534
```

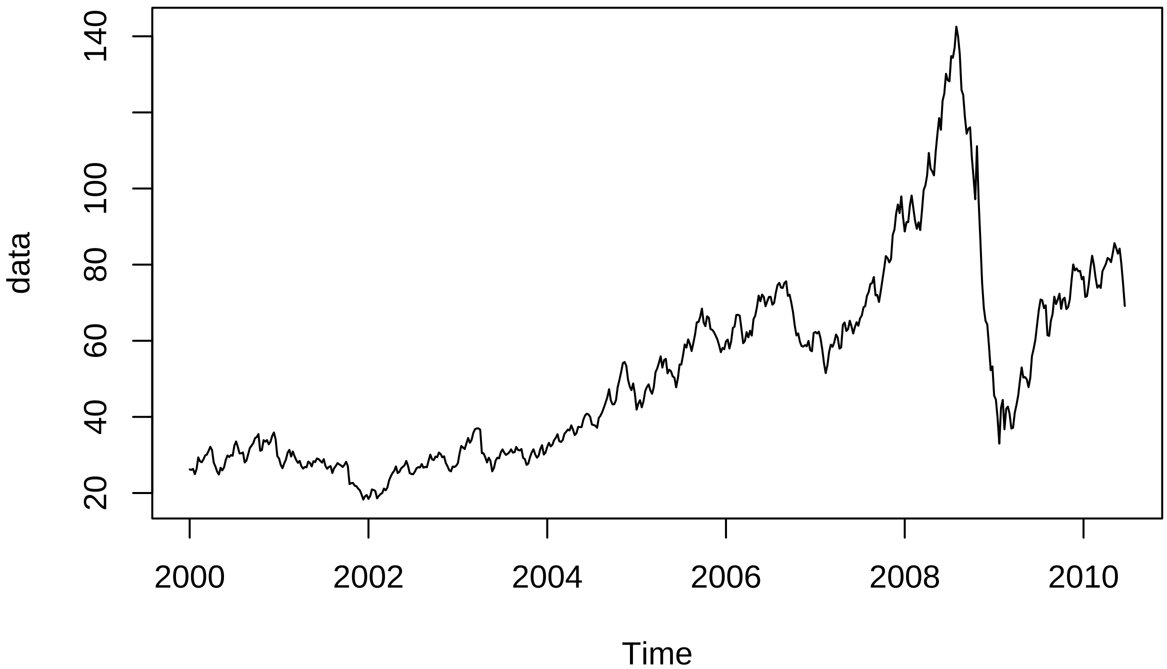
```
par(mfrow = c(1,3))
plot(HW025)
plot(HW050)
plot(HW075)
```



Apesar dos coeficientes gerados pelo algoritmo de HoltWinters serem extremamente próximos, podemos ver o efeito pesado da suavisação duplicando e triplicando o coeficiente Alpha pelos gráficos

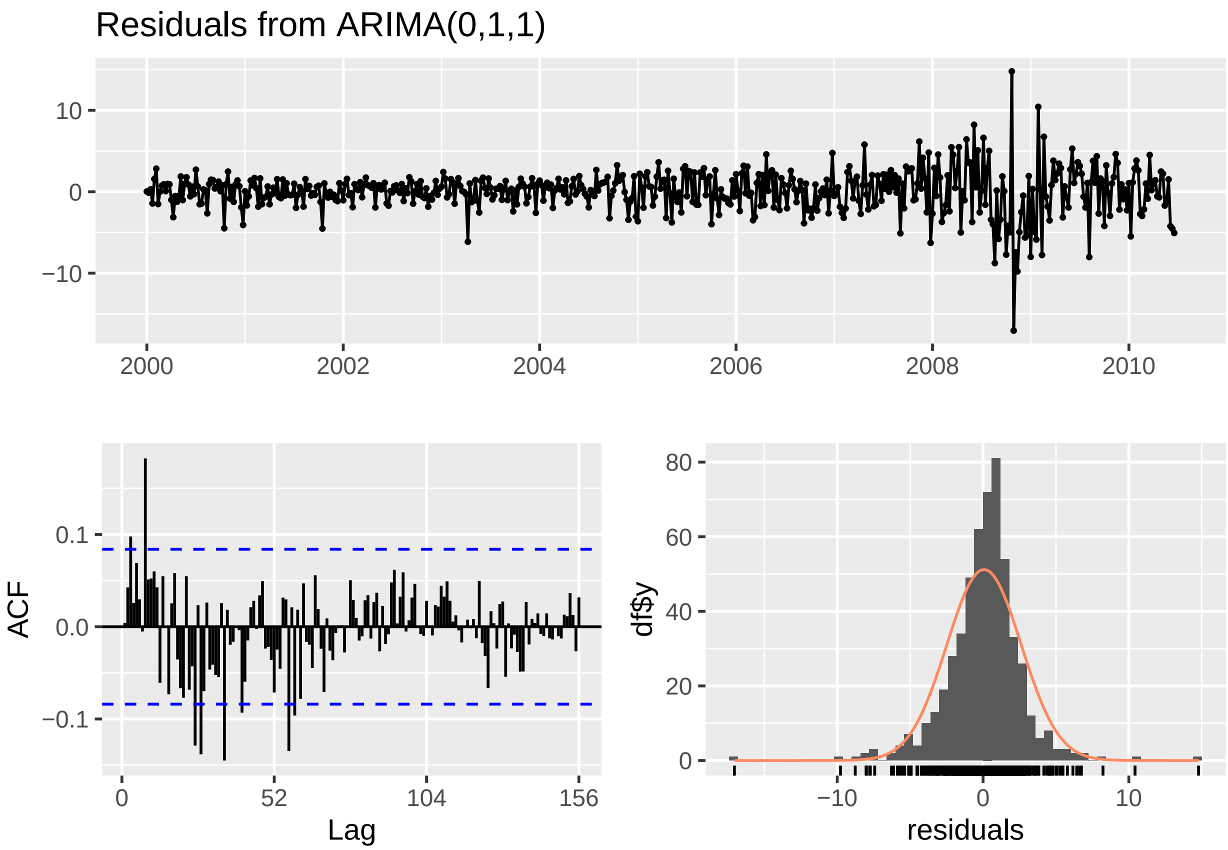
Questão 32

```r
data <- oil
plot(data)
```




```r
# Ajustando Arima(0,1,1)
ARIMA011<- arima(data, order = c(0,1,1))

RESID.011 <- checkresiduals(ARIMA011)
```

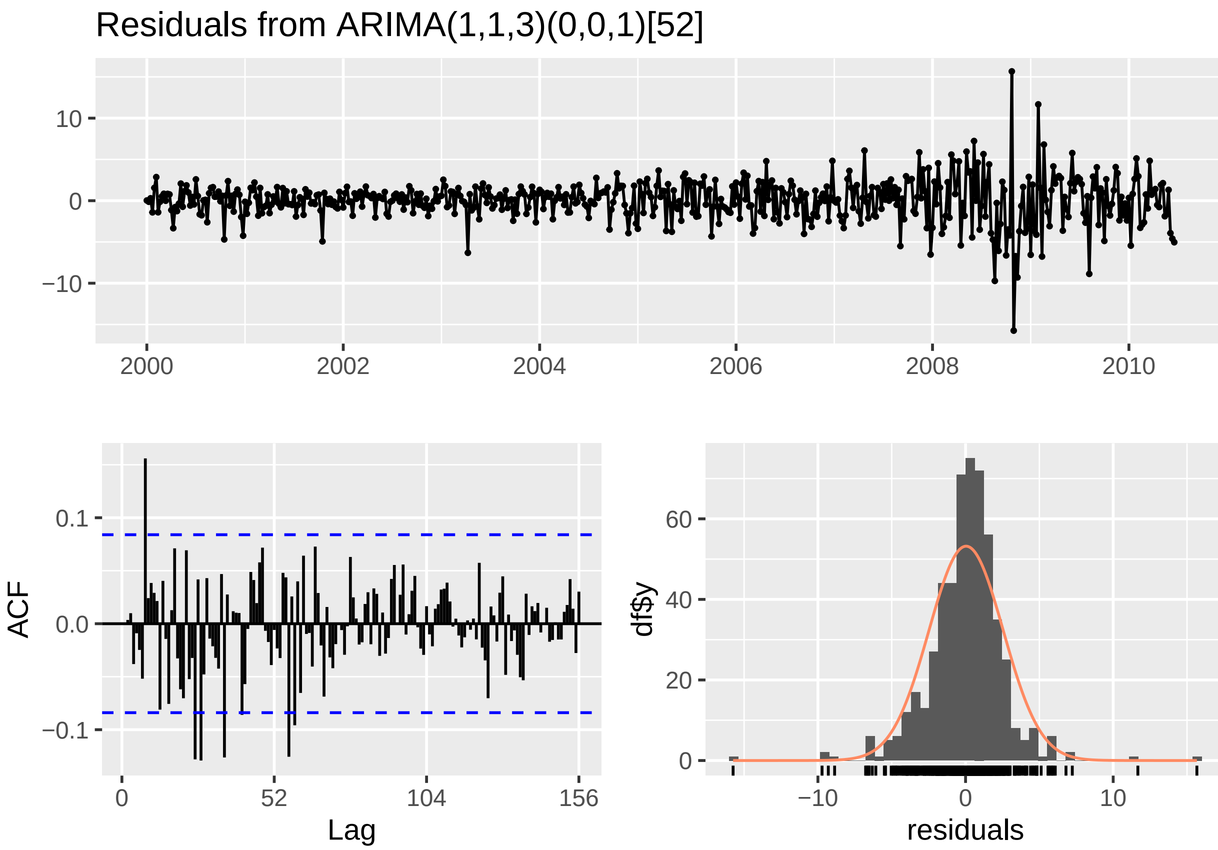



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,1,1)
## Q* = 163.35, df = 103, p-value = 0.0001423
##
## Model df: 1.   Total lags used: 104
```

Para um primeiro ajuste está rasoável, os resíduos são aproximadamente normais, os resíduos está em torno do zero, porém o ACF está bem irregular.

```
#Utilizando o algoritmo auto.arima, minimizando soma de quadrados condicionais
ARIMAAUTO <- auto.arima(data)

(RESID.AUTO <- checkresiduals(ARIMAAUTO))
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,1,3)(0,0,1)[52]
## Q* = 142.6, df = 99, p-value = 0.002724
##
## Model df: 5.   Total lags used: 104
```

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,1,3)(0,0,1)[52]
## Q* = 142.6, df = 99, p-value = 0.002724
```

```
(df <- data.frame(
RESID.011$p.value,
RESID.AUTO$p.value
))
```

```
##   RESID.011.p.value RESID.AUTO.p.value
## 1      0.0001422741        0.002723503
```

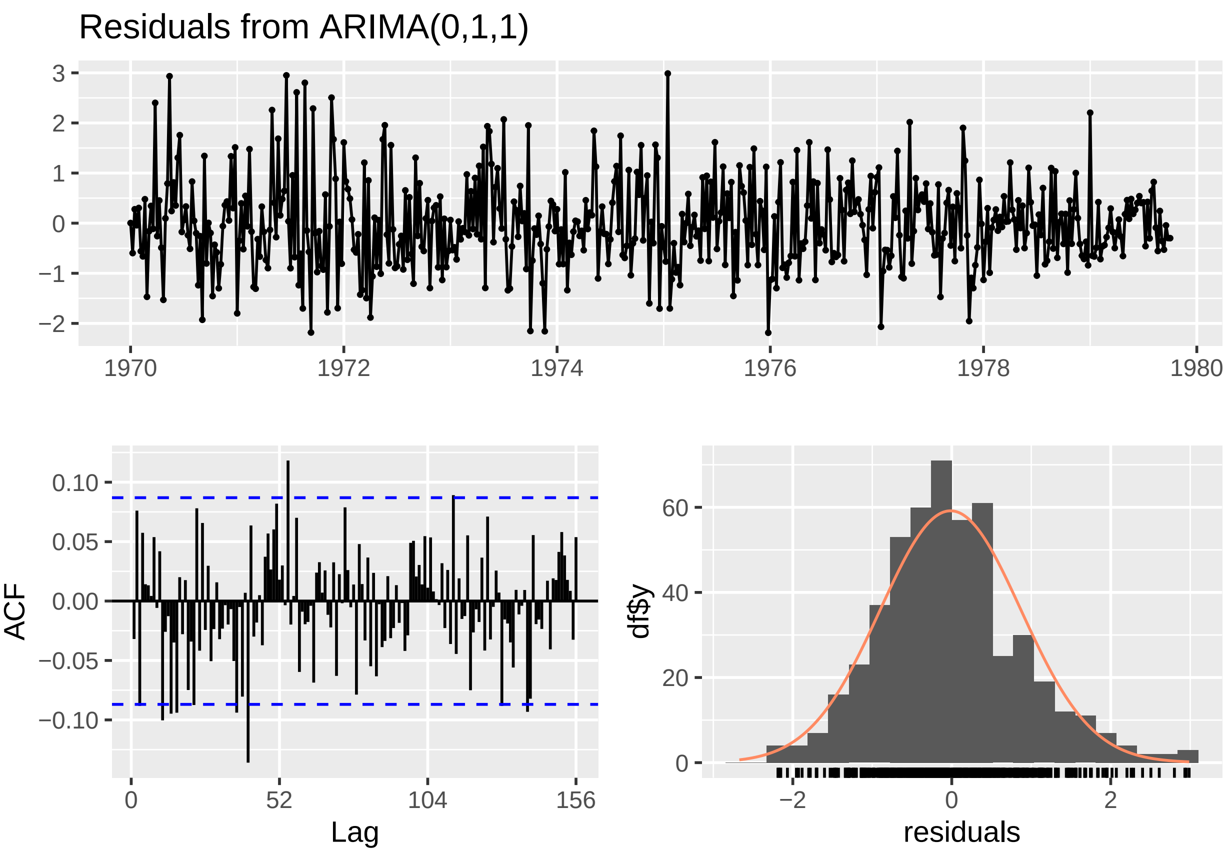
Curiosamente podemos ver a saída da função checkresiduals() já nos fornece o pvalor do teste Ljung-Box no qual podemos ver a maldição de adicionarmos mais parâmetros nos modelos autoregressivos, onde o maior grau de liberdade, do modelo, contribuiu para um pvalor maior que o modelo ARIMA(0,1,1), mais simples.

Se eu fosse escolher um dos modelos utlizaria o gerado pelo auto.arima(), o ACF demonstrou um comportamento mais concentrado nas bandas de confiança e uma enfase maior nos meses mais próximas do evento, além disso os resíduos se aproximam mais de zero pelo que me aparenta.

Questão 34

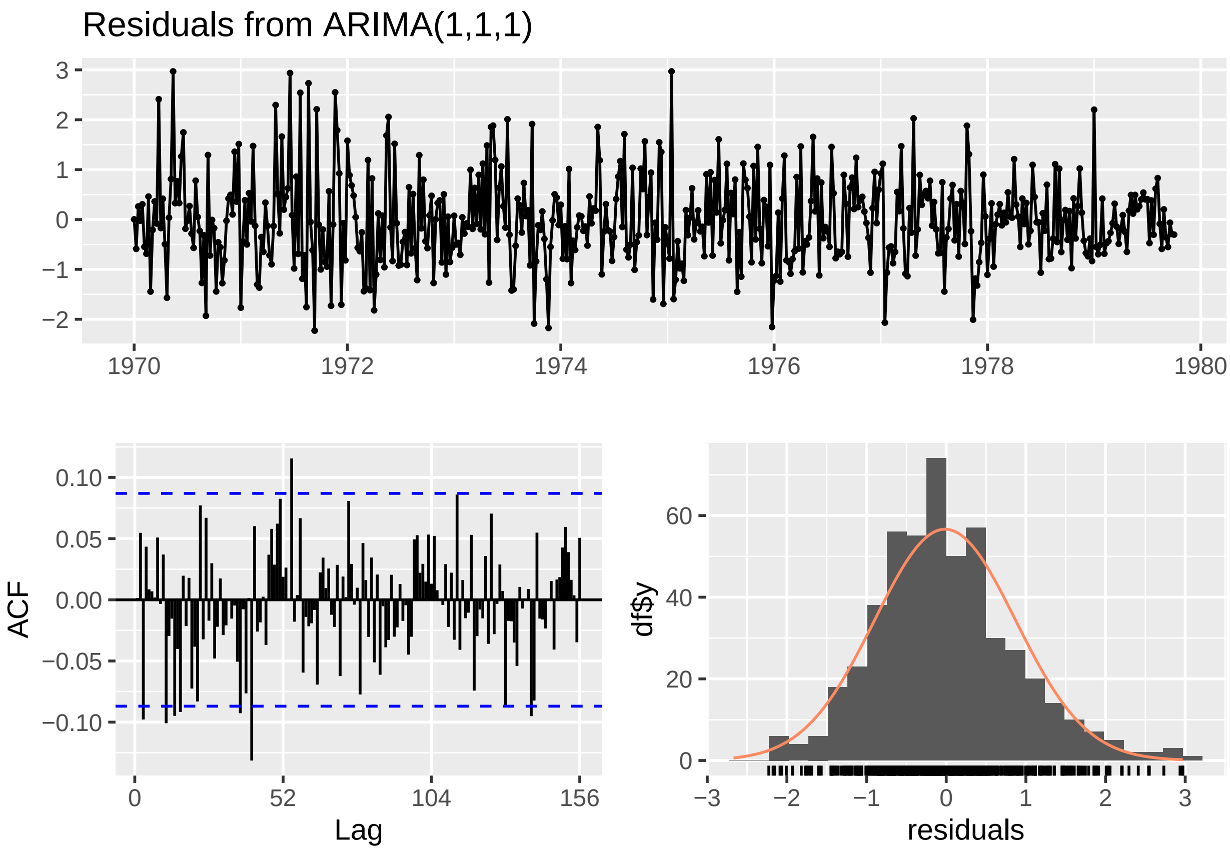
```
dados <- so2

ARIMA011 <- arima(dados,order = c(0,1,1))
checkresiduals(ARIMA011)
```



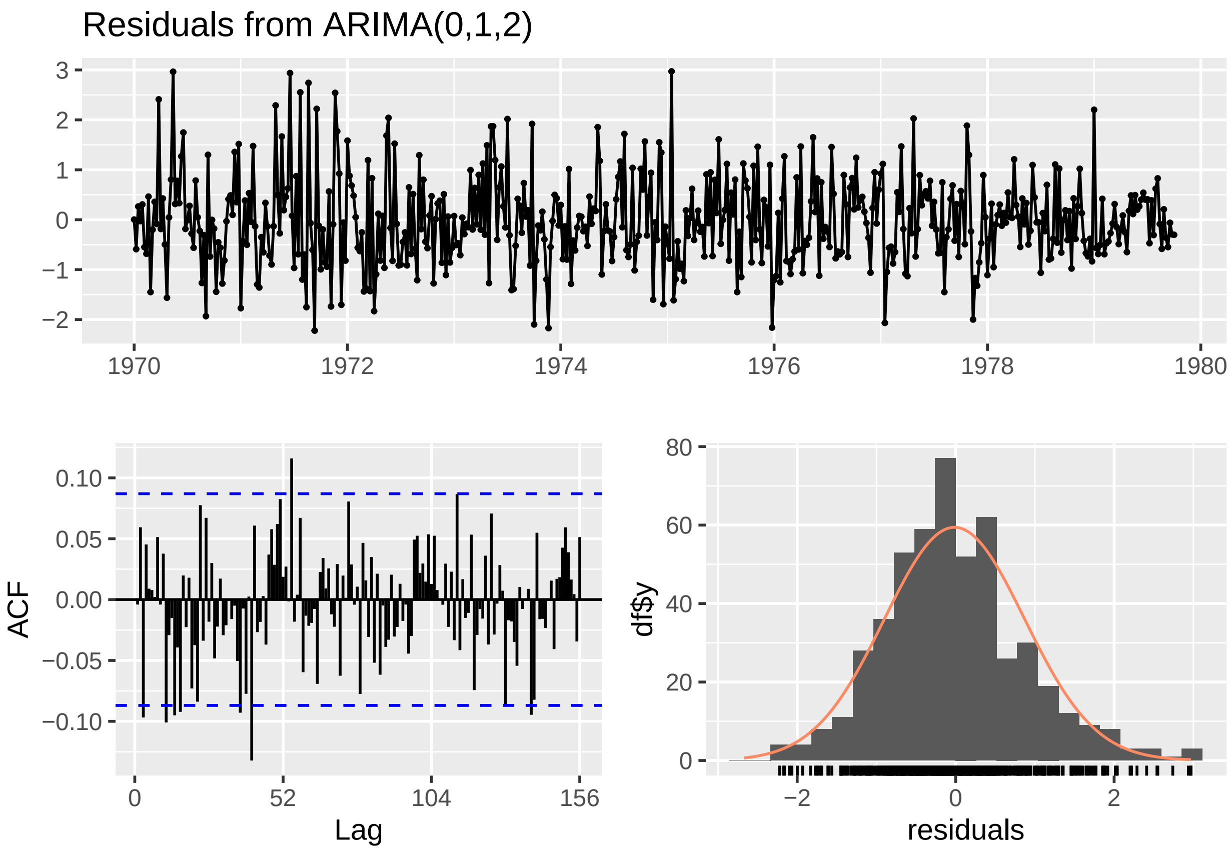

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,1,1)
## Q* = 125.48, df = 101, p-value = 0.04987
##
## Model df: 1.   Total lags used: 102
```

```
ARIMA111 <- arima(dados,order = c(1,1,1))
checkresiduals(ARIMA111) # Aumento de um grau no processo auto regressivo fez o resultado do Ljung-Box
```



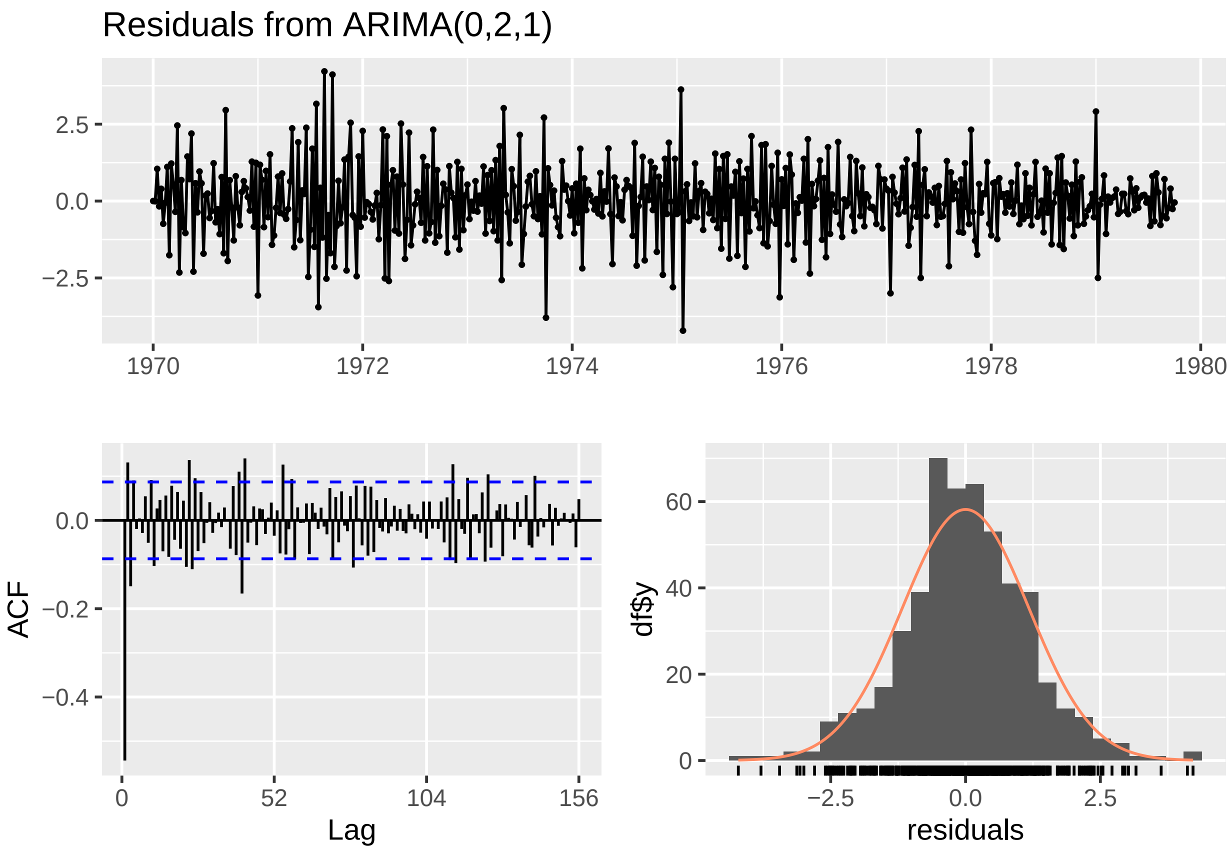

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,1,1)
## Q* = 119.59, df = 100, p-value = 0.08843
##
## Model df: 2.   Total lags used: 102
```

```
ARIMA012 <- arima(dados,order = c(0,1,2))
checkresiduals(ARIMA012)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,1,2)
## Q* = 120.58, df = 100, p-value = 0.0789
##
## Model df: 2.   Total lags used: 102
```

```r
ARIMA021 <- arima(dados,order = c(0,2,1))
(RES021 <- checkresiduals(ARIMA021)) # Modelo escolhido
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,2,1)
## Q* = 376.46, df = 101, p-value < 2.2e-16
##
## Model df: 1.   Total lags used: 102
```

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,2,1)
## Q* = 376.46, df = 101, p-value < 2.2e-16
```

```
RES021$p.value # p valor adquirido no teste Ljung Box
```

```
## [1] 0
```

O modelo que não utiliza ordem de auto regressão, e usando o operador de segunda ordem de diferenciação nas médias móveis apresentou a melhor modelagem para os dados de So2.

```
predict(ARIMA021, n.ahead = 4)
```

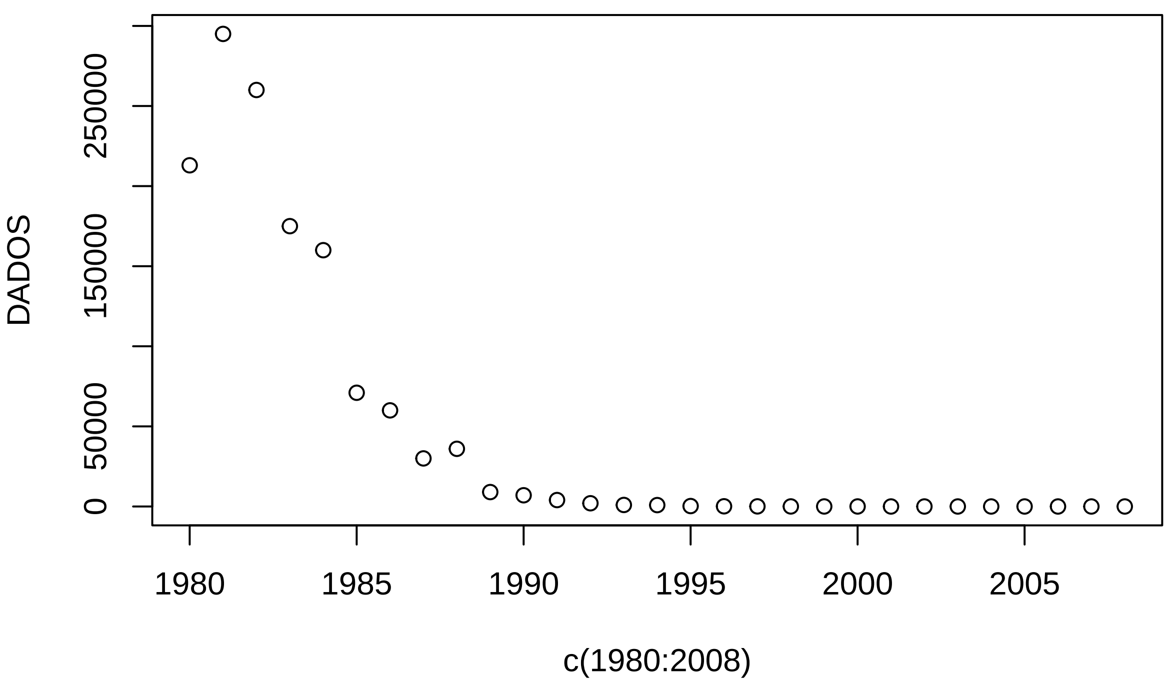
```
## $pred
```

```
## Time Series:
## Start = c(1979, 41)
## End = c(1979, 44)
## Frequency = 52
## [1] 1.576469 1.572939 1.569408 1.565878
##
## $se
## Time Series:
## Start = c(1979, 41)
## End = c(1979, 44)
## Frequency = 52
## [1] 1.177067 1.666262 2.042750 2.361075
```

Questão 36

A)

```r
DADOS <- cpg
plot(y = DADOS, x = c(1980:2008))
```



Como mencionado no enunciado, vemos que o preço por GB de armazenamento decaiu extremamente rápido do inicio da decada de 80 até o ano de 95

B)