

Modelos Arma

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```
library(tseries)

## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo

load("dados_arma_4.RData")

plot_acf_pacf <- function(series){
  par(mfrow = c(2, 1))
  acf(series, main = "ACF")
  pacf(series, main = "PACF")
}

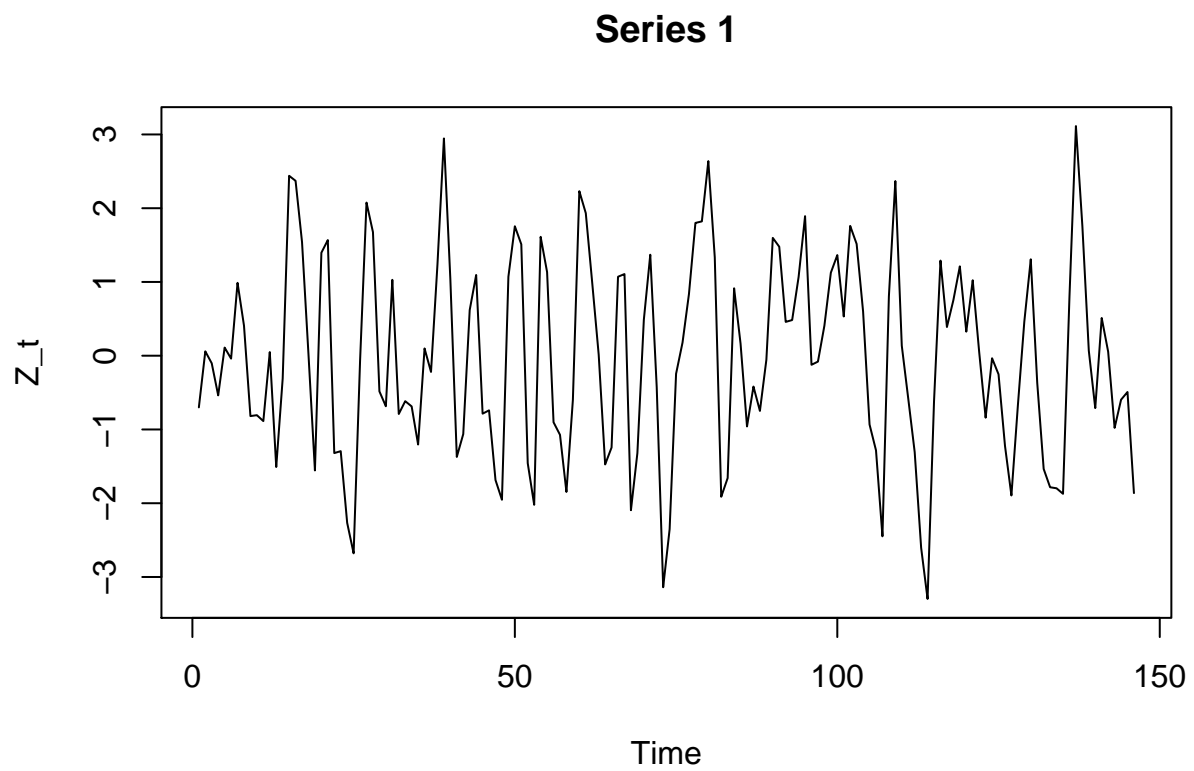
plot_res <- function(res){
  plot(res, main = "Residuals of model",
       ylab = "Residual", type = "p")
  abline(0, 0)
}
```

Modelos ARMA

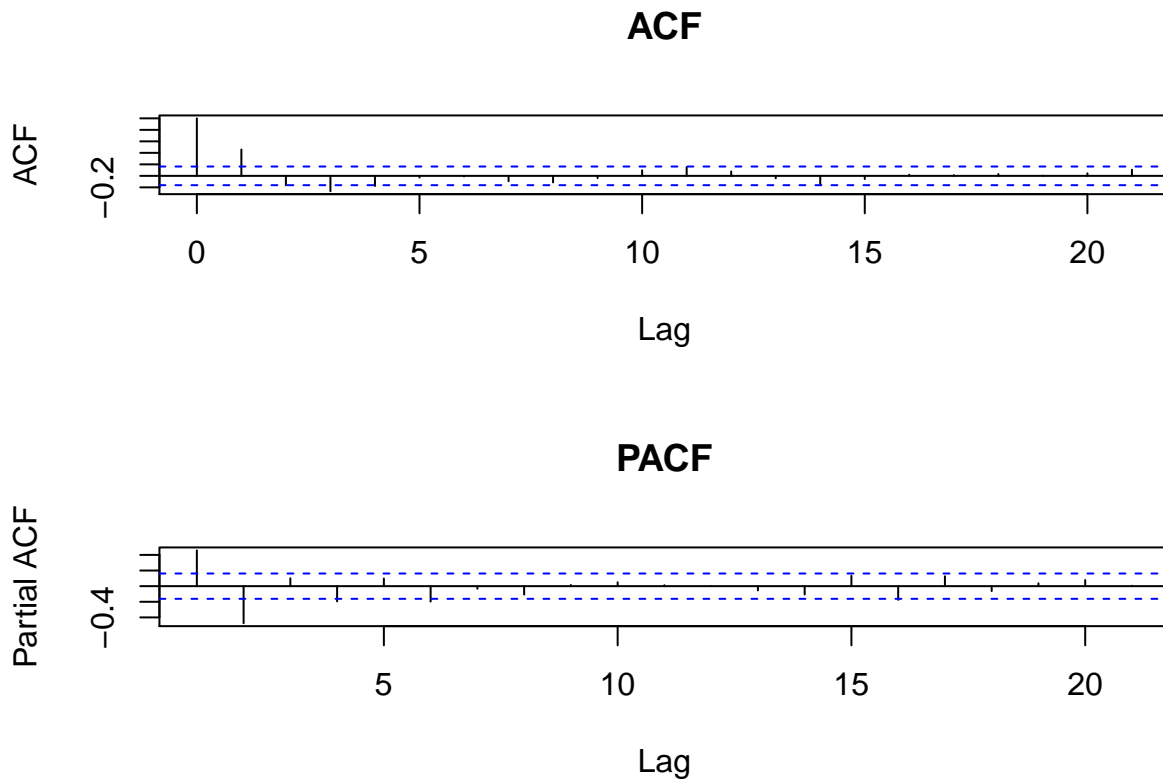
Com 9 séries temporais, iremos avaliar cada uma delas e identificar se ela é gerada por um modelo $AR(p)$, um modelo $MA(q)$ ou um modelo $ARMA(p, q)$. Em todas as diferentes séries iremos inicialmente visualizar a série, a função de autocorrelação e a função de autocorrelação parcial.

Série 1

```
plot(X[[1]], main = "Series 1", ylab = "Z_t")
```



```
plot_acf_pacf(X[[1]])
```



Vemos que a ACF e a PACF decrescem de forma brusca, tendo valores significativos para os dois primeiros lags, dessa forma, iremos considerar dois modelos, o modelo AR(2) e o modelo ARMA(2, 2). Vamos tentar fitar um modelo AR(2).

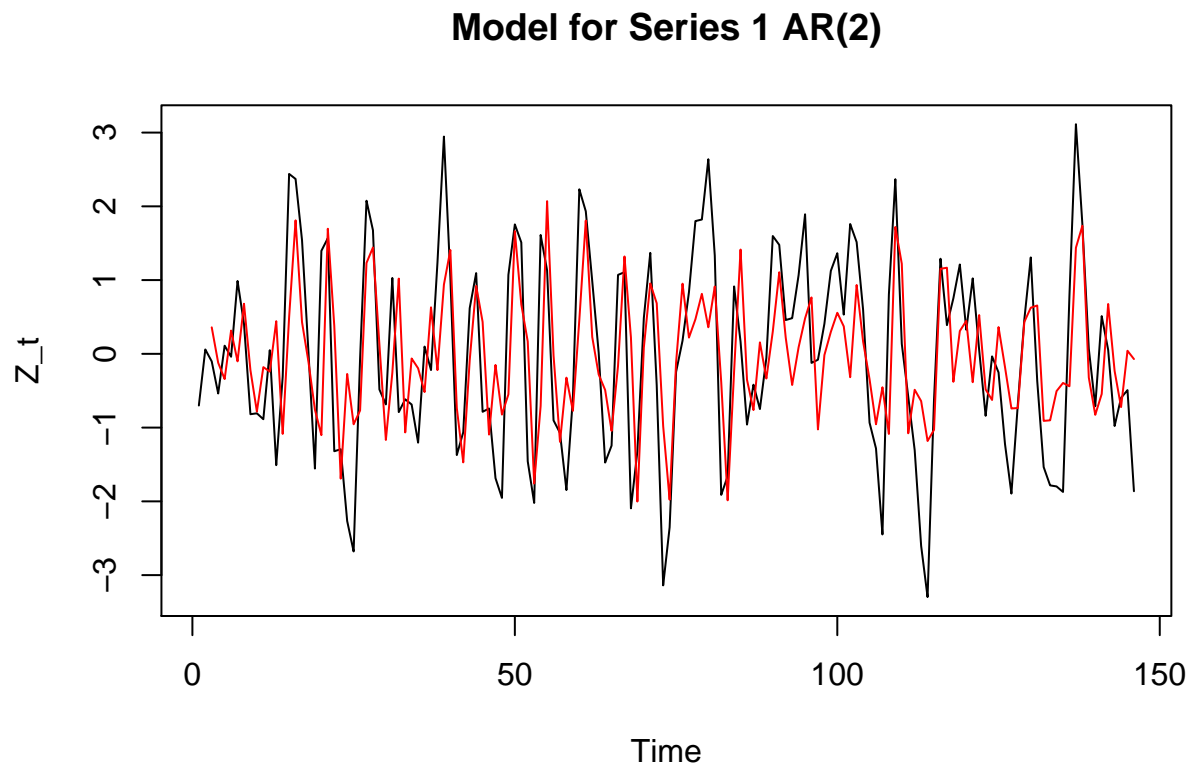
```
model11 <- arma(X[[1]], order = c(2, 0))
summary(model11)
```

```
##
## Call:
## arma(x = X[[1]], order = c(2, 0))
##
## Model:
## ARMA(2,0)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.3168 -0.7743  0.1256  0.6870  2.4984
##
## Coefficient(s):
##              Estimate Std. Error t value Pr(>|t|)
## ar1           0.68921    0.07292   9.451  < 2e-16 ***
## ar2          -0.48531    0.07289  -6.658 2.77e-11 ***
## intercept    -0.02129    0.08702  -0.245  0.807
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Fit:
## sigma^2 estimated as 1.113, Conditional Sum-of-Squares = 159.18, AIC = 435.98
```

Vamos visualizar inicialmente o modelo real e o previsto, e em sequência, o plot de resíduos.

```
plot(X[[1]], main = "Model for Series 1 AR(2)", ylab = "Z_t")
lines(model1$fitted.values, col = "red")
```



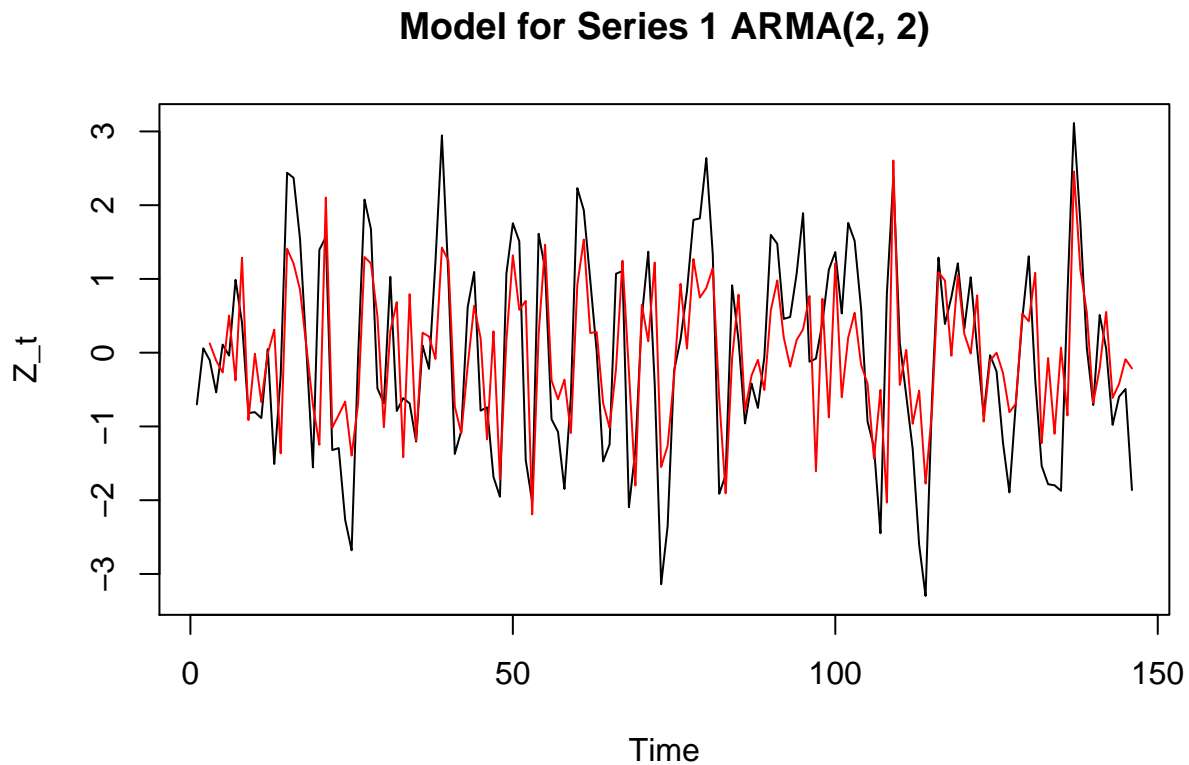
Realizando o mesmo procedimento, mas para o modelo ARMA(2, 2).

```
model1 <- arma(X[[1]], order = c(2, 2))
summary(model1)
```

```
##
## Call:
## arma(x = X[[1]], order = c(2, 2))
##
## Model:
## ARMA(2,2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.1588765 -0.5967001  0.0001618  0.7185817  2.8350422
##
## Coefficient(s):
```

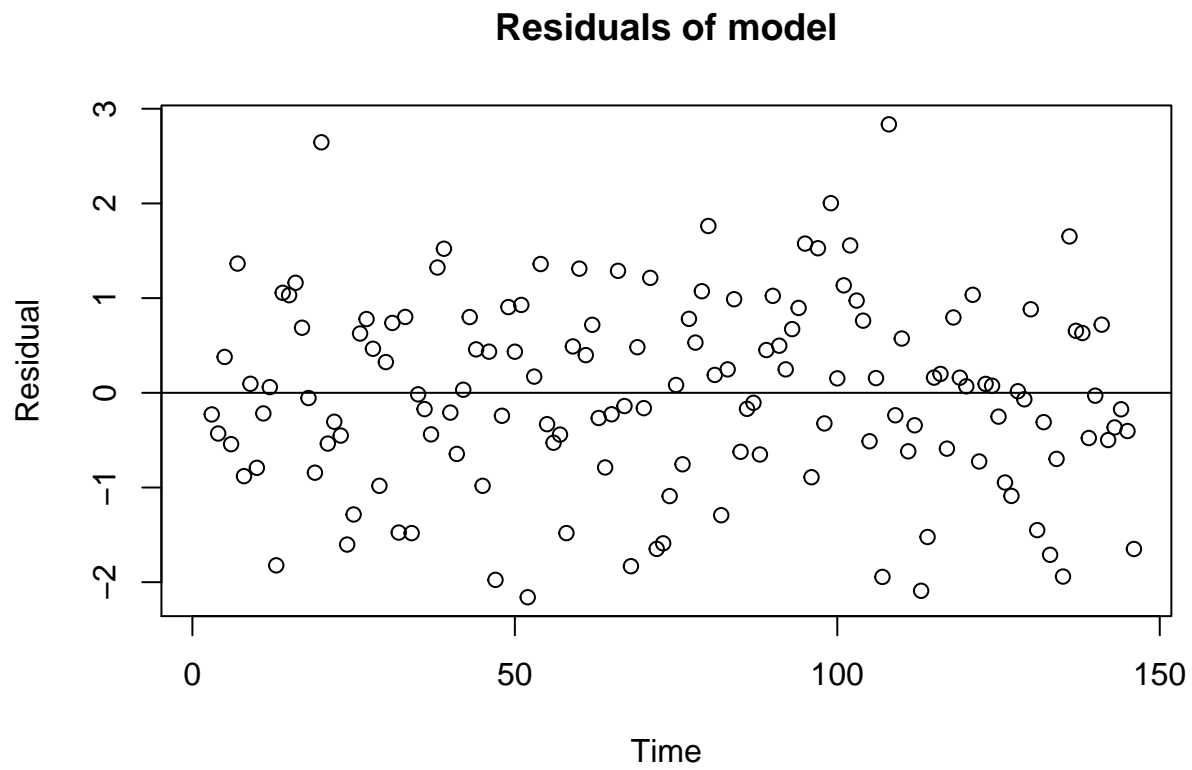
```
##           Estimate Std. Error t value Pr(>|t|)
## ar1      0.792873   0.133253   5.950 2.68e-09 ***
## ar2     -0.119687   0.107696  -1.111   0.266
## ma1      0.060935   0.110778   0.550   0.582
## ma2     -0.775825   0.116414  -6.664 2.66e-11 ***
## intercept -0.005245   0.024207  -0.217   0.828
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Fit:
## sigma^2 estimated as 0.9758, Conditional Sum-of-Squares = 139.55, AIC = 420.76
```

```
plot(X[[1]], main = "Model for Series 1 ARMA(2, 2)", ylab = "Z_t")
lines(model1$fitted.values, col = "red")
```



Vemos que o AIC é menor para o modelo ARMA(2, 2), e apesar de ambos se encaixarem bem aos dados, o modelo ARMA(2, 2) representa melhor os pontos extremos da série. Vamos visualizar os resíduos obtidos:

```
plot_res(model1$residuals)
```

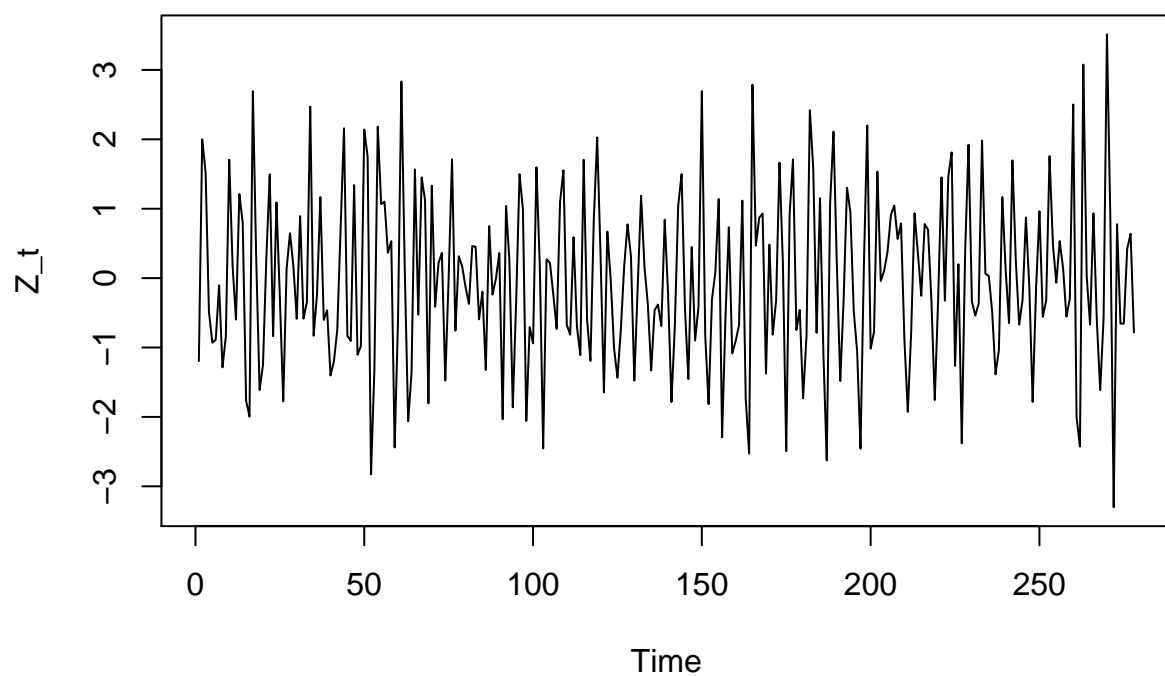


O modelo parece se adequar bem aos dados e também os resíduos não apresentam um padrão de comportamento.

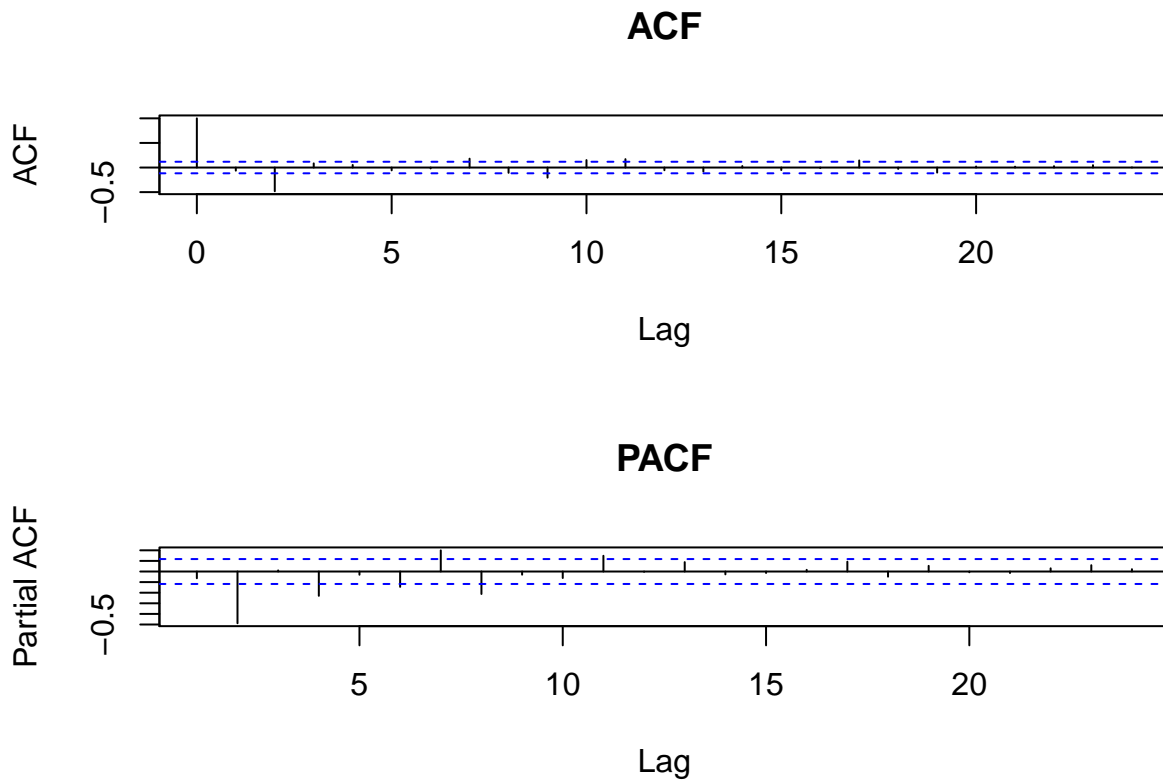
Série 2

```
plot(X[[2]], main = "Series 2", ylab = "Z_t")
```

Series 2



```
plot_acf_pacf(X[[2]])
```



Agora, visualizamos um situação inversa, o lag 2 é significativo na ACF e nos demais não, e na PACF o decrescimento é gradual, o que nos faz pensar se tratar de um modelo MA(2). No entanto, como na PACF o lag 2 também é significativo, iremos comparar com o modelo ARMA(2, 2).

```
model2 <- arma(X[[2]], order = c(0, 2))
summary(model2)
```

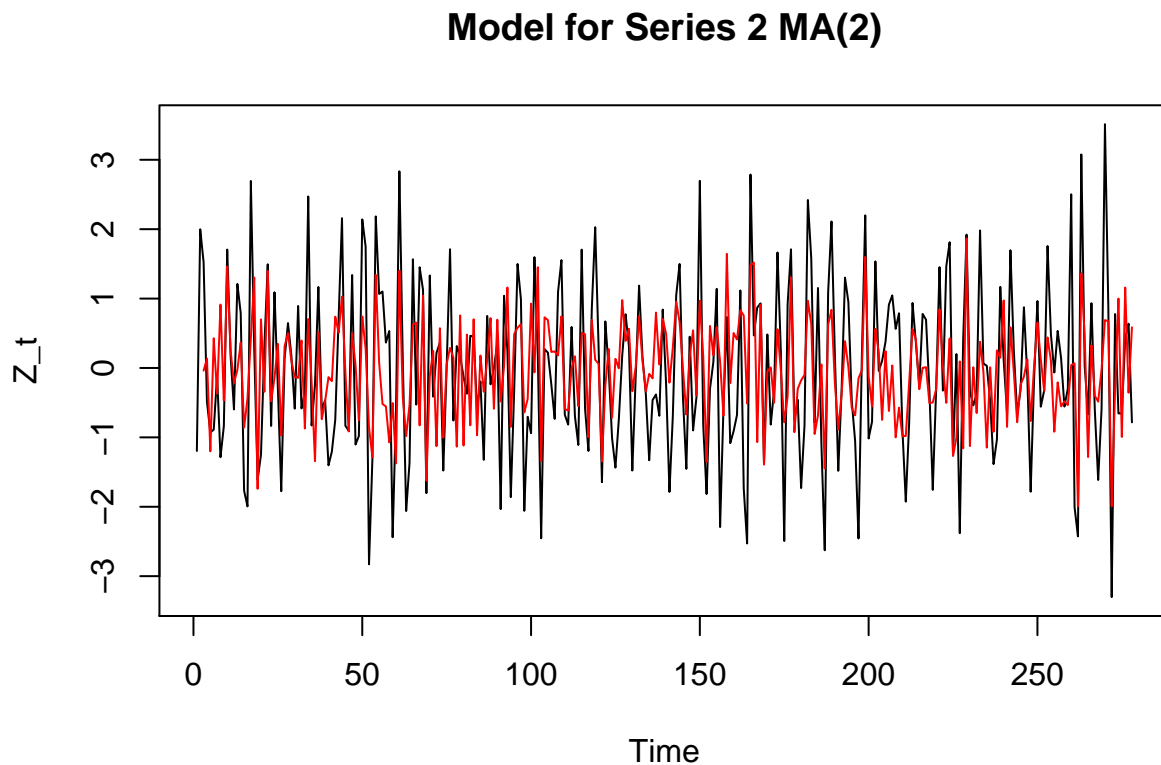
```
##
## Call:
## arma(x = X[[2]], order = c(0, 2))
##
## Model:
## ARMA(0,2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.49044 -0.77251  0.01282  0.77130  2.82319
##
## Coefficient(s):
##           Estimate Std. Error t value Pr(>|t|)
## ma1          0.11057    0.04029   2.745  0.00606 **
## ma2         -0.70037    0.03931 -17.818 < 2e-16 ***
## intercept -0.03815    0.02510  -1.520  0.12855
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```



```
## Fit:
## sigma^2 estimated as 1.025, Conditional Sum-of-Squares = 281.95, AIC = 801.86
```

O modelo se encaixou bem, vamos comparar a previsão e o real, e em sequência, o plot de resíduos.

```
plot(X[[2]], main = "Model for Series 2 MA(2)", ylab = "Z_t")
lines(model2$fitted.values, col = "red")
```



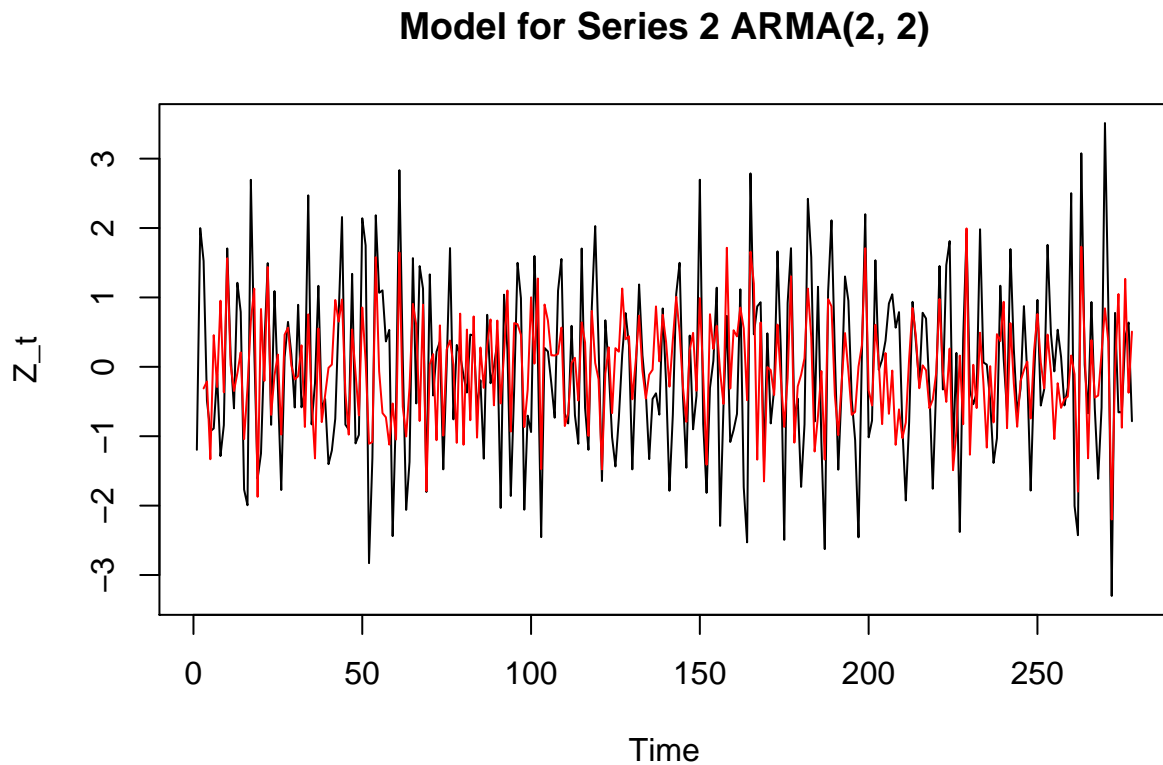
Realizando o mesmo processo com o modelo ARMA(2, 2).

```
model2 <- arma(X[[2]], order = c(2, 2))
summary(model2)
```

```
##
## Call:
## arma(x = X[[2]], order = c(2, 2))
##
## Model:
## ARMA(2,2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.54256 -0.76754  0.01269  0.73690  2.67023
##
## Coefficient(s):
```

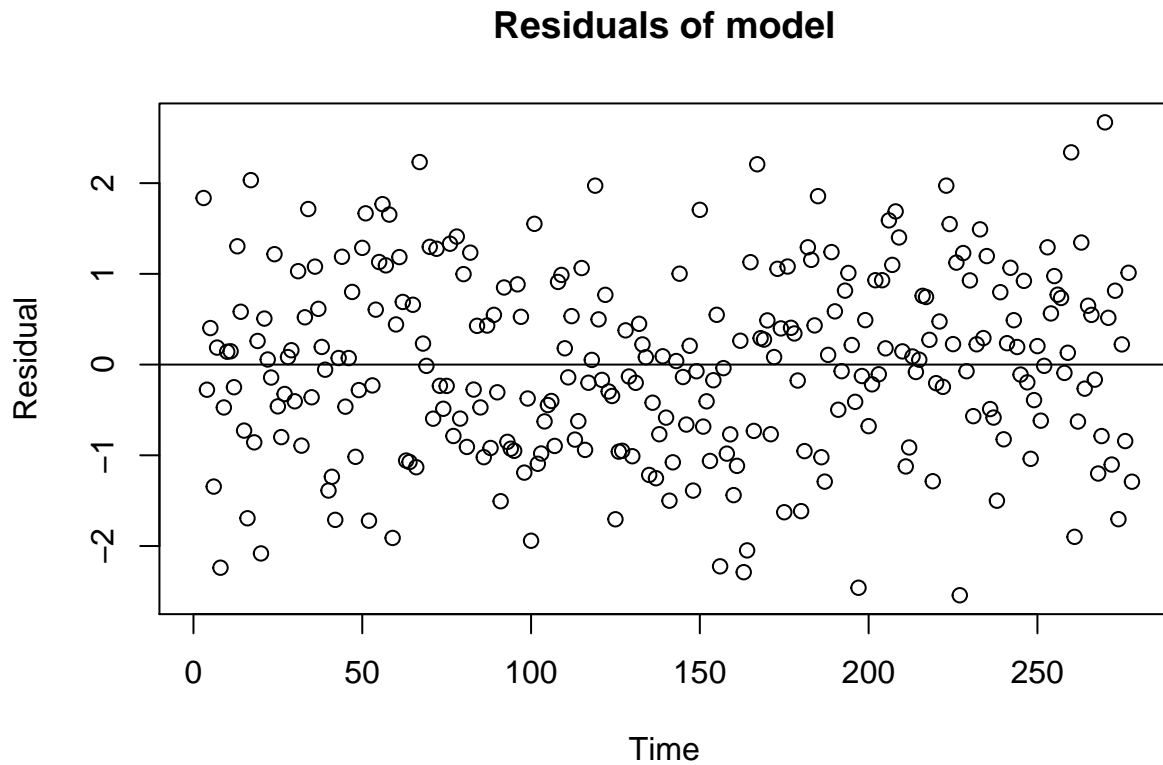
```
##           Estimate Std. Error t value Pr(>|t|)
## ar1      -0.20365    0.08558  -2.380  0.01733 *
## ar2      -0.12123    0.07719  -1.571  0.11627
## ma1       0.21277    0.06716   3.168  0.00153 **
## ma2      -0.61986    0.06320  -9.808 < 2e-16 ***
## intercept -0.04935    0.03605  -1.369  0.17106
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Fit:
## sigma^2 estimated as 1.003, Conditional Sum-of-Squares = 275.78, AIC = 799.72
```

```
plot(X[[2]], main = "Model for Series 2 ARMA(2, 2)", ylab = "Z_t")
lines(model2$fitted.values, col = "red")
```



Vemos que apesar de extramamente parecidos, o modelo ARMA(2, 2) teve o AIC um pouquinho menor. Vamos visualizar o resíduo obtido com ele:

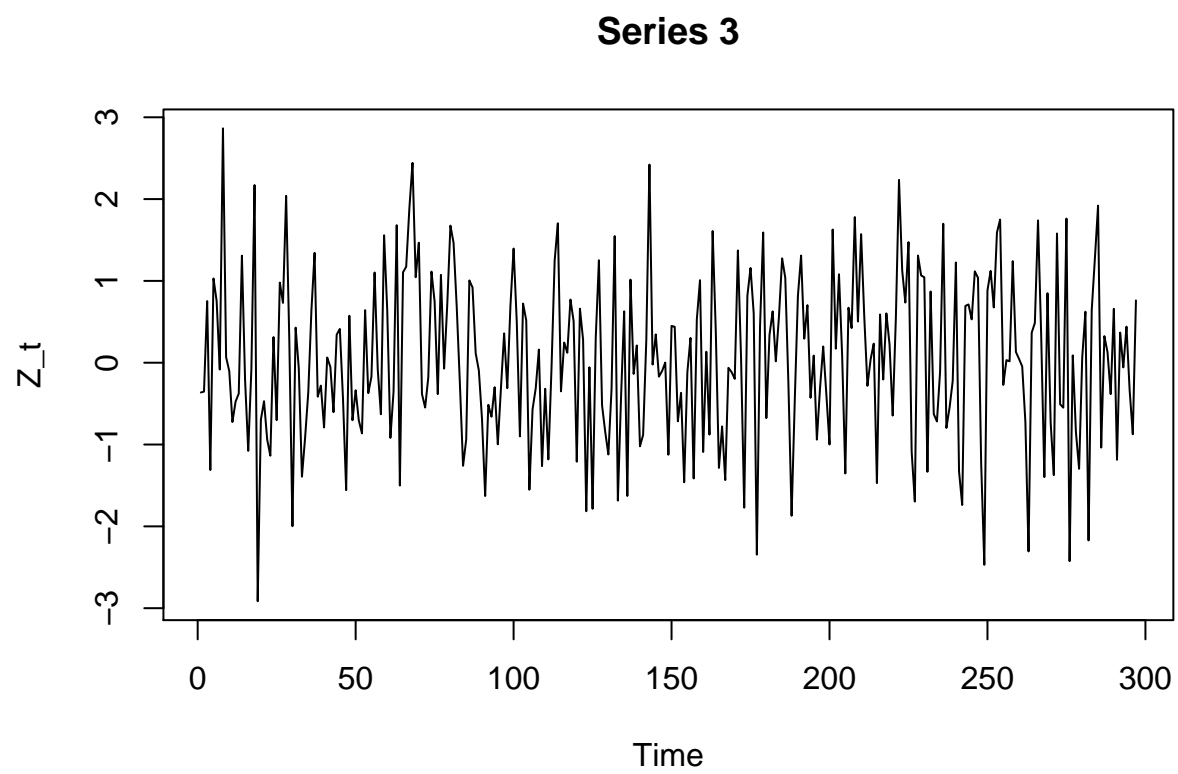
```
plot_res(model2$residuals)
```



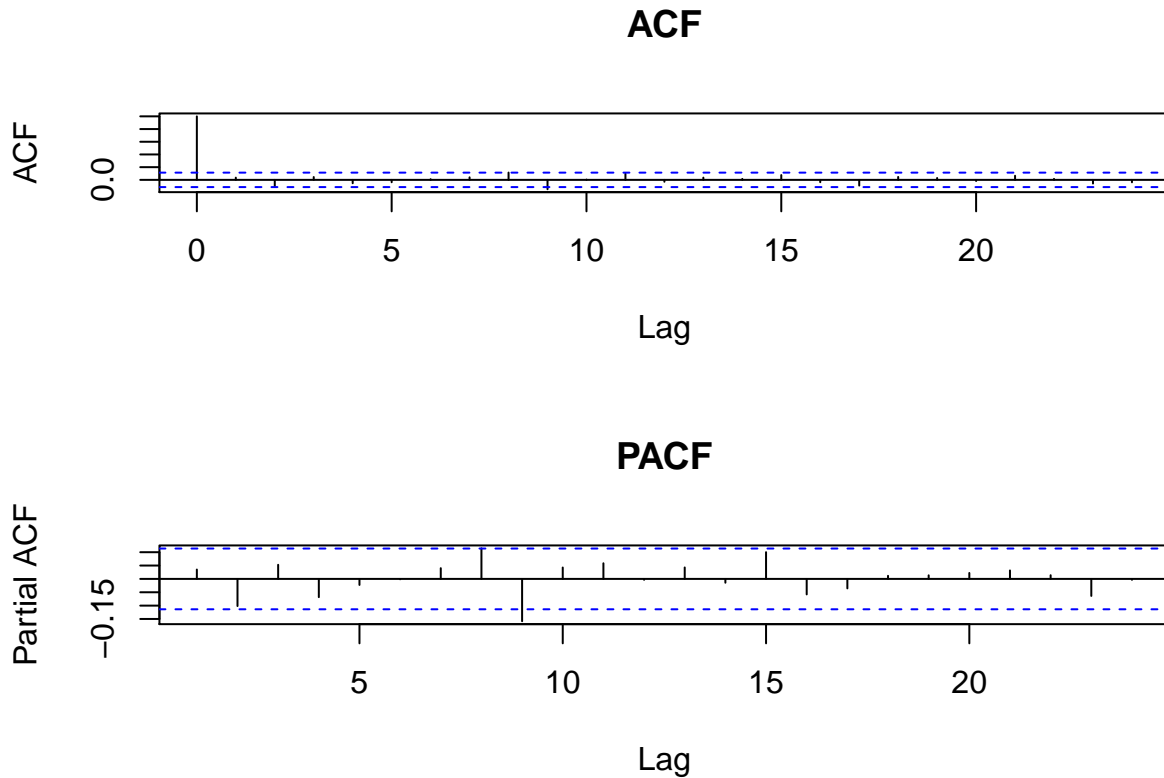
O modelo aparentemente se adequa bem a sazonalidade da série real, no entanto, não conseguimos capturar os picos extremos como ocorrem na série real, e os resíduos também se distribuem uniformemente ao longo da série.

Série 3

```
plot(X[[3]], main = "Series 3", ylab = "Z_t")
```



```
plot_acf_pacf(X[[3]])
```



Nesse modelo existe um comportamento diferente dos demais, tanto a ACF quanto a PACF são praticamente nulas para todos os valores, menos para a ACF de 0, o que indica que as amostras não possuem covariância, se comportando como um ruído branco. Vamos verificar a média e a variância da série.

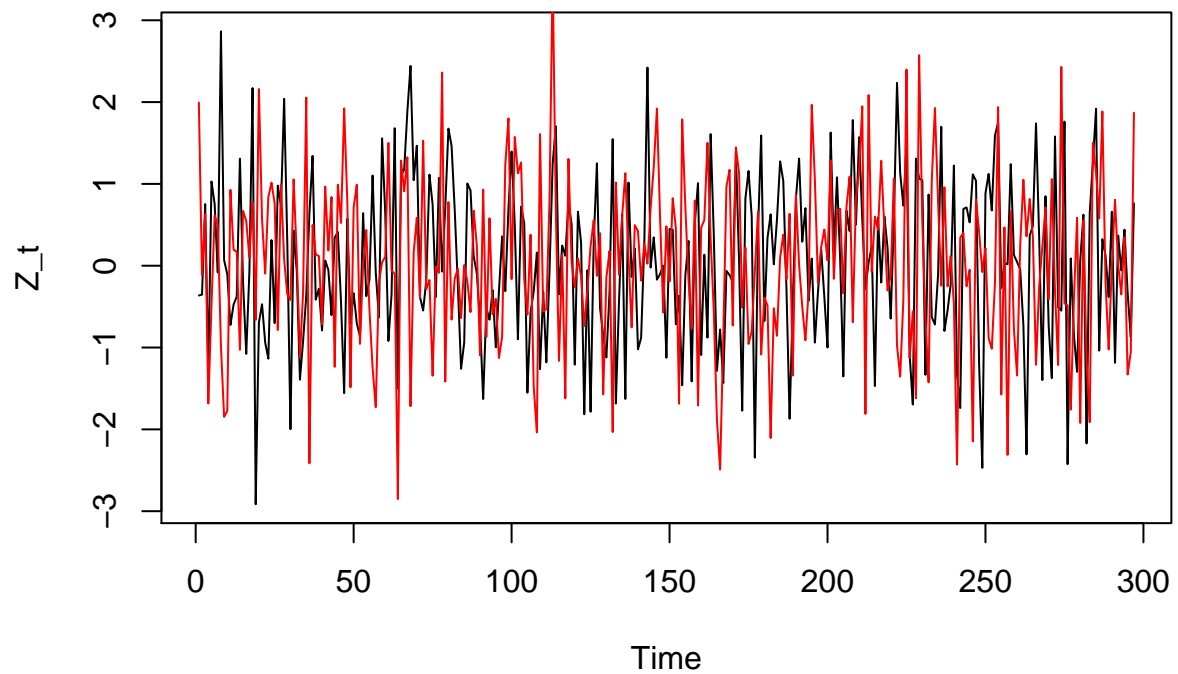
```
data.frame(mean = mean(X[[3]]), variance = var(X[[3]])*296/297)
```

```
##          mean variance
## 1 0.03941307 1.021629
```

Vemos que o modelo se comporta como um ruído branco, isto é, a_t com $E(a_t) = 0$ e $Var(a_t) = 1$. Se nós gerarmos 297 amostras de a_t e visualizarmos tanto o modelo e predição, quanto o residual, teremos:

```
model3 <- rnorm(297)
plot(X[[3]], main = "Model for Series 3", ylab = "Z_t")
lines(model3, col = "red")
```

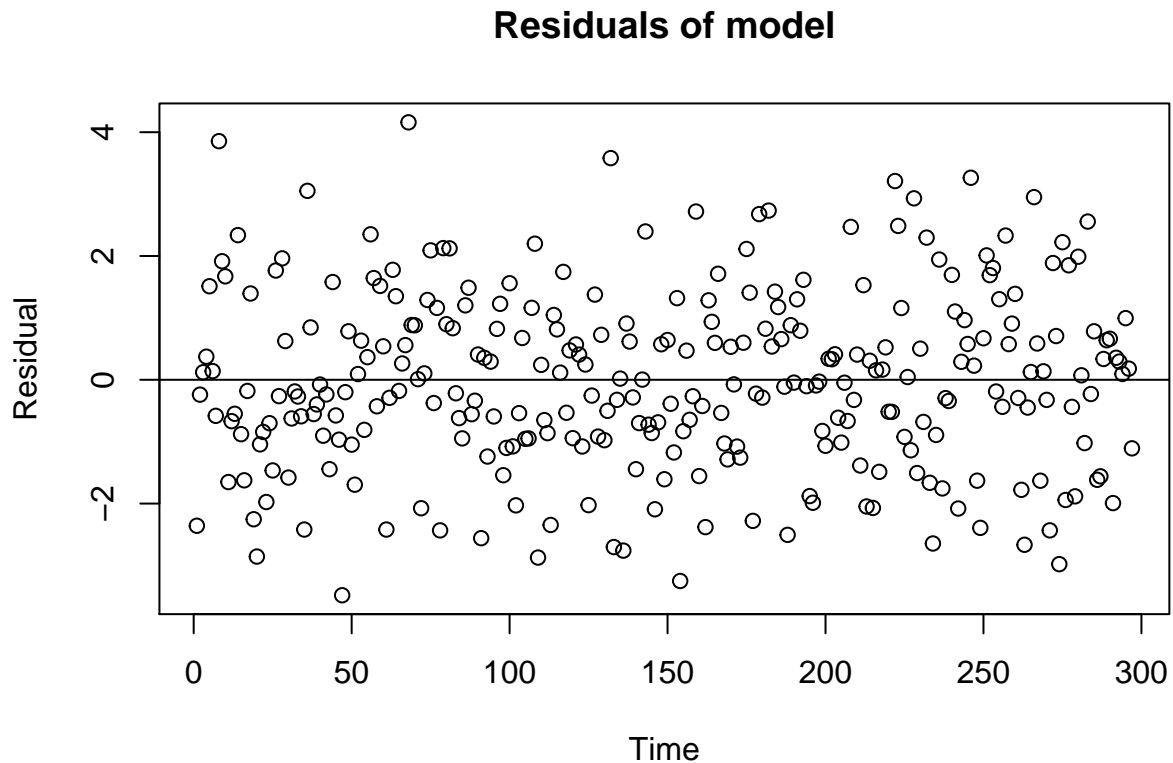
Model for Series 3



```
model3$residual <- X[[3]] - model3
```

```
## Warning in model3$residual <- X[[3]] - model3: Realizando coerção de LHD para  
## uma lista
```

```
plot_res(model3$residual)
```



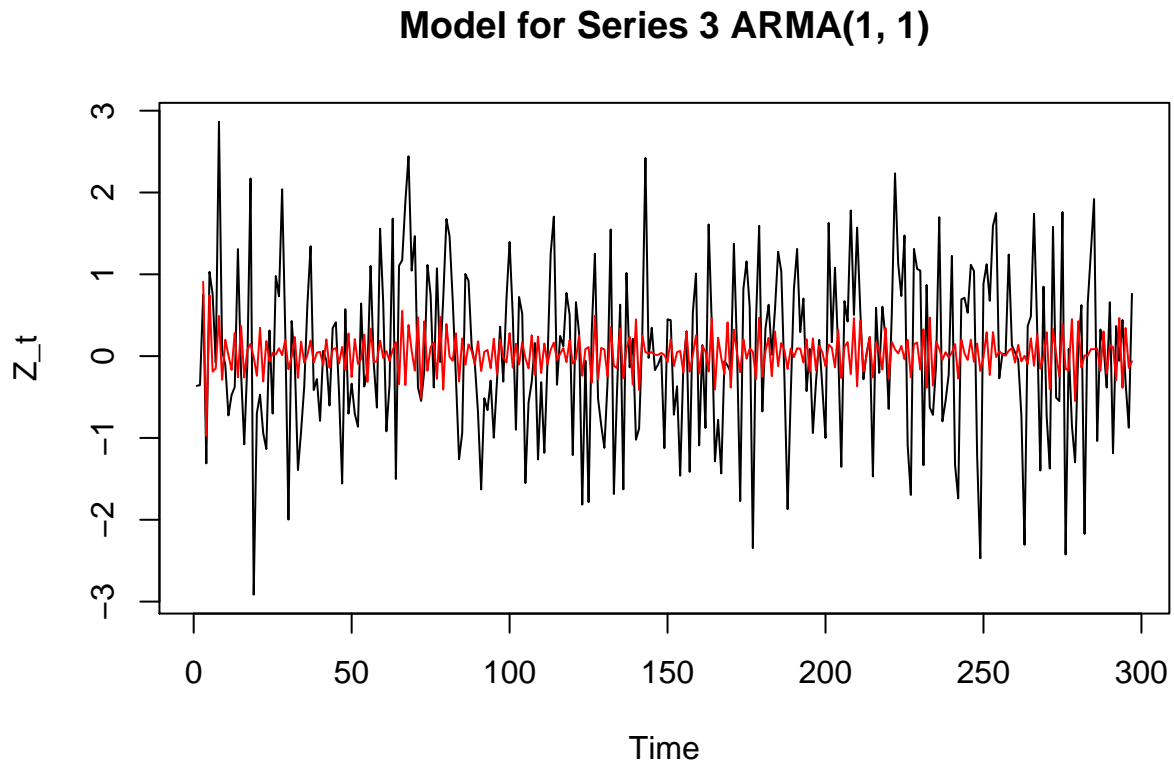
No entanto, também existe a possibilidade de se tratar de um modelo $\text{ARMA}(p, p)$, pois a PACF possui valores baixos, mas esses valores se mantêm ao longo dos lags, sem diminuir. Além disso, a ACF de uma $\text{ARMA}(p, p)$ se comporta como um $\text{AR}(p - p)$, isto é, não possui valores significantes para os lags diferentes de 0.

```
model3 <- arma(X[[3]], order = c(2, 2))
summary(model3)
```

```
##
## Call:
## arma(x = X[[3]], order = c(2, 2))
##
## Model:
## ARMA(2,2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.90256 -0.63458  0.01191  0.73813  2.37413
##
## Coefficient(s):
##           Estimate Std. Error t value Pr(>|t|)
## ar1        -1.47421    0.11724  -12.575  <2e-16 ***
## ar2        -0.82126    0.05847  -14.045  <2e-16 ***
## ma1         1.56787    0.15409   10.175  <2e-16 ***
## ma2         0.84398    0.09274    9.101  <2e-16 ***
## intercept    0.08961    0.19398    0.462    0.644
```

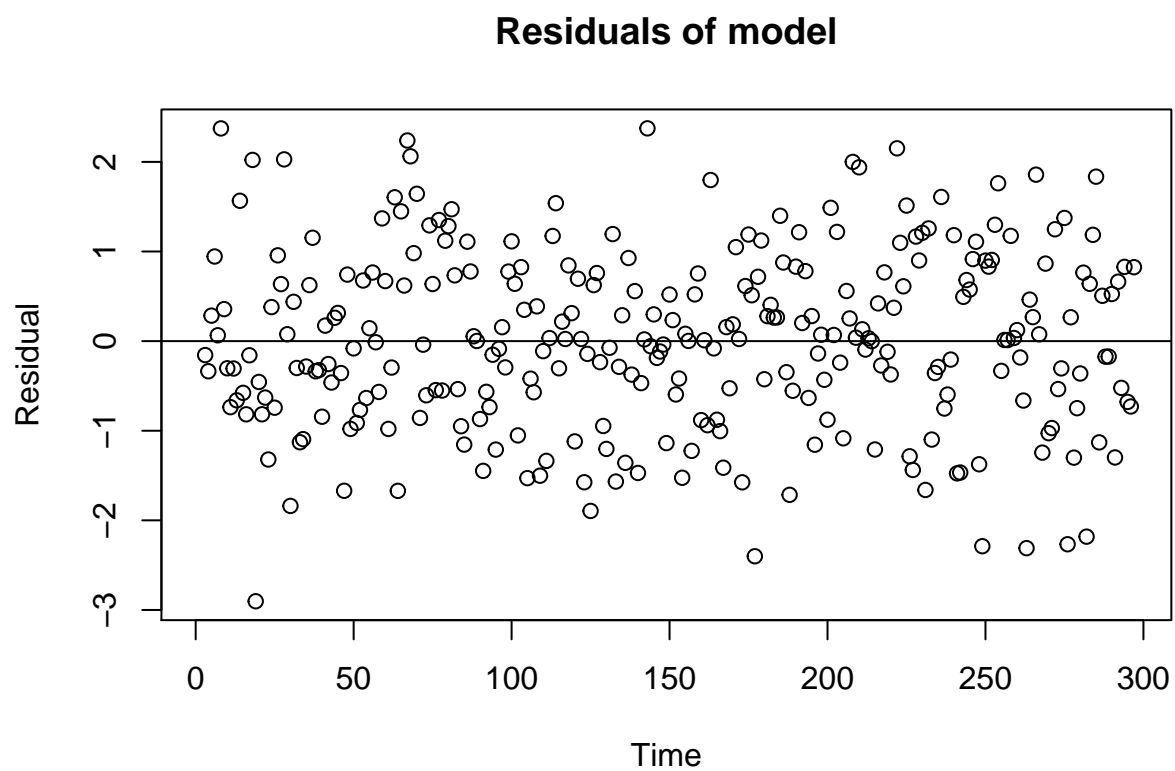
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Fit:
## sigma^2 estimated as 0.9752,  Conditional Sum-of-Squares = 286.77,  AIC = 845.39
```

```
plot(X[[3]], main = "Model for Series 3 ARMA(1, 1)", ylab = "Z_t")
lines(model3$fitted.values, col = "red")
```



O modelo não apresentou os valores da série real, se mantendo próximo da média 0. Os resíduos serão uniformemente distribuídos, mas com valores altos.

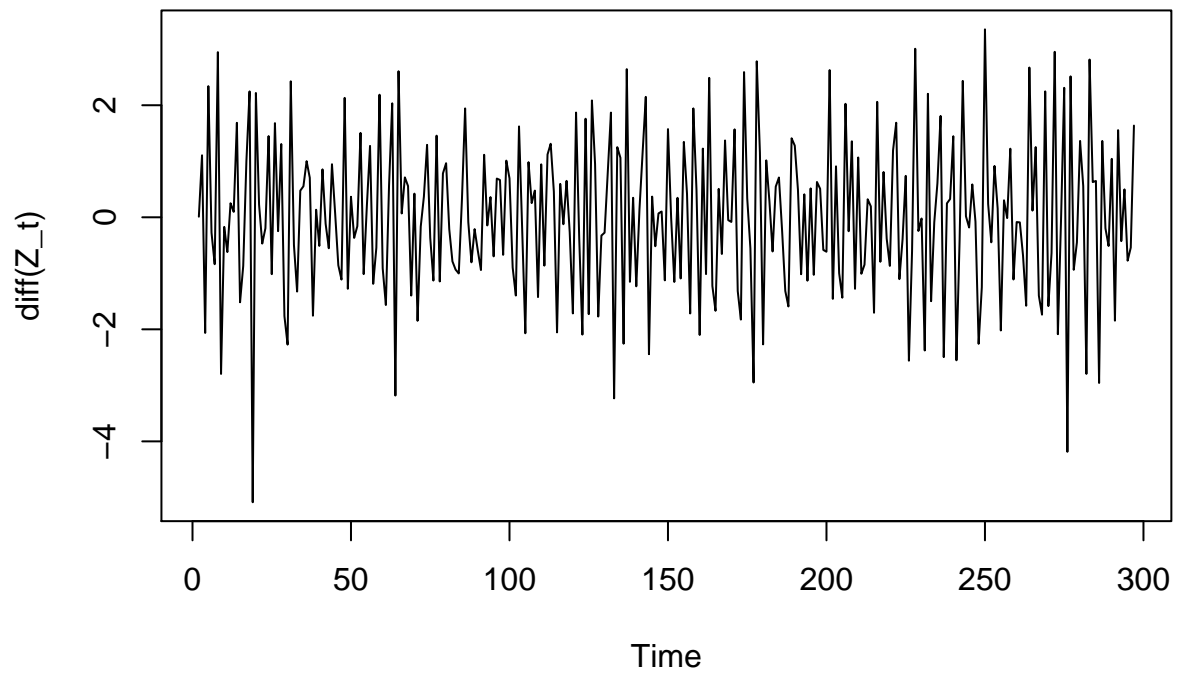
```
plot_res(model3$residuals)
```

Agora, para fazer mais uma análise, vamos considerar a série 3 diferenciada.

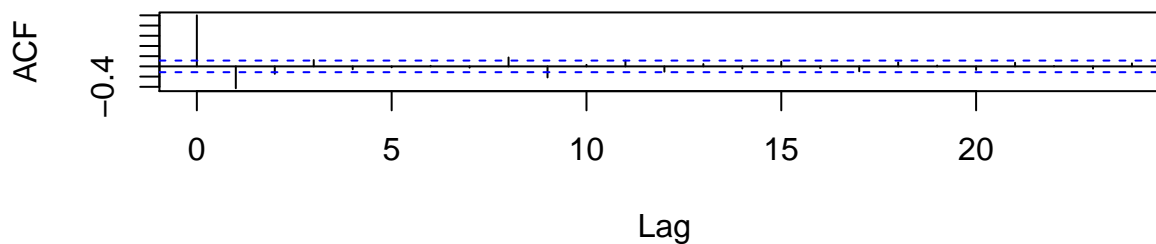
```
plot(diff(X[[3]]), main = "Diff Series 3", ylab = "diff(Z_t)")
```

Diff Series 3

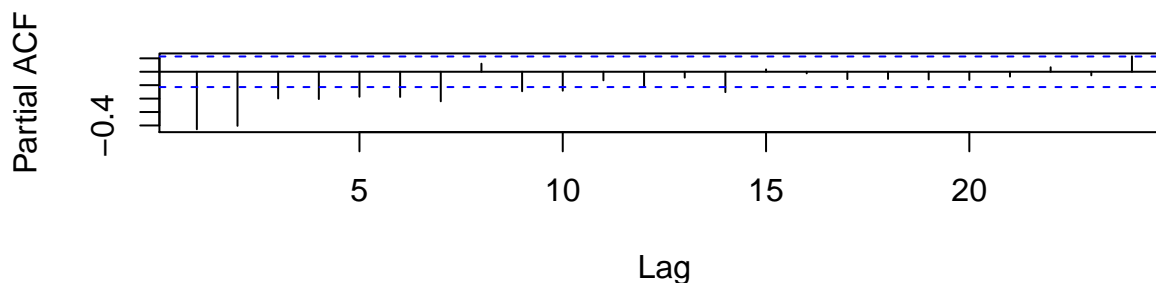


```
plot_acf_pacf(diff(X[[3]]))
```

ACF



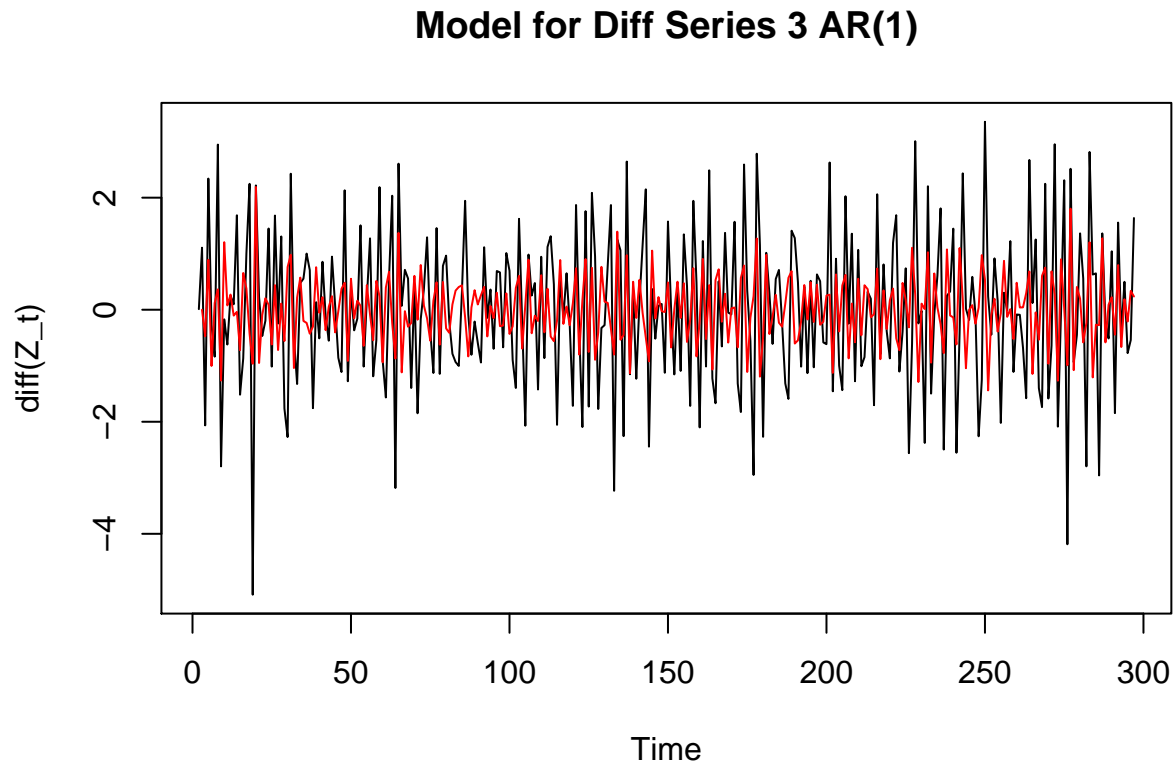
PACF



```
model3 <- arma(diff(X[[3]]), order= c(1, 0))
summary(model3)
```

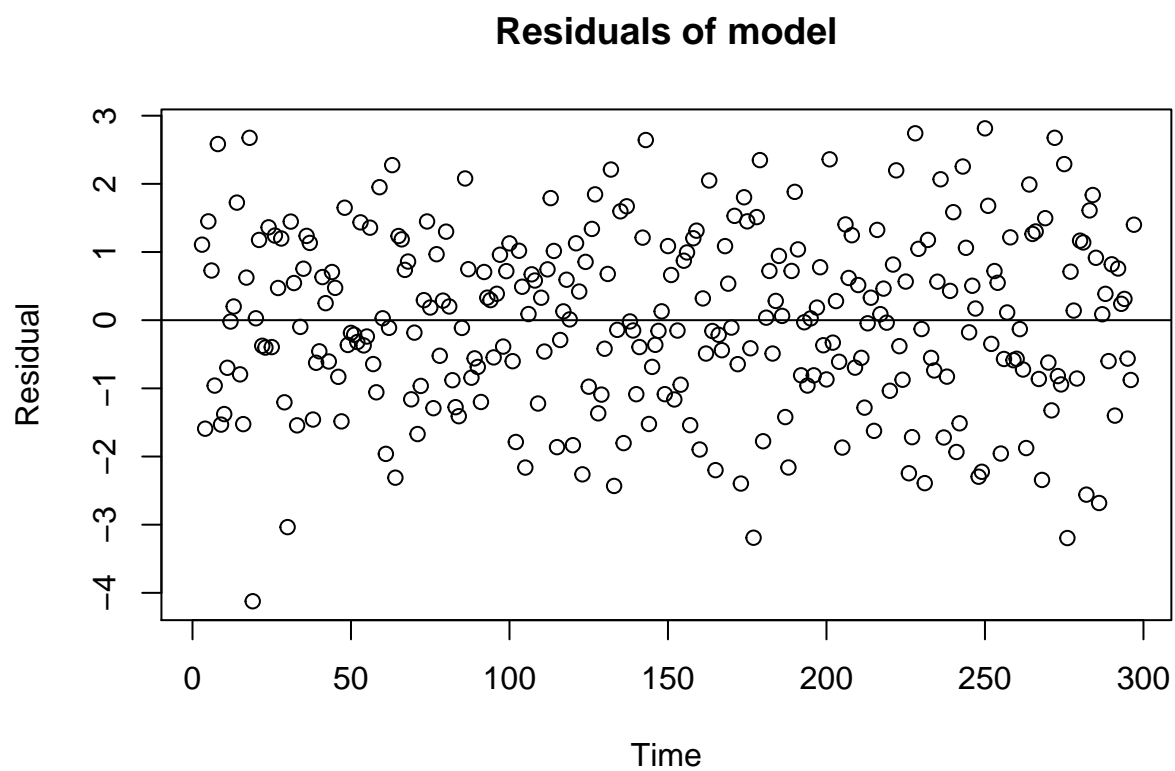
```
##
## Call:
## arma(x = diff(X[[3]]), order = c(1, 0))
##
## Model:
## ARMA(1,0)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.12297 -0.83723  0.02588  0.96413  2.81438
##
## Coefficient(s):
##              Estimate Std. Error  t value Pr(>|t|)
## ar1          -0.430168    0.052618   -8.175 2.22e-16 ***
## intercept    0.003035    0.073914    0.041  0.967
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Fit:
## sigma^2 estimated as 1.623,  Conditional Sum-of-Squares = 477.05,  AIC = 987.29
```

```
plot(diff(X[[3]]), main = "Model for Diff Series 3 AR(1)", ylab = "diff(Z_t)")  
lines(model3$fitted.values, col = "red")
```



Vemos que o modelo se encaixou melhor para essa série diferenciada, representando melhor os picos.

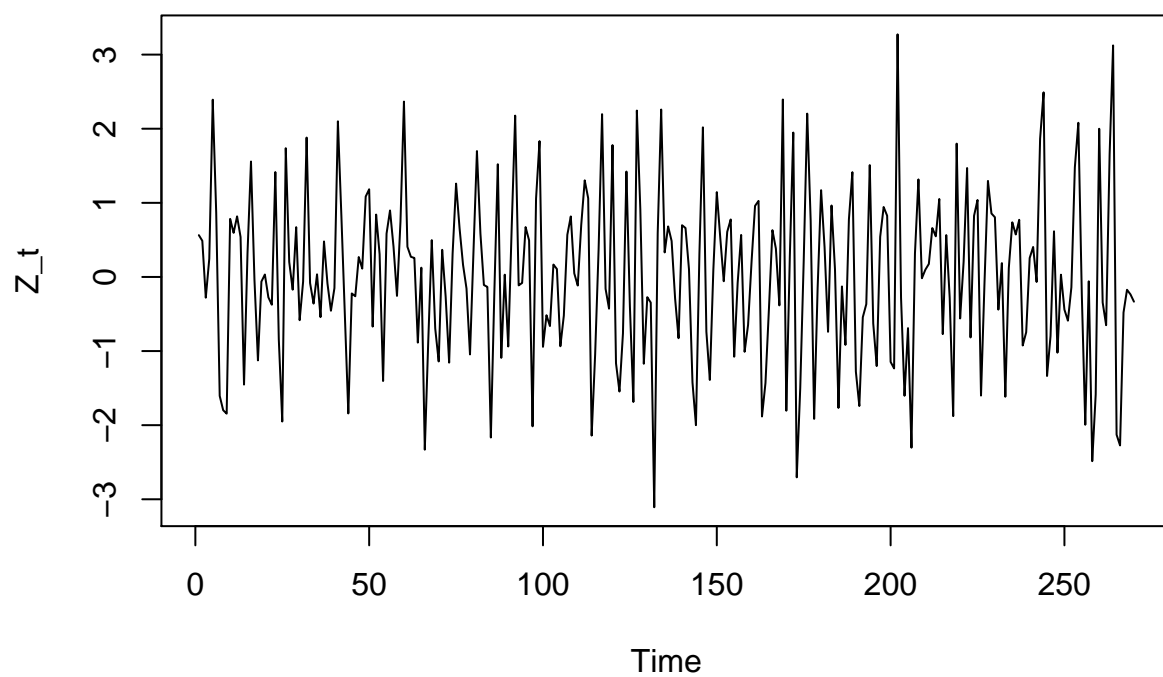
```
plot_res(model3$residuals)
```



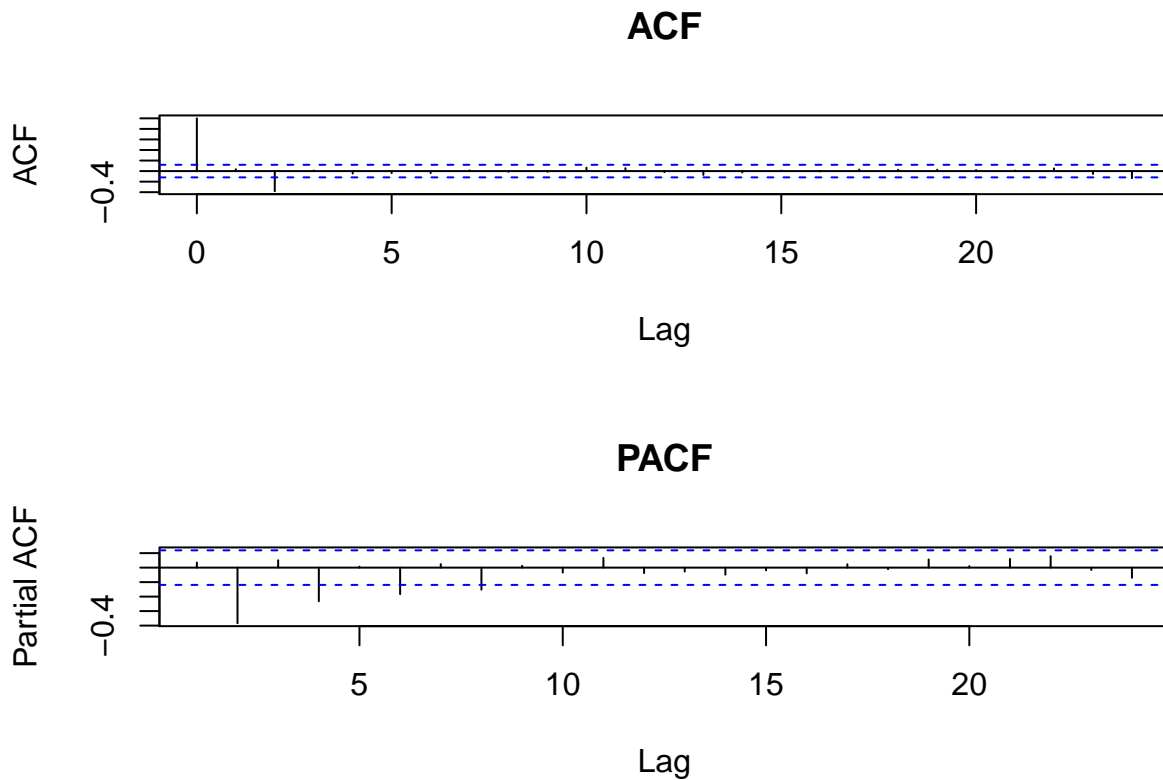
Série 4

```
plot(X[[4]], main = "Series 4", ylab = "Z_t")
```

Series 4



```
plot_acf_pacf(X[[4]])
```



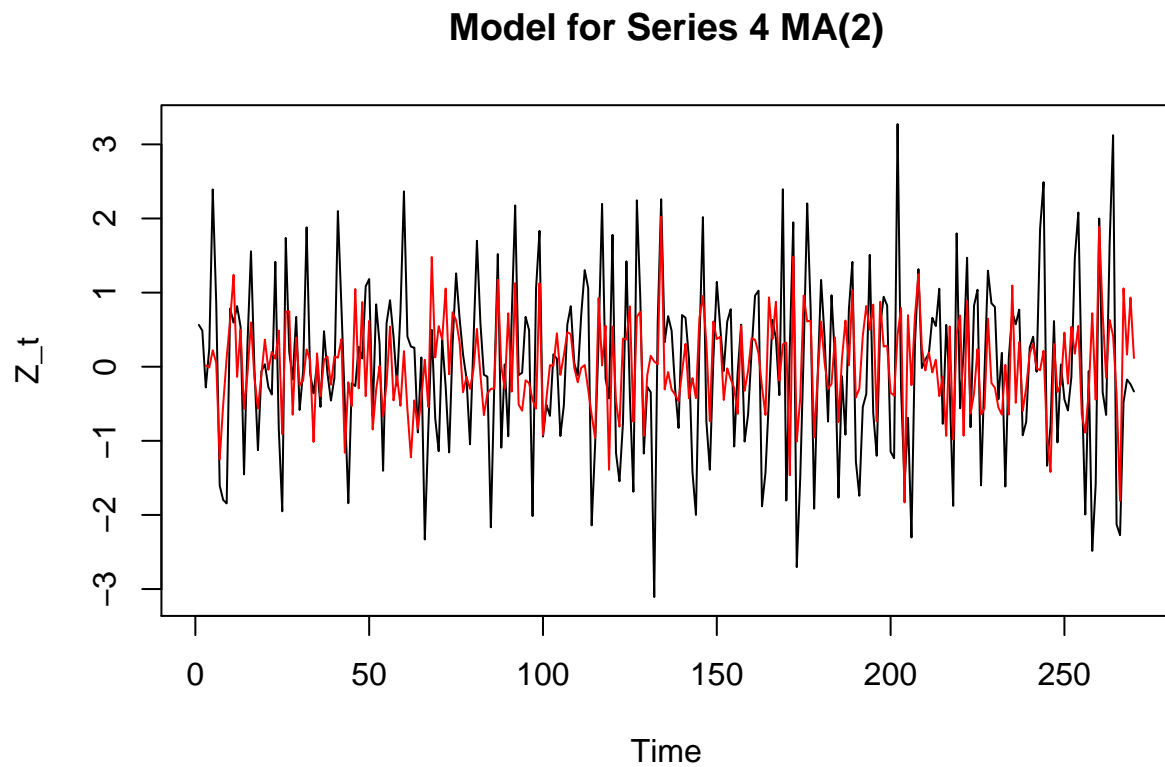
A série apresenta uma função de ACF que cai drasticamente após o lag 2, enquanto a PACF cai mais gradualmente de forma exponencial, o que dá a noção de se tratar de um modelo MA(2). Utilizando dessa observação, fitamos:

```
model4 <- arma(X[[4]], order = c(0, 2))
summary(model4)
```

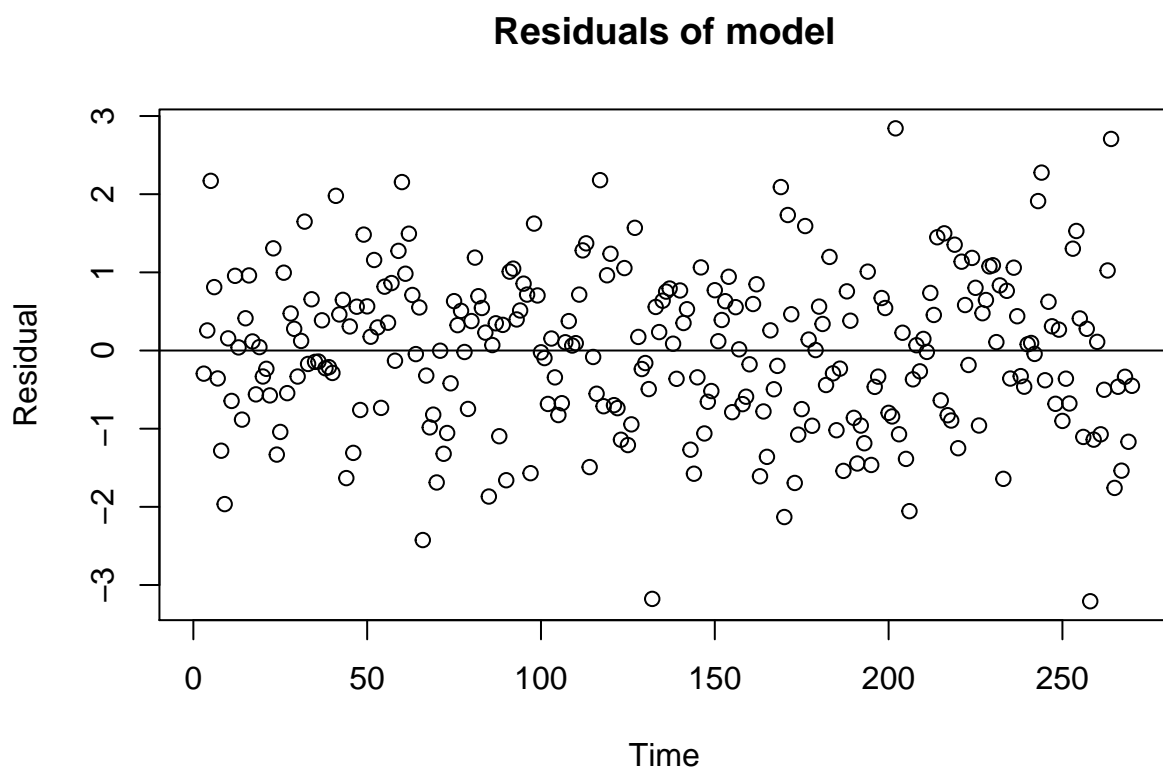
```
##
## Call:
## arma(x = X[[4]], order = c(0, 2))
##
## Model:
## ARMA(0,2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.20748 -0.68404  0.06891  0.64994  2.84235
##
## Coefficient(s):
##              Estimate Std. Error t value Pr(>|t|)
## ma1           0.09013    0.05112   1.763  0.0779 .
## ma2          -0.61589    0.05318 -11.581 <2e-16 ***
## intercept     0.01590    0.02884   0.551  0.5813
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Fit:  
## sigma^2 estimated as 0.9865, Conditional Sum-of-Squares = 263.41, AIC = 768.57
```

```
plot(X[[4]], main = "Model for Series 4 MA(2)", ylab = "Z_t")  
lines(model4$fitted.values, col = "red")
```



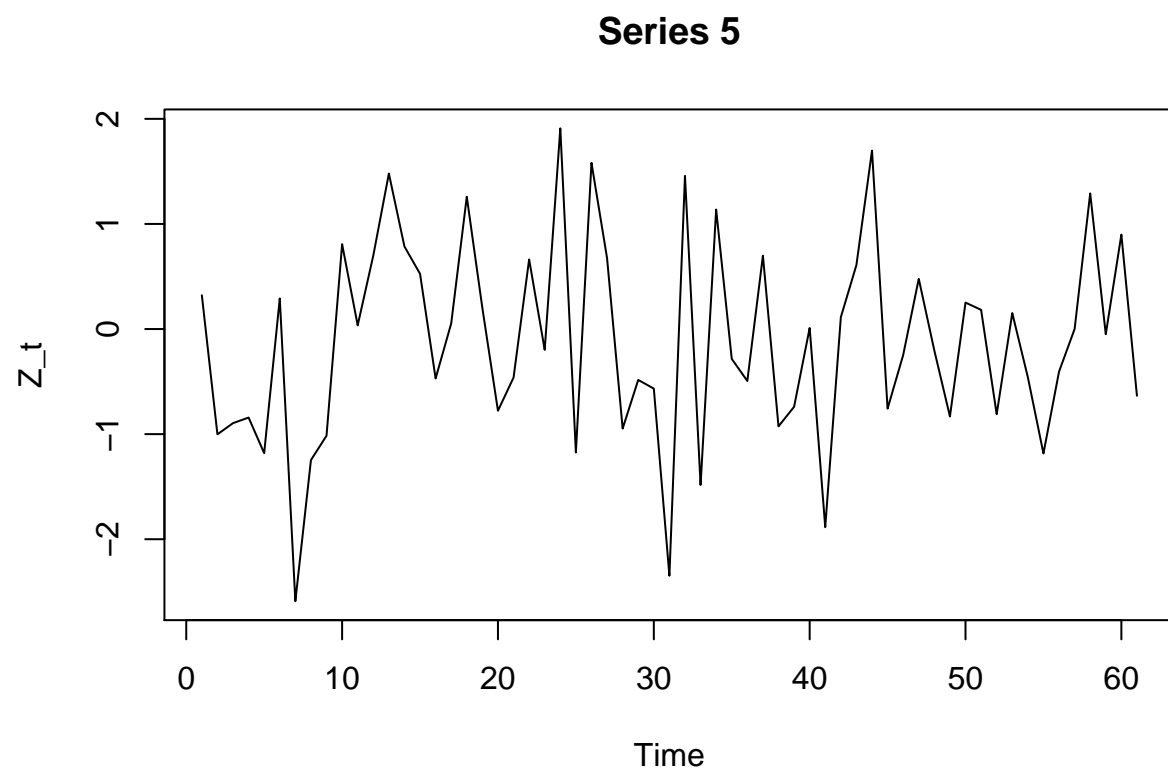
```
plot_res(model4$residuals)
```

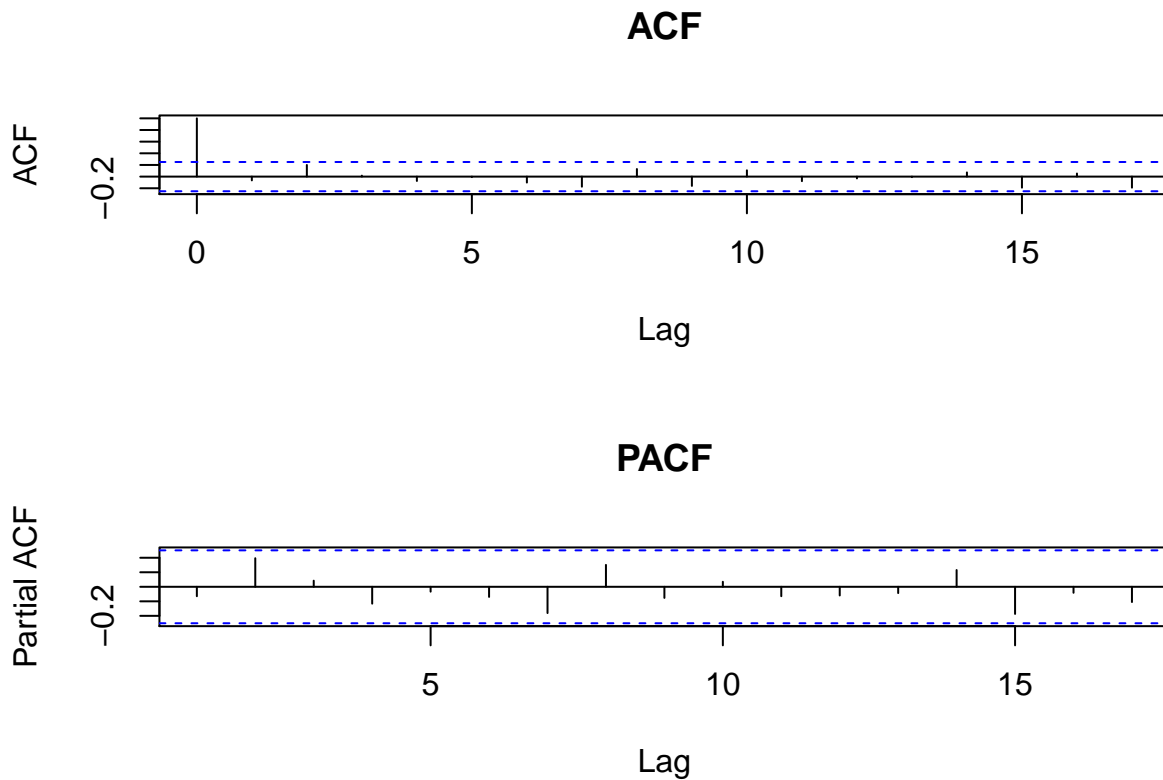
O modelo se encaixou bem aos dados, incluindo apresentando uma distribuição uniforme dos ruídos.

Série 5

```
plot(X[[5]], main = "Series 5", ylab = "Z_t")
```



```
plot_acf_pacf(X[[5]])
```



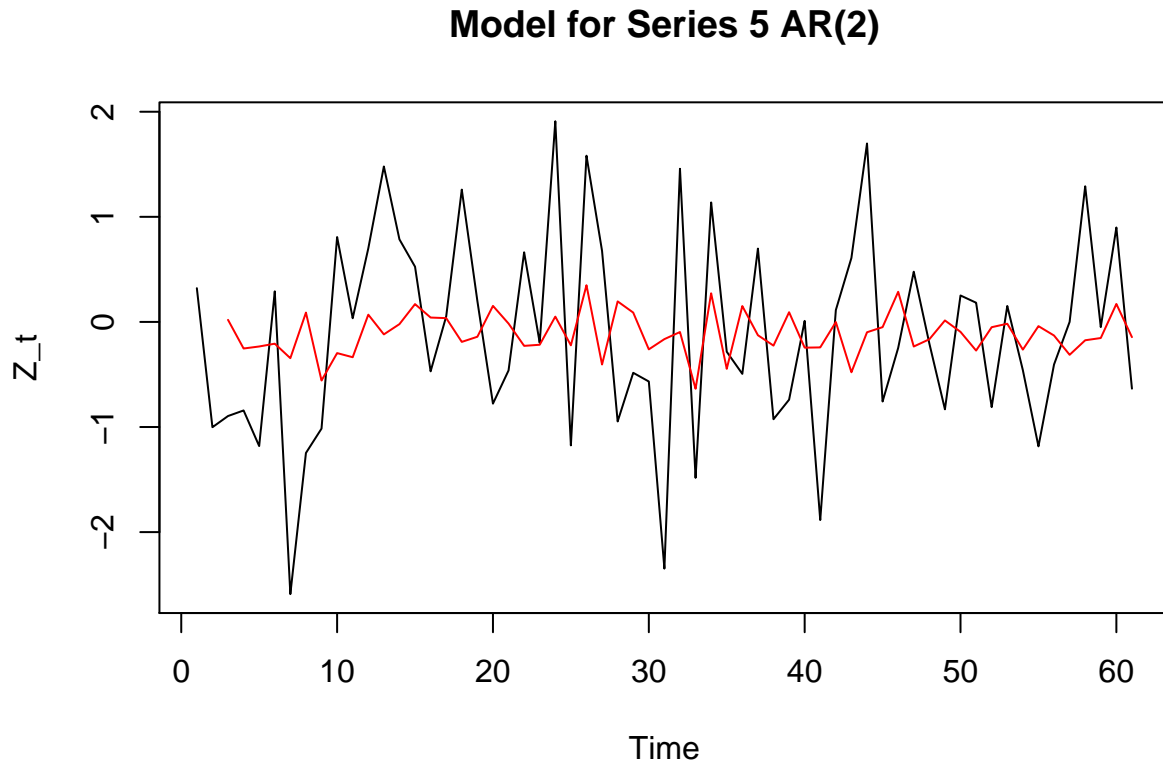
Vemos que tanto a ACF quanto a PACF são extremamente baixas para valores diferentes de 0, no entanto, nessa série possuímos bem menos amostras que as demais, possuindo apenas 61 amostras. Por esse motivo, iremos considerar que a importância do segundo lag na PACF e avaliar dois modelos distintos, AR(2) e ARMA(2, 2). Considerando primeiro o modelo AR(2).

```
model5 <- arma(X[[5]], order = c(2, 0))
summary(model5)
```

```
##
## Call:
## arma(x = X[[5]], order = c(2, 0))
##
## Model:
## ARMA(2,0)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.24498 -0.70396  0.01893  0.71961  1.85873
##
## Coefficient(s):
##           Estimate Std. Error t value Pr(>|t|)
## ar1         -0.04726    0.12481  -0.379   0.705
## ar2          0.20225    0.12576   1.608   0.108
## intercept   -0.09259    0.12355  -0.749   0.454
##
## Fit:
```

```
## sigma^2 estimated as 0.9154, Conditional Sum-of-Squares = 53.09, AIC = 173.72
```

```
plot(X[[5]], main = "Model for Series 5 AR(2)", ylab = "Z_t")  
lines(model5$fitted.values, col = "red")
```



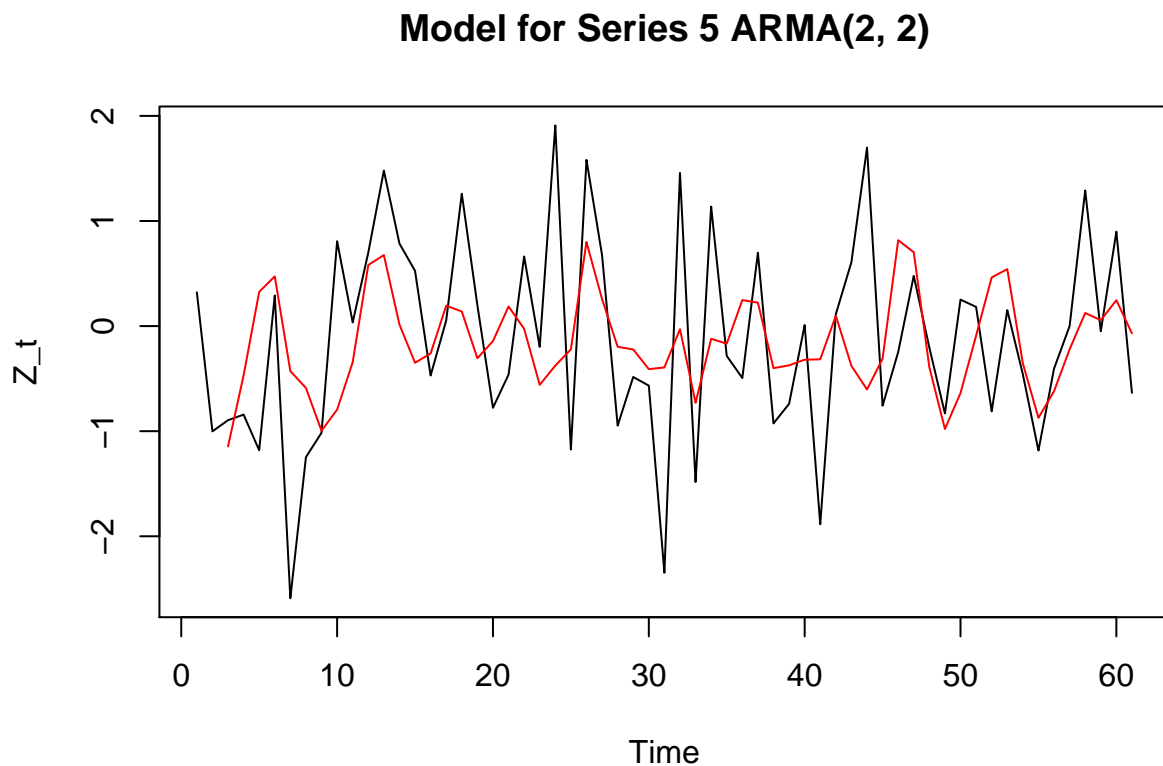
E agora o modelo ARMA(2, 2).

```
model5 <- arma(X[[5]], order = c(2, 2))  
summary(model5)
```

```
##  
## Call:  
## arma(x = X[[5]], order = c(2, 2))  
##  
## Model:  
## ARMA(2,2)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -2.16208 -0.48610 -0.01902  0.57863  2.30147   
##  
## Coefficient(s):  
##      Estimate Std. Error t value Pr(>|t|)      
## ar1      0.81736   0.17739   4.608 4.07e-06 ***  
## ar2     -0.62001   0.10722  -5.783 7.35e-09 ***
```

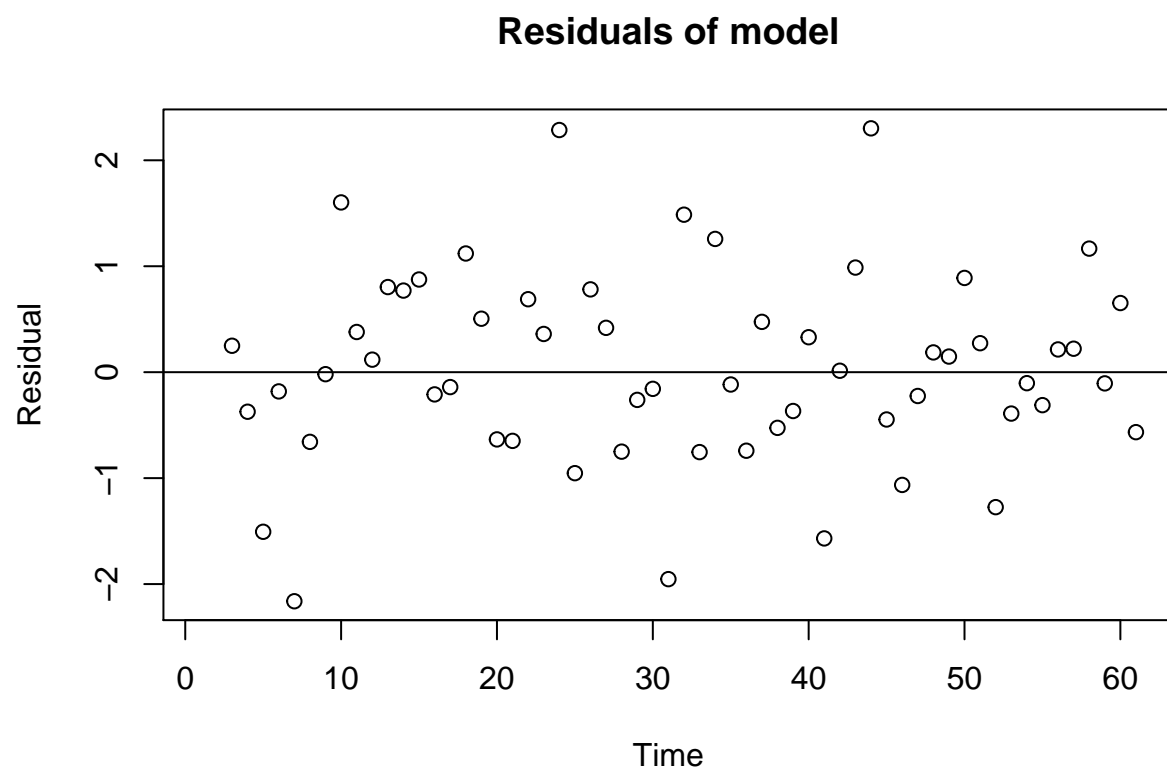
```
## ma1      -0.92912      0.09675     -9.603 < 2e-16 ***
## ma2       0.95619      0.10319      9.266 < 2e-16 ***
## intercept -0.12685      0.11679     -1.086  0.277
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Fit:
## sigma^2 estimated as 0.8179,  Conditional Sum-of-Squares = 47.54,  AIC = 170.85
```

```
plot(X[[5]], main = "Model for Series 5 ARMA(2, 2)", ylab = "Z_t")
lines(model5$fitted.values, col = "red")
```



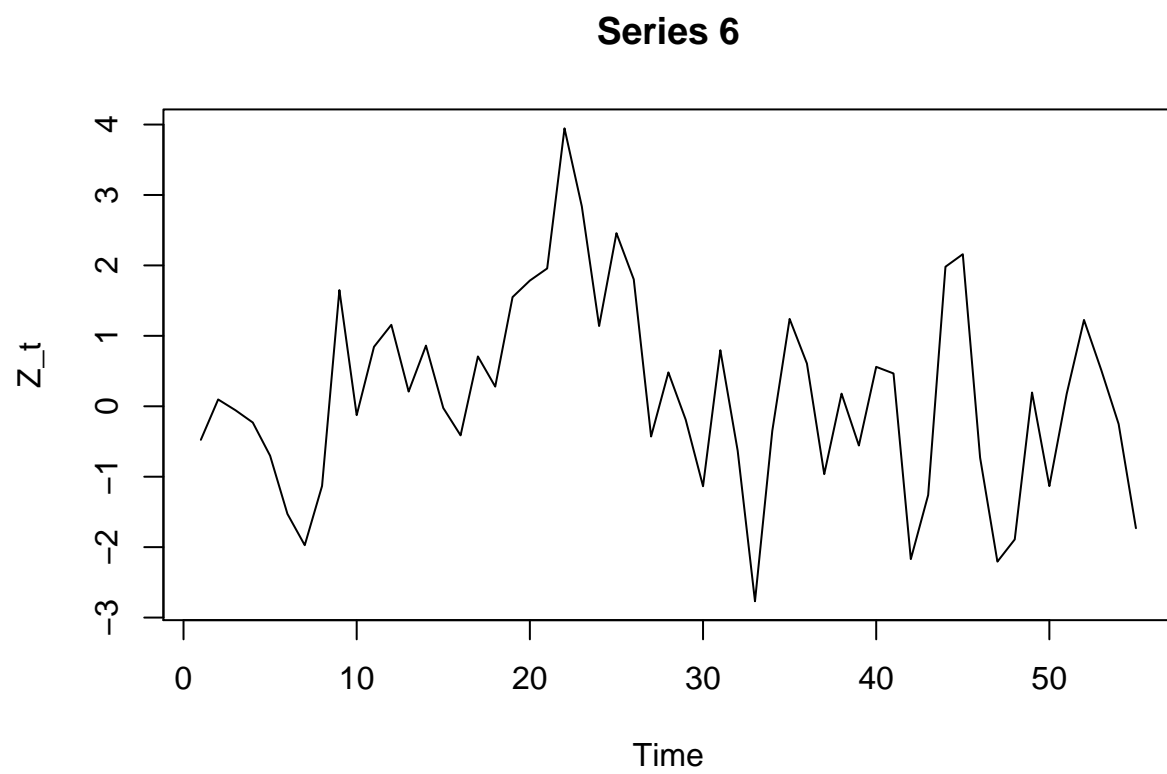
Vemos que o modelo ARMA(2, 2) apresentou um AIC menor, de 170, em comparação com o AR(2), além disso, ele também encaixou melhor na curva real dos dados. Vamos visualizar os resíduos:

```
plot_res(model5$residuals)
```

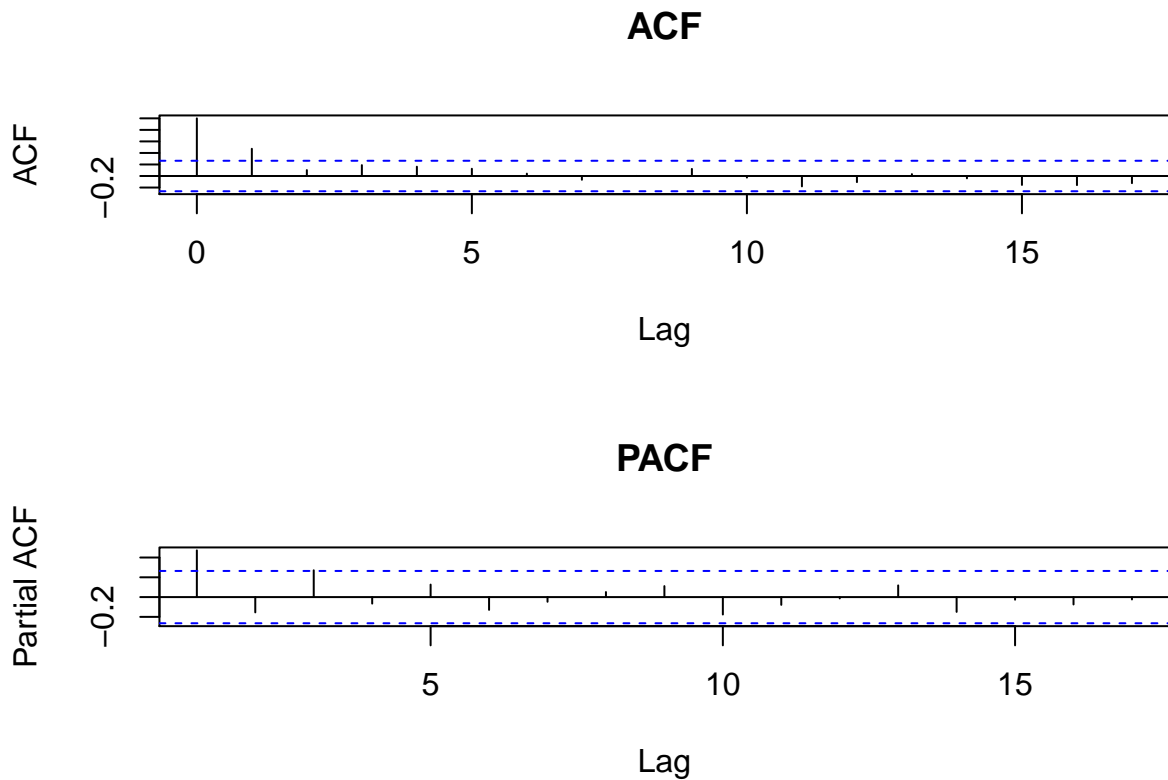


Série 6

```
plot(X[[6]], main = "Series 6", ylab = "Z_t")
```



```
plot_acf_pacf(X[[6]])
```



Aqui temos que o ACF diminui bastante para lag acima de 1 enquanto que o PACF se mantém consistentemente baixo para lag maior que 0, o que indica que o modelo MA(1) pode ser apropriada para essa série.

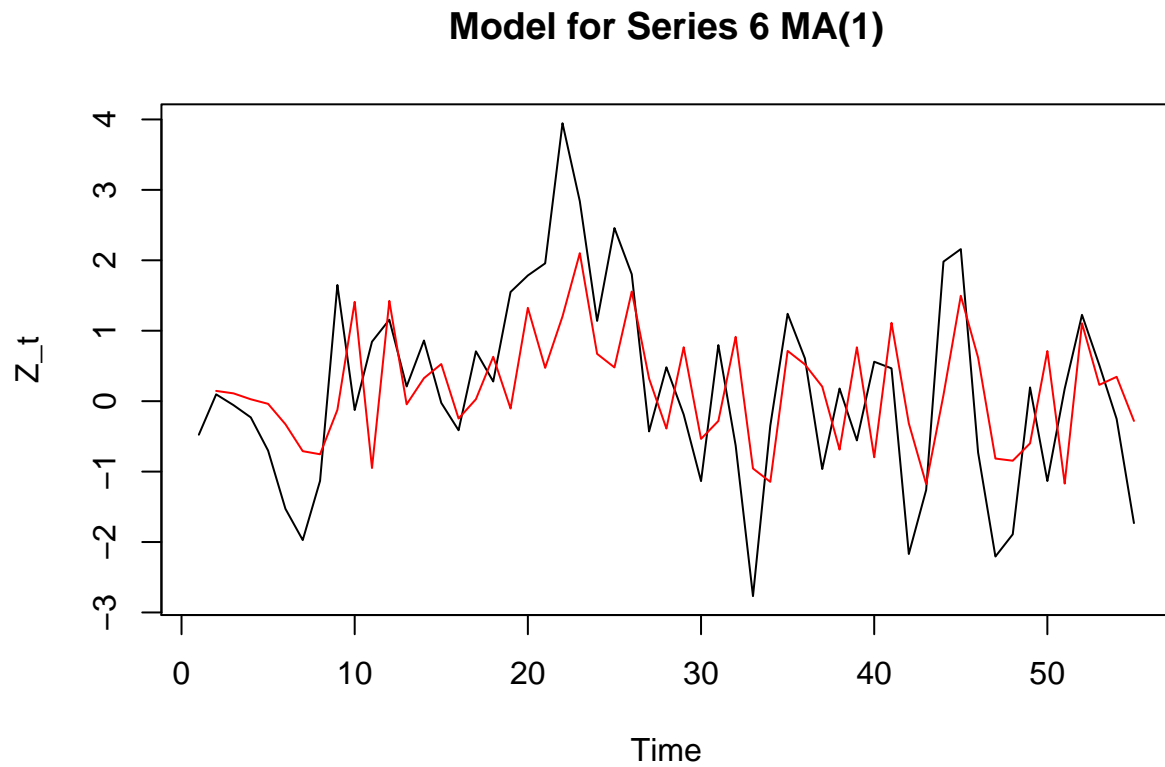
```
model6 <- arma(X[[6]], order = c(0, 1))
summary(model6)
```

```
##
## Call:
## arma(x = X[[6]], order = c(0, 1))
##
## Model:
## ARMA(0,1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.85487 -0.90462 -0.06636  0.78021  2.74265
##
## Coefficient(s):
##              Estimate Std. Error t value Pr(>|t|)
## ma1             0.7129    0.0991   7.194 6.31e-13 ***
## intercept       0.1458    0.2557   0.570  0.569
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Fit:
```

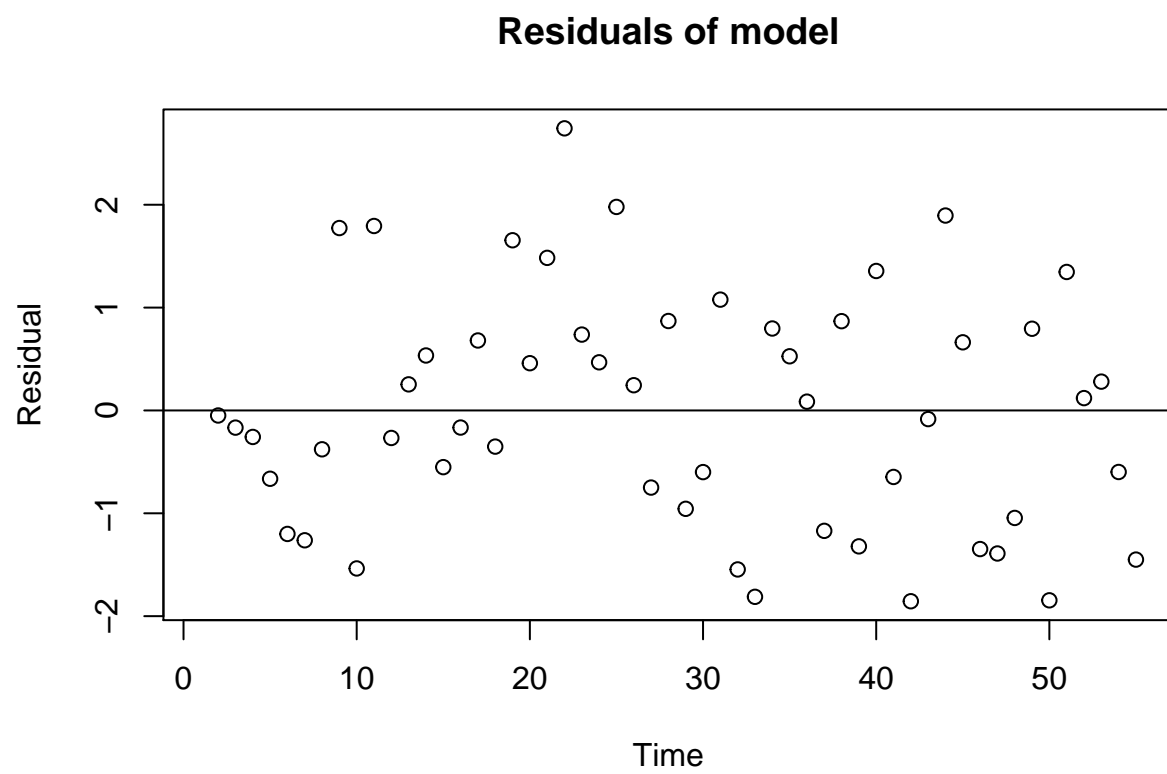


```
## sigma^2 estimated as 1.29, Conditional Sum-of-Squares = 68.38, AIC = 174.1
```

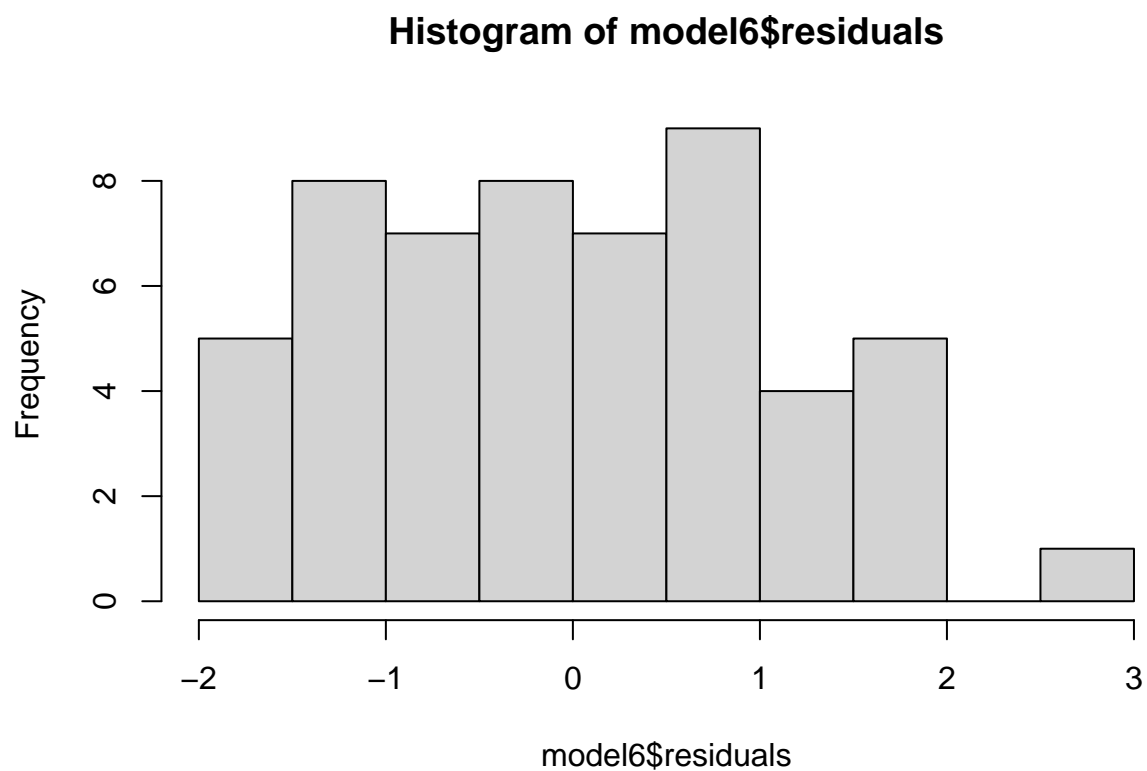
```
plot(X[[6]], main = "Model for Series 6 MA(1)", ylab = "Z_t")  
lines(model6$fitted.values, col = "red")
```



```
plot_res(model6$residuals)
```



```
hist(model6$residuals)
```

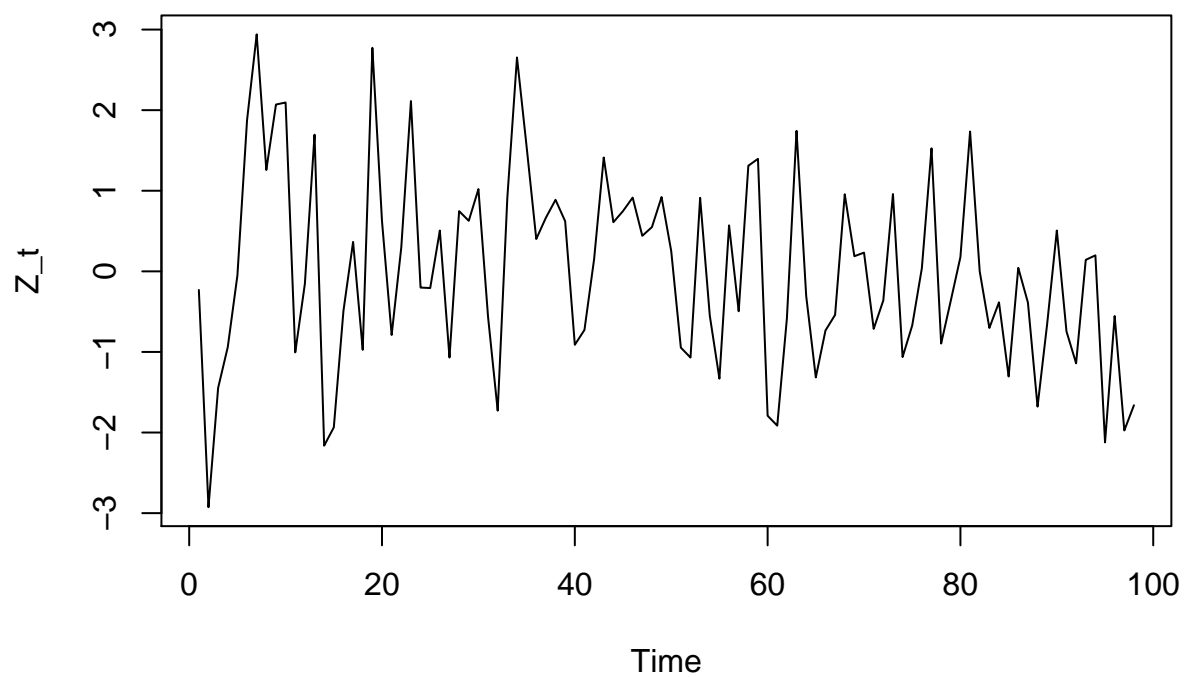


O modelo não conseguiu capturar bem os picos da série real, mas se encaixou razoavelmente bem.

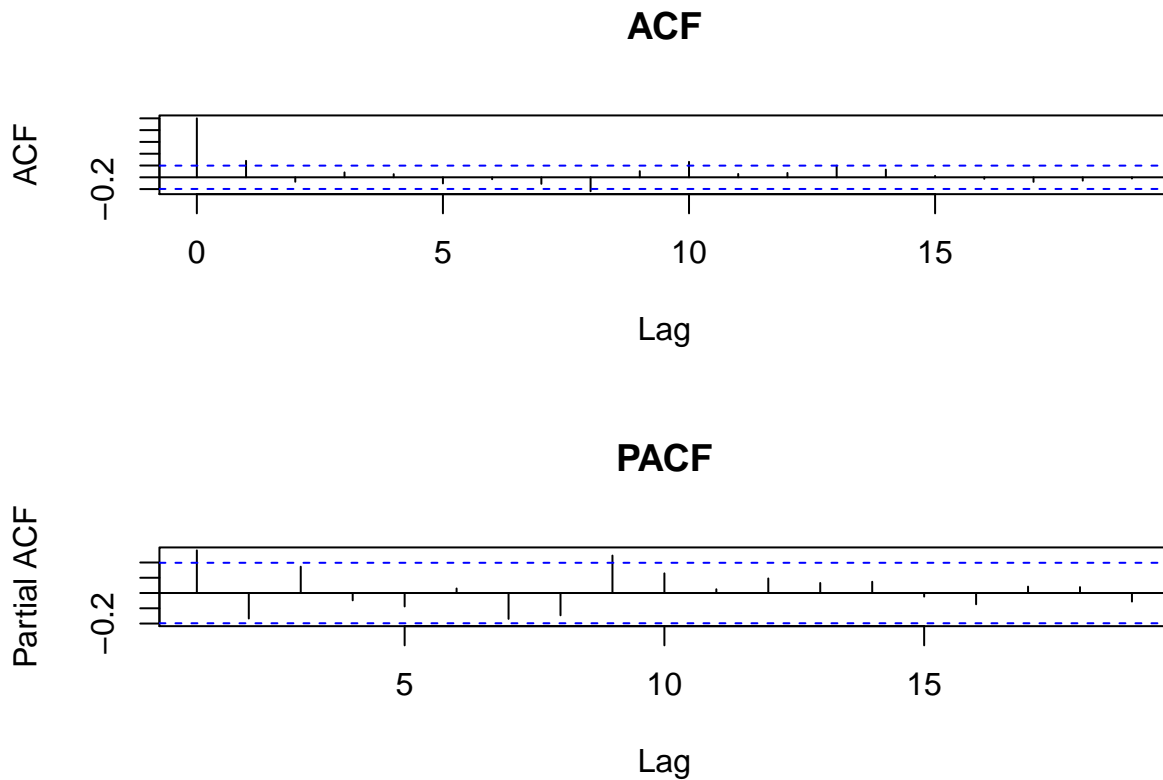
Série 7

```
plot(X[[7]], main = "Series 7", ylab = "Z_t")
```

Series 7



```
plot_acf_pacf(X[[7]])
```

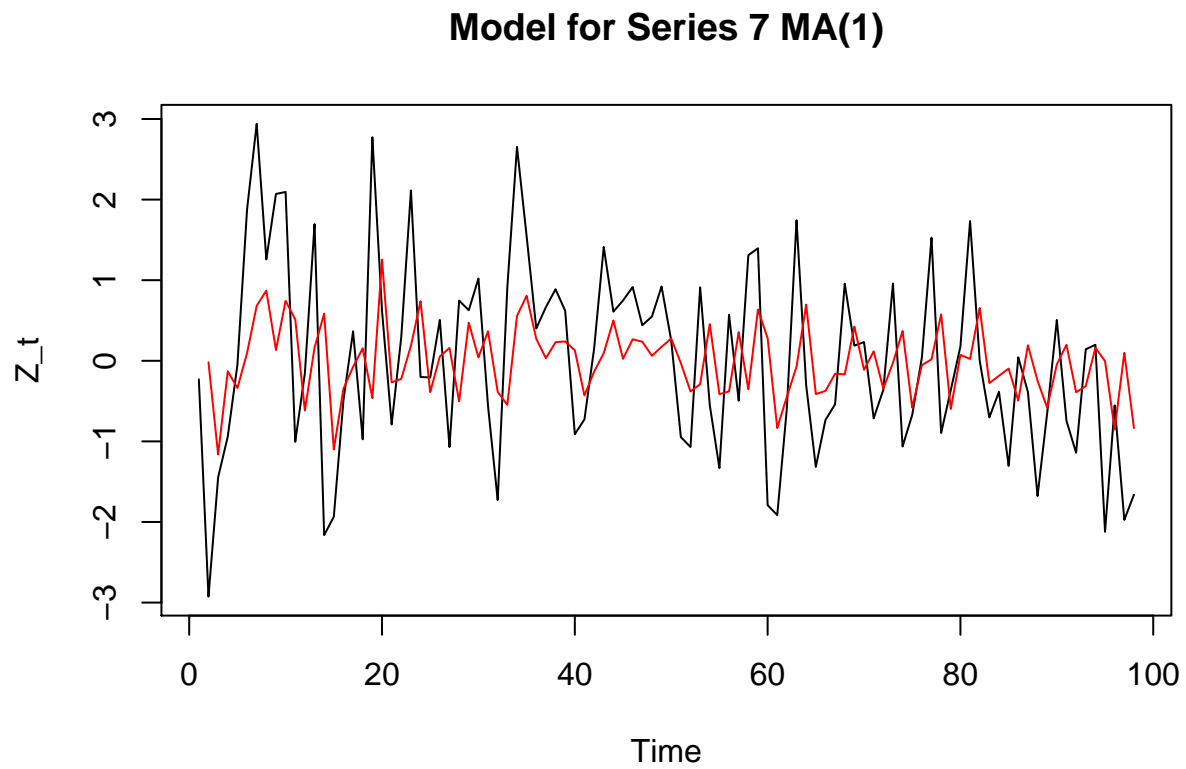


O ACF decai rapidamente para lag maior do que 1, enquanto que o PACF decresce bem lentamente, o que indica que o modelo MA(1) é uma boa escolha aqui.

```
model7 <- arma(X[[7]], order = c(0, 1))
summary(model7)
```

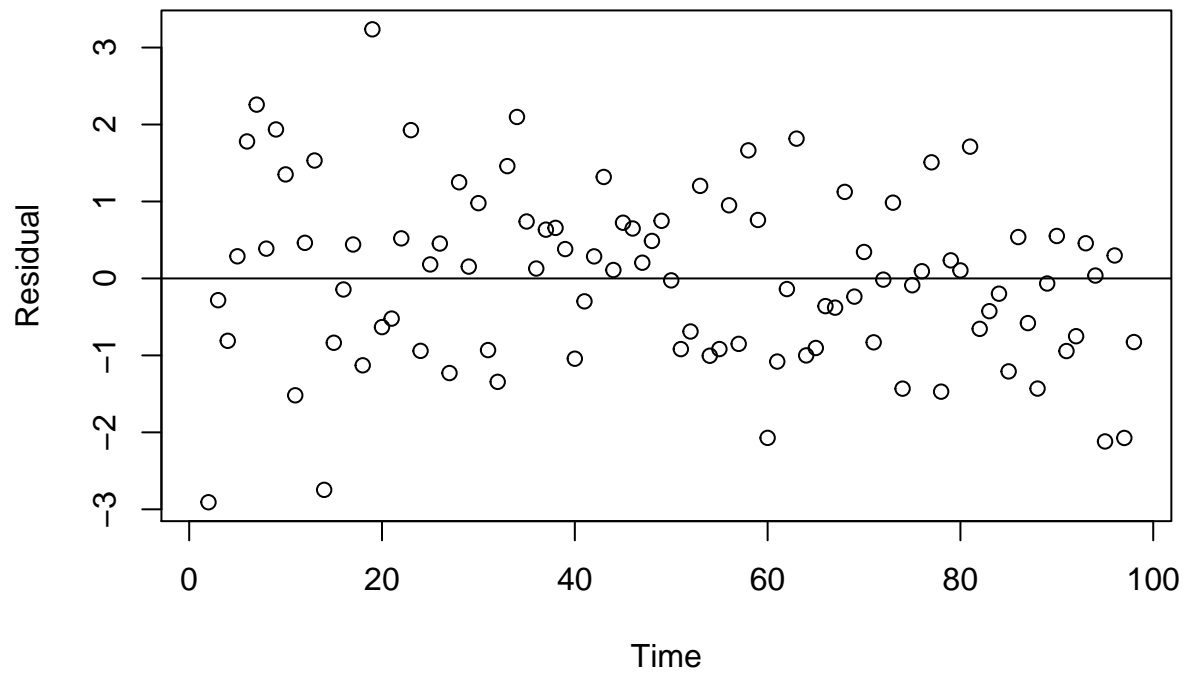
```
##
## Call:
## arma(x = X[[7]], order = c(0, 1))
##
## Model:
## ARMA(0,1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.90811 -0.83574  0.09345  0.65703  3.23671
##
## Coefficient(s):
##              Estimate Std. Error t value Pr(>|t|)
## ma1           0.39365   0.10095   3.900 9.64e-05 ***
## intercept    -0.01875   0.15811  -0.119   0.906
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Fit:
## sigma^2 estimated as 1.282,  Conditional Sum-of-Squares = 123.1,  AIC = 306.47
```

```
plot(X[[7]], main = "Model for Series 7 MA(1)", ylab = "Z_t")  
lines(model7$fitted.values, col = "red")
```

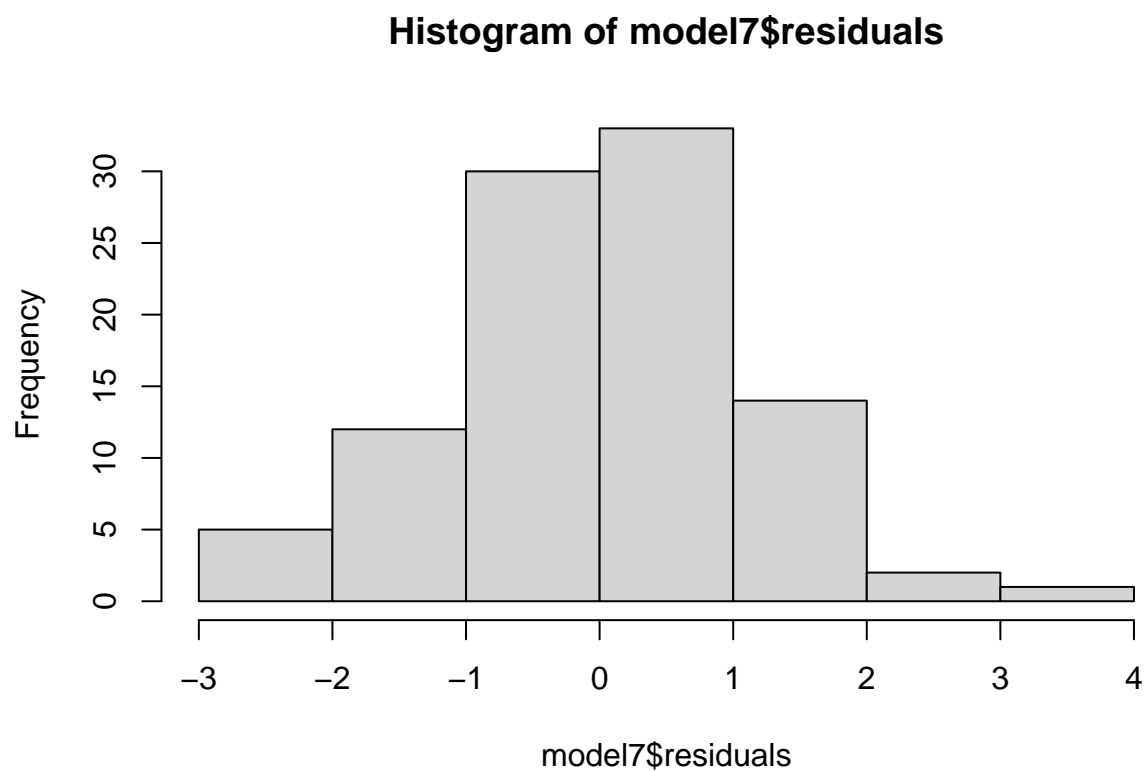


```
plot_res(model7$residuals)
```

Residuals of model



```
hist(model7$residuals)
```

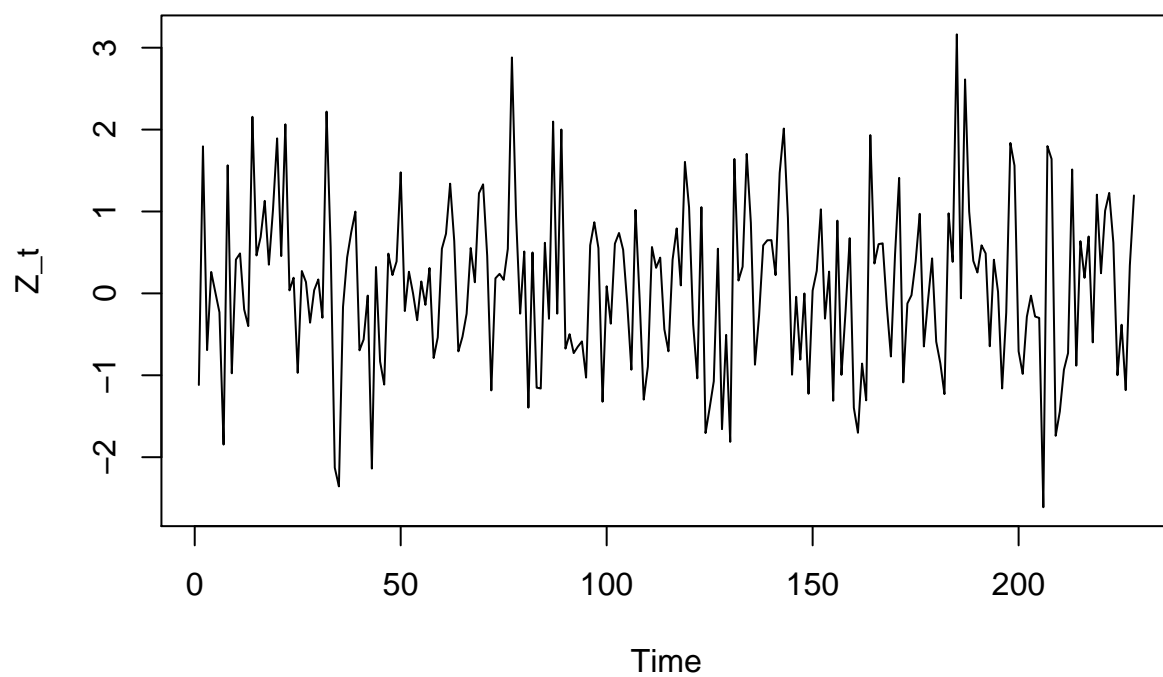


O modelo se encaixou razoavelmente aos dados, mas não capturou bem os picos apresentados.

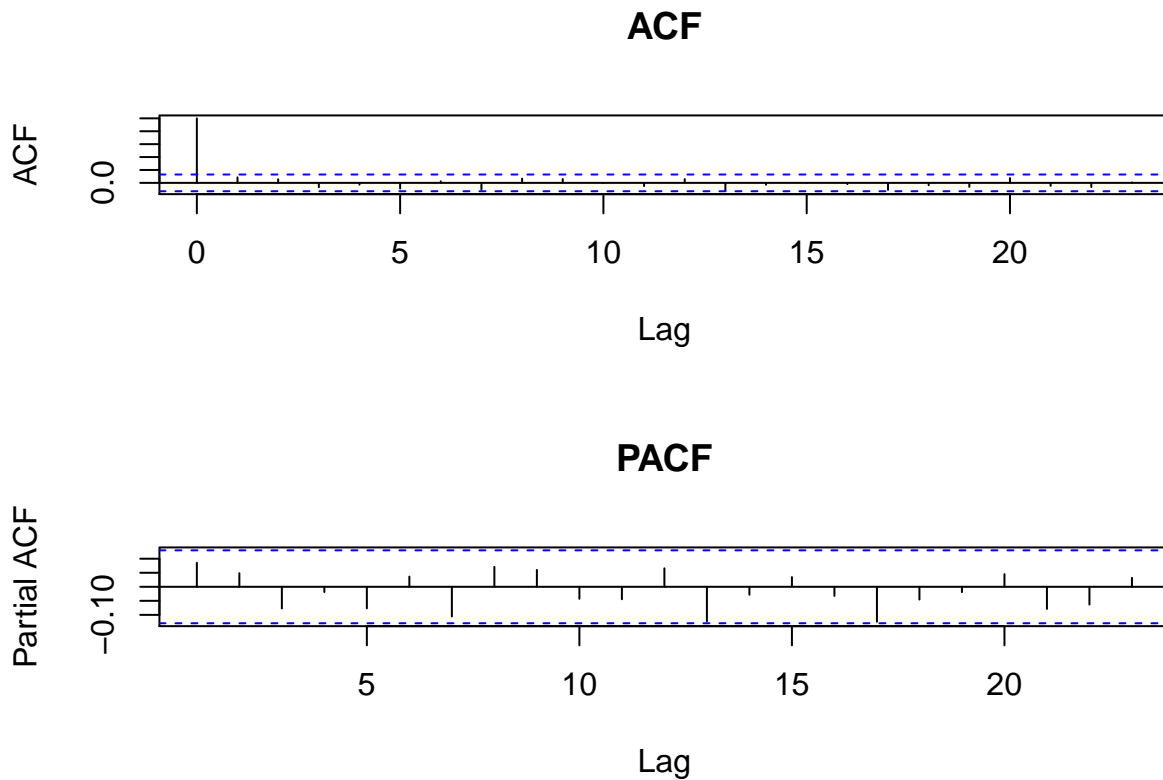
Série 8

```
plot(X[[8]], main = "Series 8", ylab = "Z_t")
```


Series 8



```
plot_acf_pacf(X[[8]])
```



Tanto ACF quanto PACF são bem pequenas para lag maiores que zero, indicando que é um ruído branco.

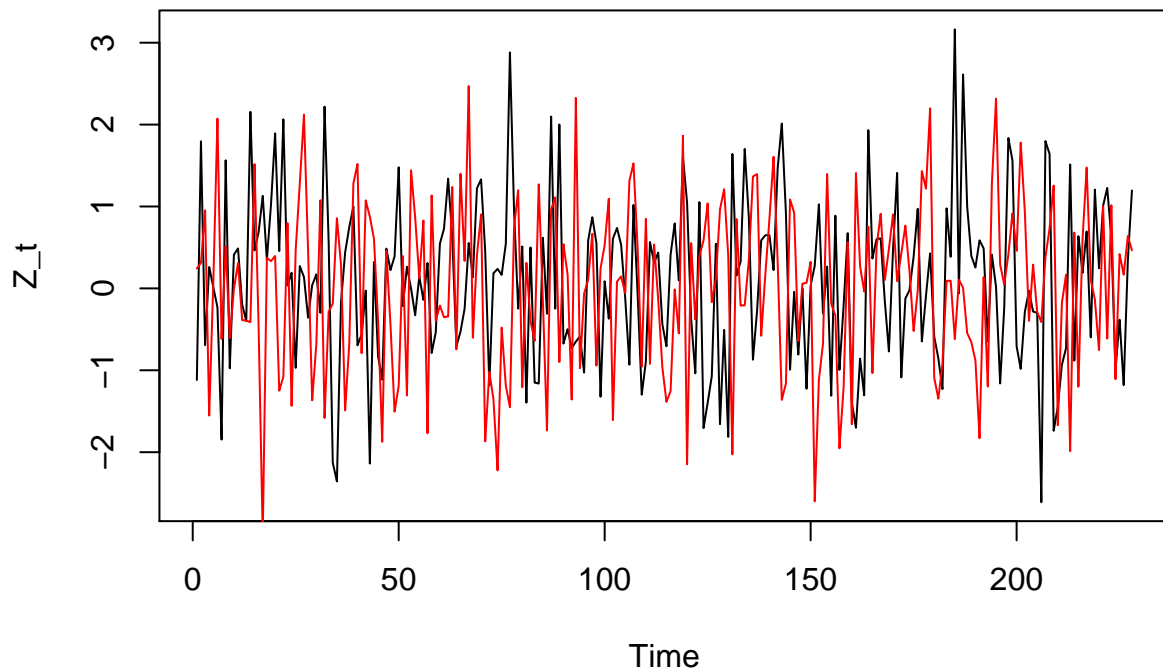
```
data.frame(mean = mean(X[[8]]), variance = var(X[[8]])*227/228)
```

```
##          mean variance
## 1 0.09216291 0.996732
```

Temos que $E(a_t) = 0$ e $Var(a_t) = 1$, o que indica que o modelo se comporta como um ruído branco. Geramos 228 amostras de a_t e visualizarmos tanto o modelo e predição, quanto o residual:

```
model8 <- rnorm(228)
plot(X[[8]], main = "Model for Series 8", ylab = "Z_t")
lines(model8, col = "red")
```

Model for Series 8

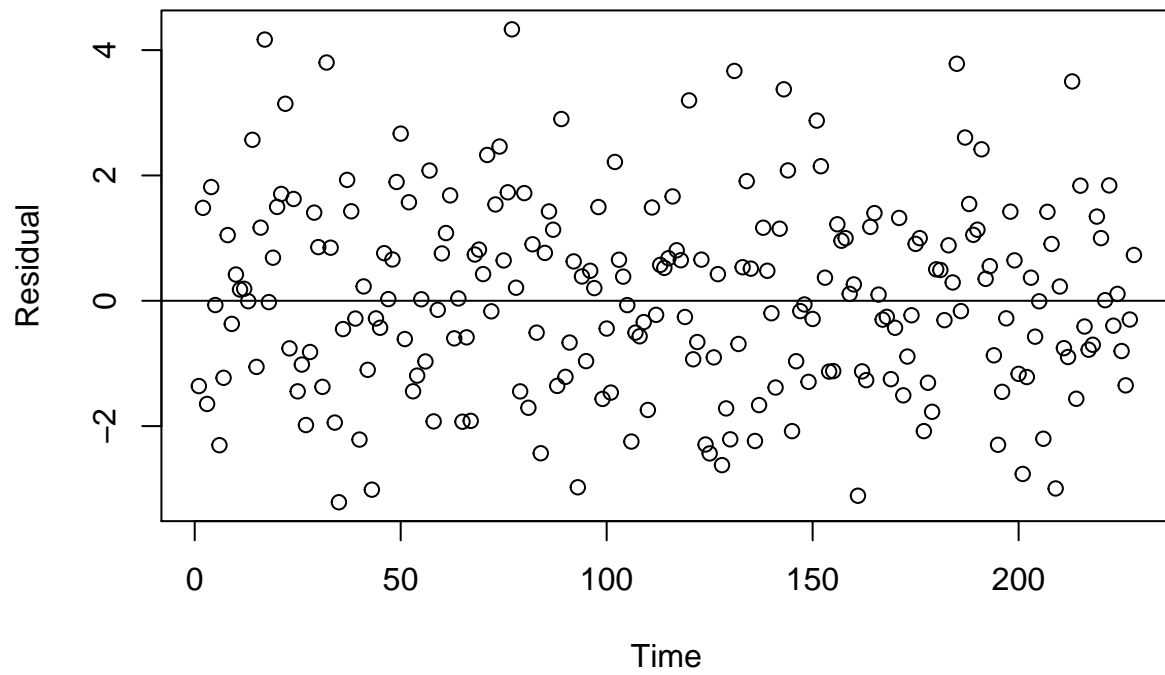


```
model8$residual <- X[[8]] - model8
```

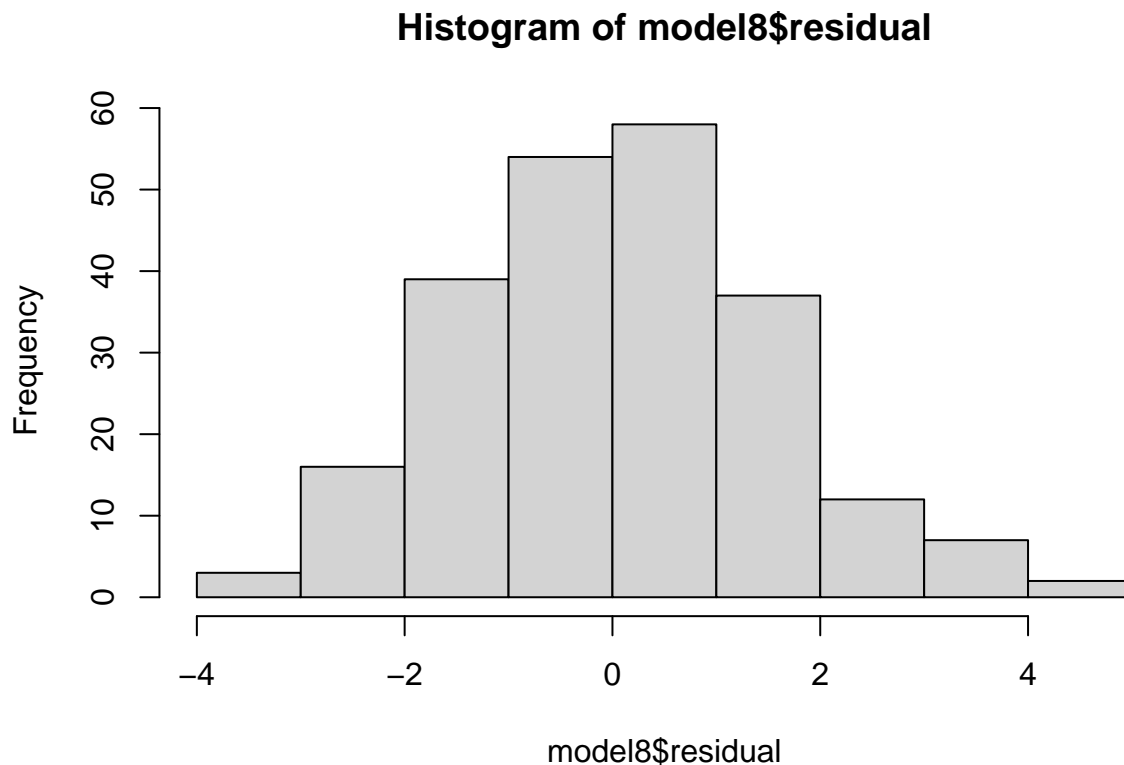
```
## Warning in model8$residual <- X[[8]] - model8: Realizando coerção de LHD para  
## uma lista
```

```
plot_res(model8$residual)
```

Residuals of model



```
hist(model8$residual)
```

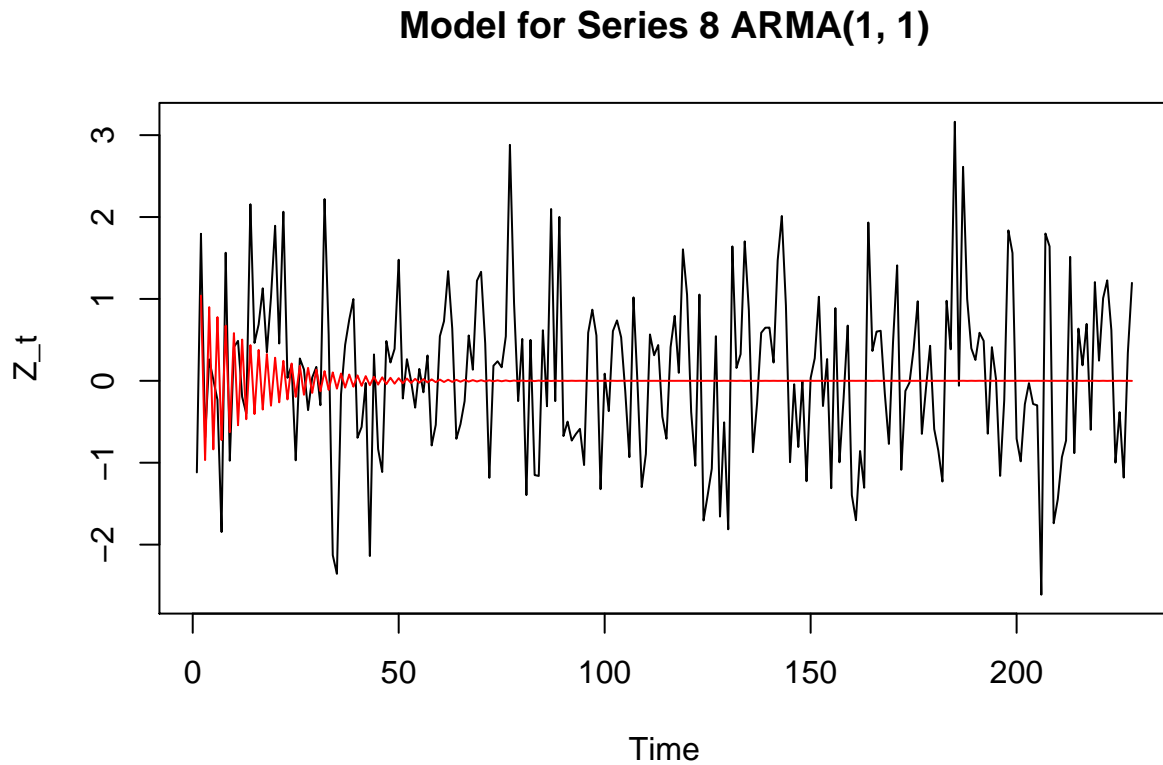


Mas da mesma forma da série 3, podemos estar tratando com um modelo ARMA(p ,p), que dessa vez novamente iremos considerar.

```
model8 <- arma(X[[8]], order = c(1, 1), include.intercept = FALSE)
summary(model8)
```

```
##
## Call:
## arma(x = X[[8]], order = c(1, 1), include.intercept = FALSE)
##
## Model:
## ARMA(1,1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.6110 -0.6468  0.1682  0.6612  3.1628
##
## Coefficient(s):
##      Estimate Std. Error t value Pr(>|t|)
## ar1  -0.93015    0.03316  -28.05  <2e-16 ***
## ma1   0.92999    0.04085   22.77  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Fit:
## sigma^2 estimated as 0.9688,  Conditional Sum-of-Squares = 221.01,  AIC = 643.82
```

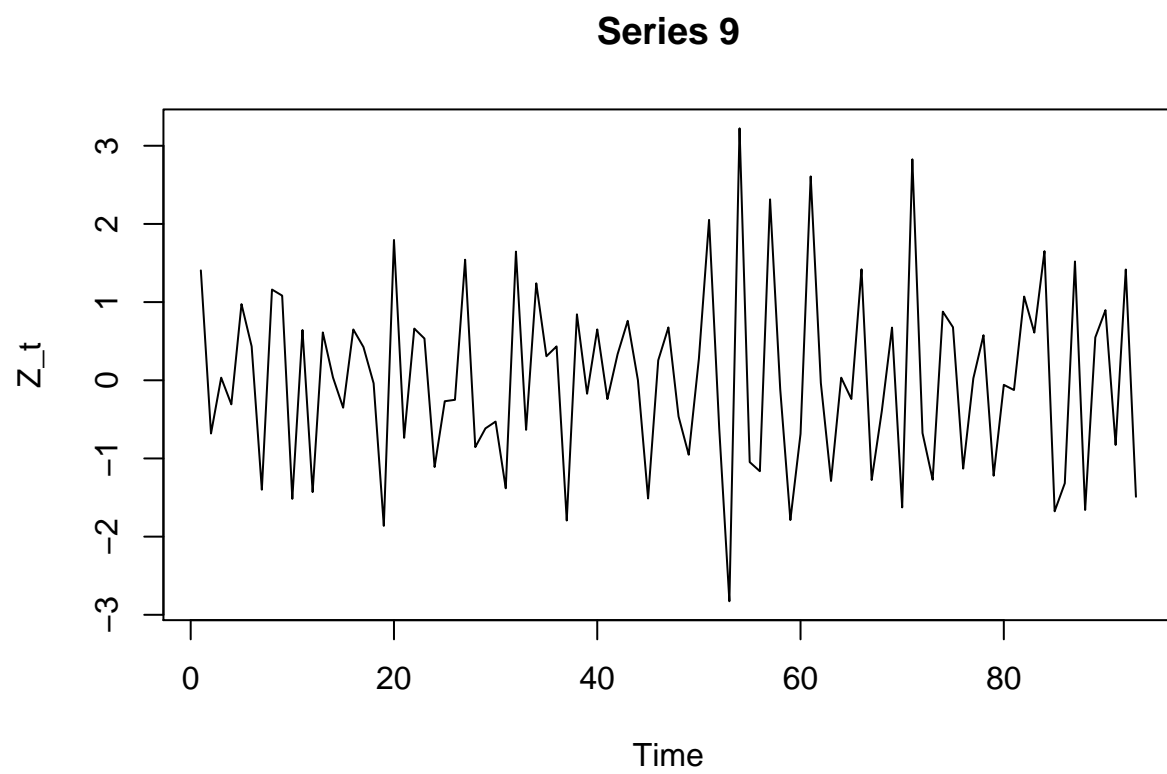
```
plot(X[[8]], main = "Model for Series 8 ARMA(1, 1)", ylab = "Z_t")  
lines(model8$fitted.values, col = "red")
```



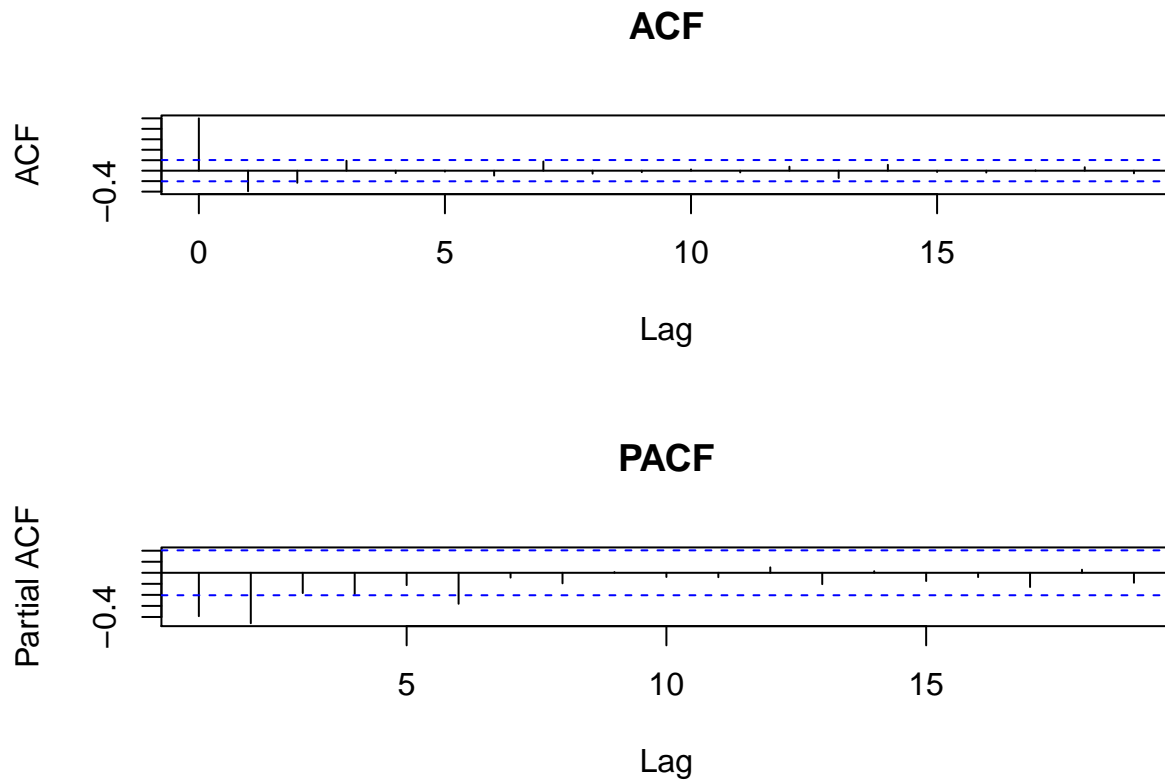
Vemos que o modelo não consegue se encaixar com os dados, produzindo uma previsão incondizente.

Série 9

```
plot(X[[9]], main = "Series 9", ylab = "Z_t")
```



```
plot_acf_pacf(X[[9]])
```



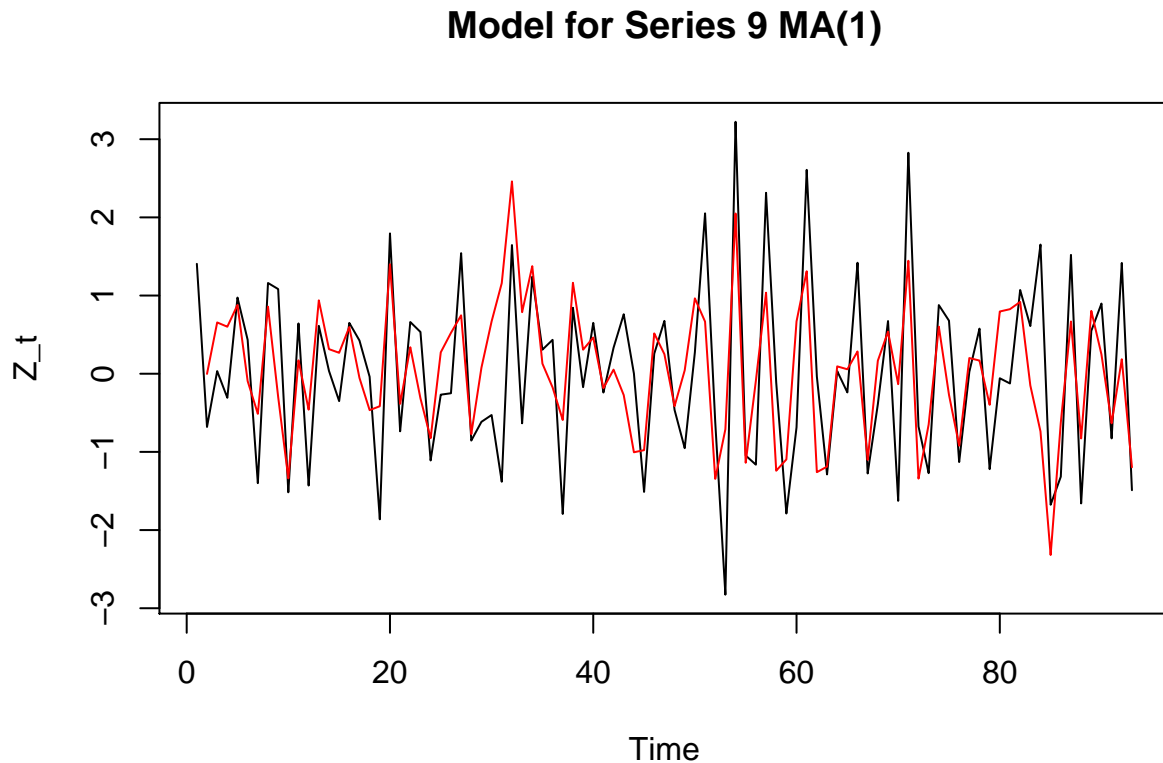
O ACF decai rapidamente para lag maior do que 1, enquanto que o PACF decai mais lentamente para lag maior do que 1. Assim, testaremos os modelos MA(1) e ARMA(1,1).

```
model9 <- arma(X[[9]], order = c(0, 1))
summary(model9)
```

```
##
## Call:
## arma(x = X[[9]], order = c(0, 1))
##
## Model:
## ARMA(0,1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.5405 -0.6815 -0.1173  0.5474  2.3902
##
## Coefficient(s):
##              Estimate Std. Error t value Pr(>|t|)
## ma1          -0.969369   0.038766 -25.006  <2e-16 ***
## intercept -0.002035    0.004299  -0.473    0.636
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Fit:
## sigma^2 estimated as 0.7455,  Conditional Sum-of-Squares = 68.05,  AIC = 240.61
```



```
plot(X[[9]], main = "Model for Series 9 MA(1)", ylab = "Z_t")
lines(model9$fitted.values, col = "red")
```



```
model9_2 <- arma(X[[9]], order = c(1, 1))
```

```
## Warning in arma(X[[9]], order = c(1, 1)): Hessian negative-semidefinite
```

```
summary(model9_2)
```

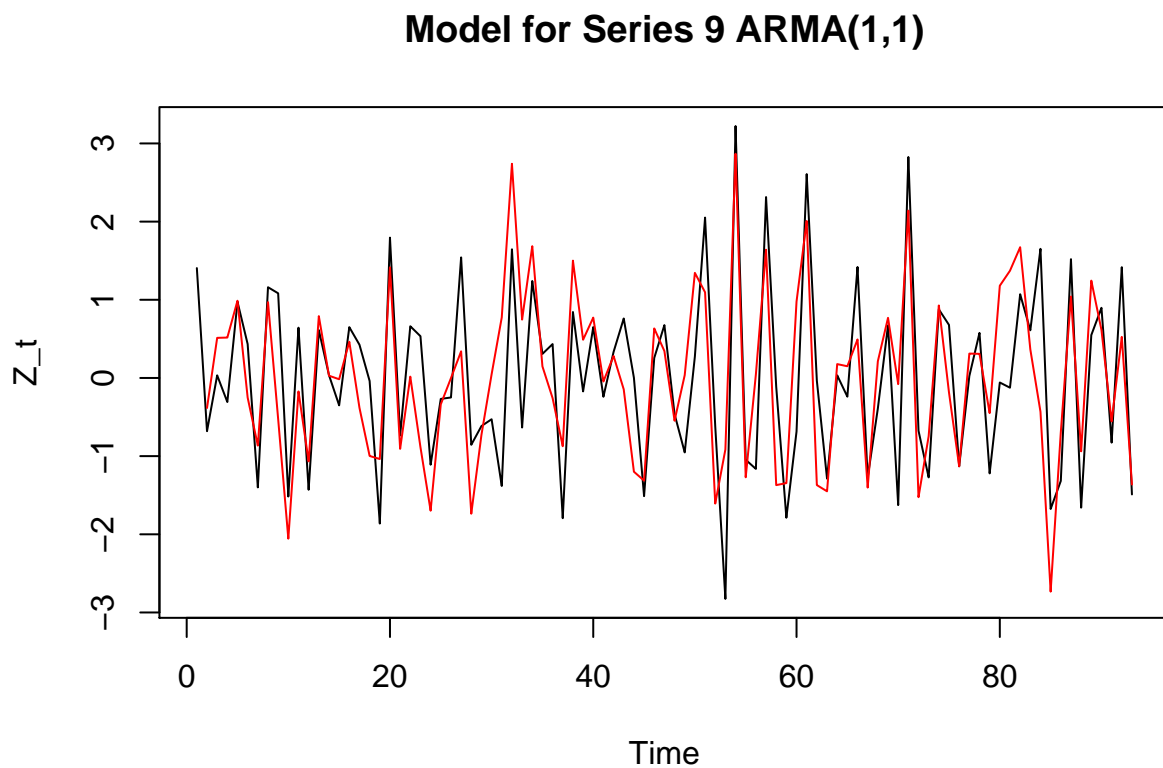
```
## Warning in sqrt(diag(object$vcov)): NaNs produzidos
```

```
## Warning in sqrt(diag(object$vcov)): NaNs produzidos
```

```
##
## Call:
## arma(x = X[[9]], order = c(1, 1))
##
## Model:
## ARMA(1,1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.156261 -0.544383  0.003433  0.651768  2.085140
```

```
##
## Coefficient(s):
##           Estimate Std. Error t value Pr(>|t|)
## ar1      -0.274298         NA      NA      NA
## ma1      -1.094195         NA      NA      NA
## intercept  0.001394         NA      NA      NA
##
## Fit:
## sigma^2 estimated as 0.6787, Conditional Sum-of-Squares = 61.76, AIC = 233.87
```

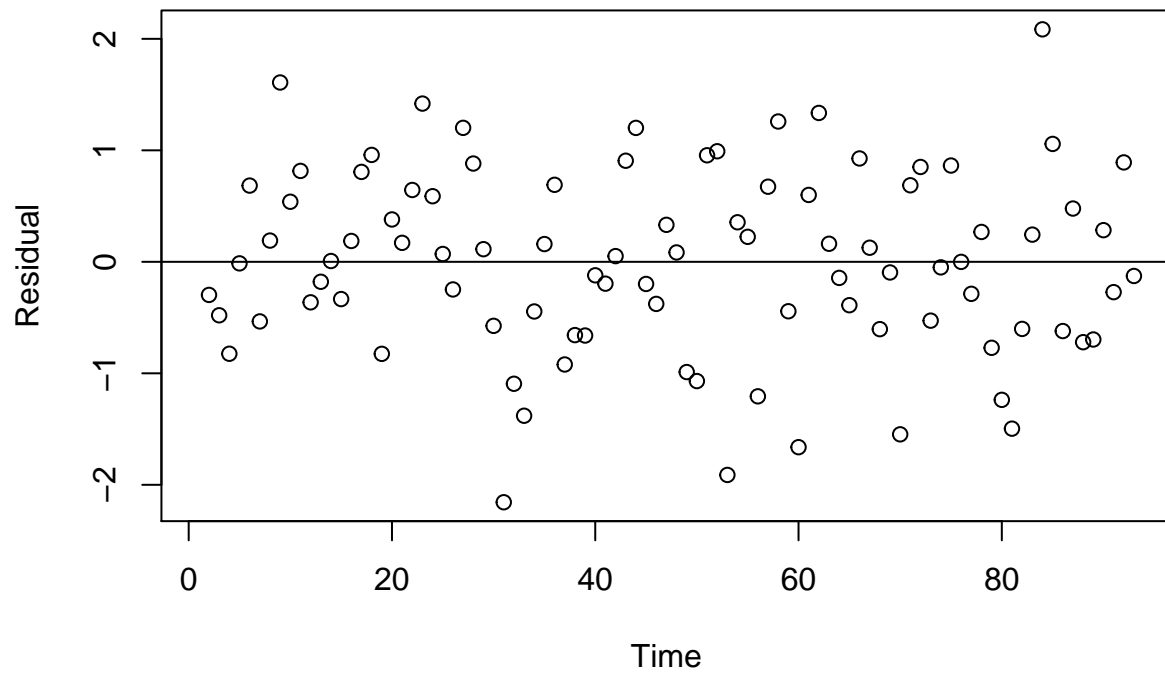
```
plot(X[[9]], main = "Model for Series 9 ARMA(1,1)", ylab = "Z_t")
lines(model9_2$fitted.values, col = "red")
```



Tivemos que o modelo ARMA(1,1) apresentou AIC menor que o modelo MA(1), além de aparentar visualmente se encaixar um pouco melhor nos dados.

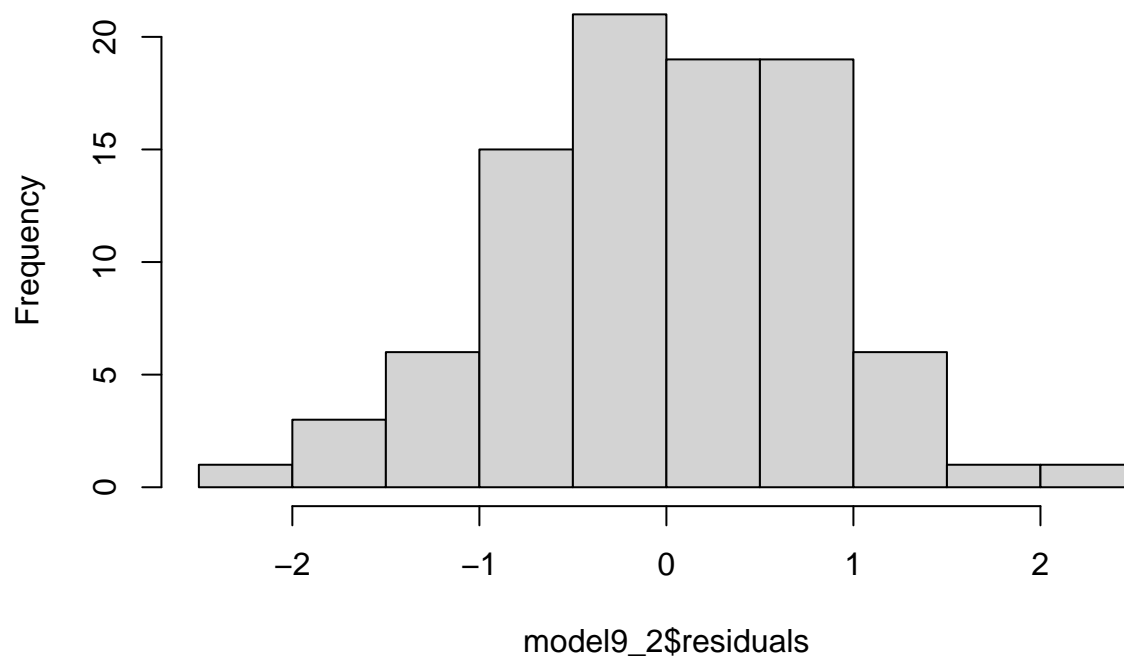
```
plot_res(model9_2$residuals)
```

Residuals of model



```
hist(model9_2$residuals)
```

Histogram of model9_2\$residuals



O modelo se encaixou bem aos dados, conseguindo capturar razoavelmente os picos.