Séries Temporais

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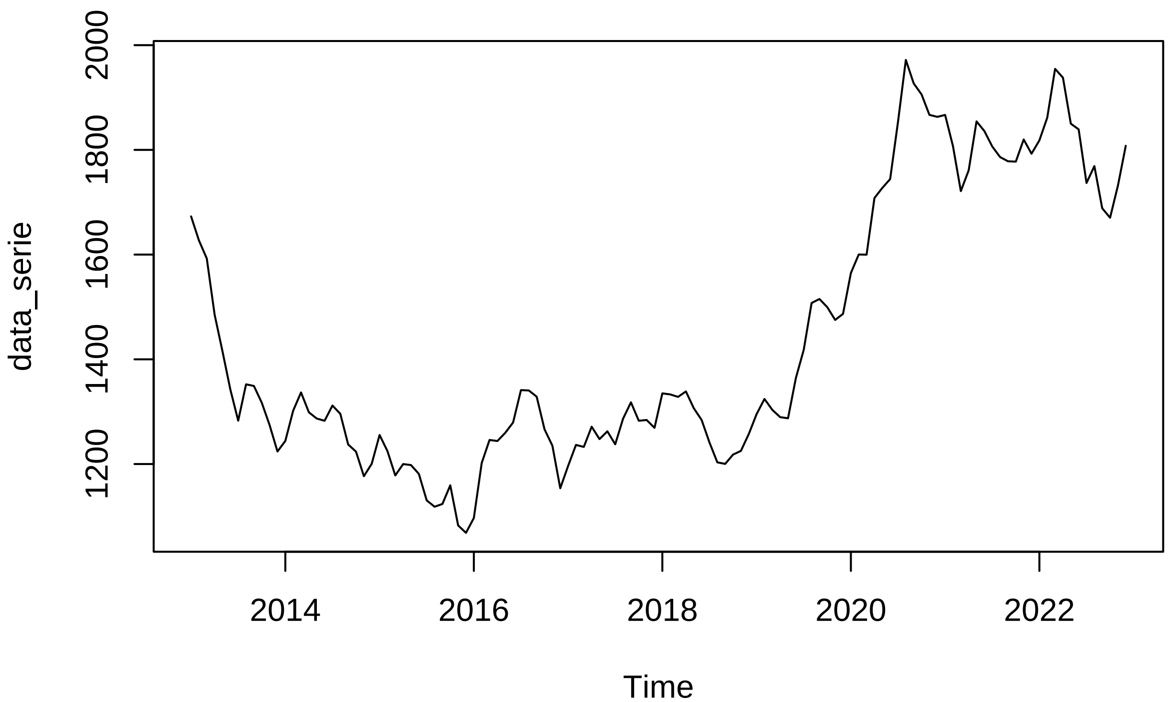
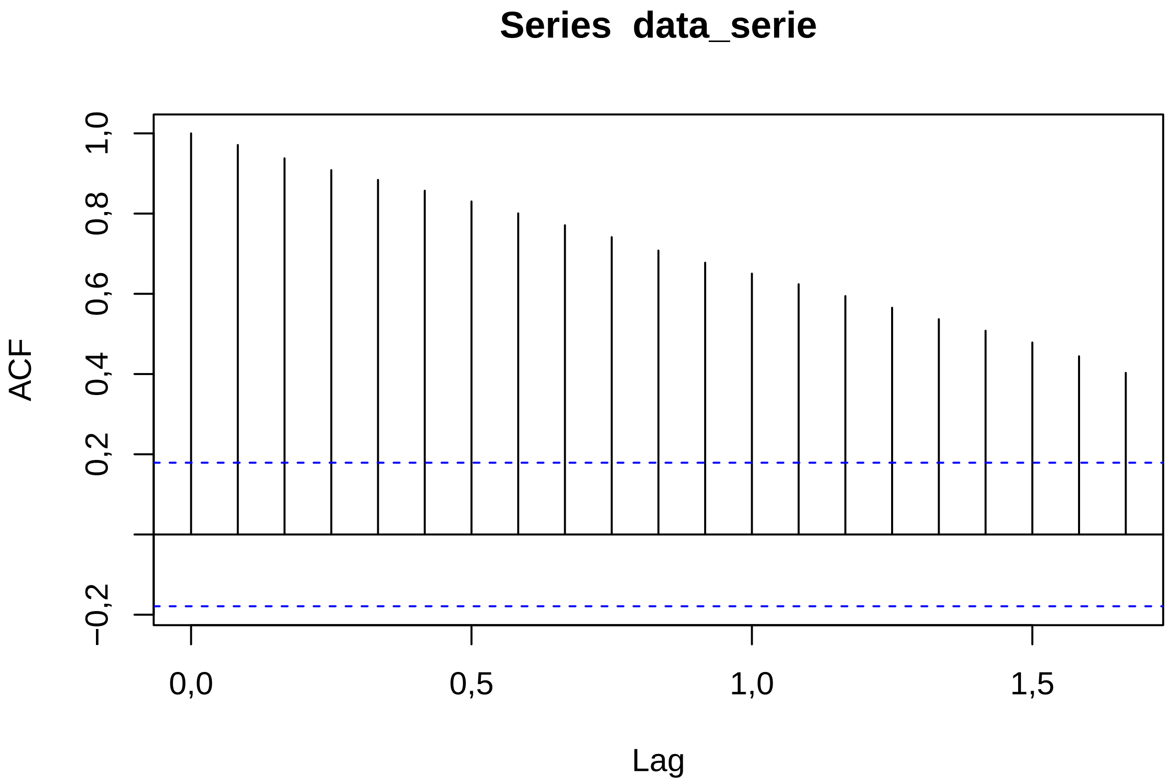
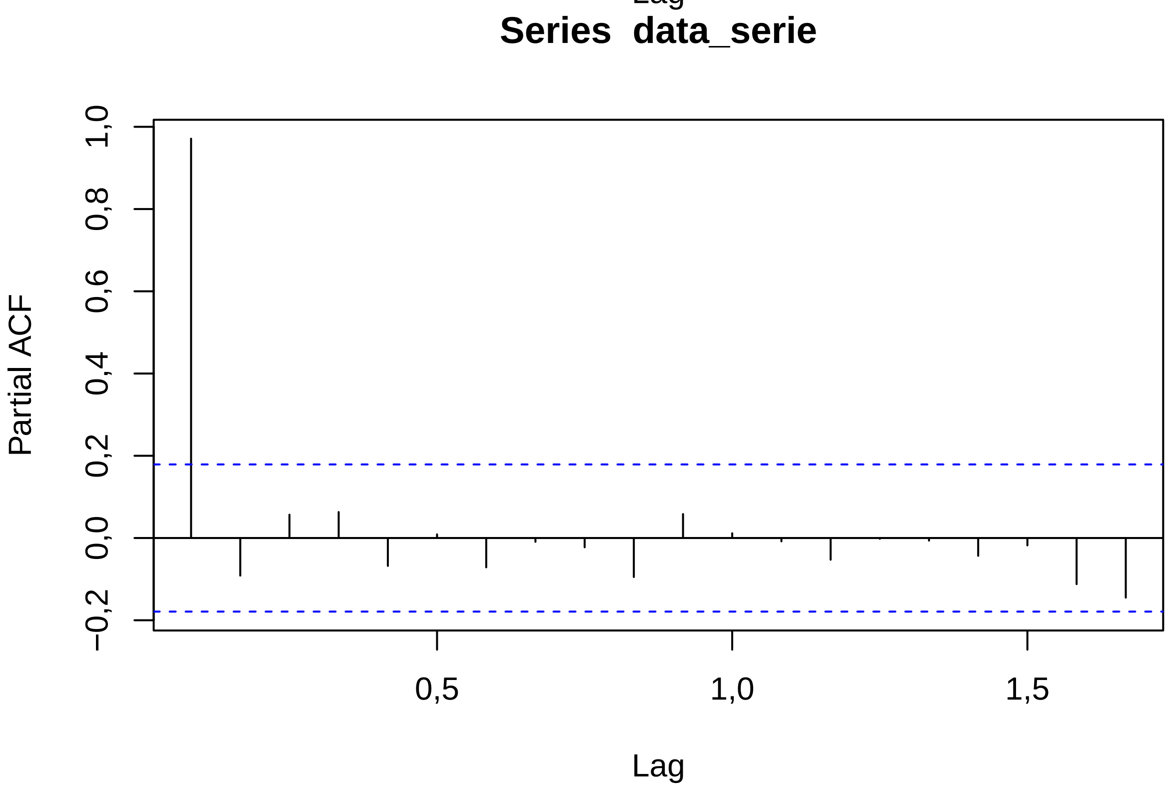
09 dezembro 2024

Sumário





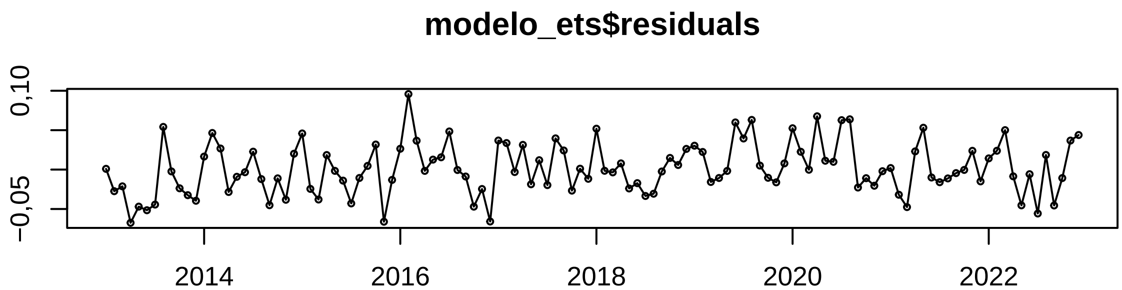


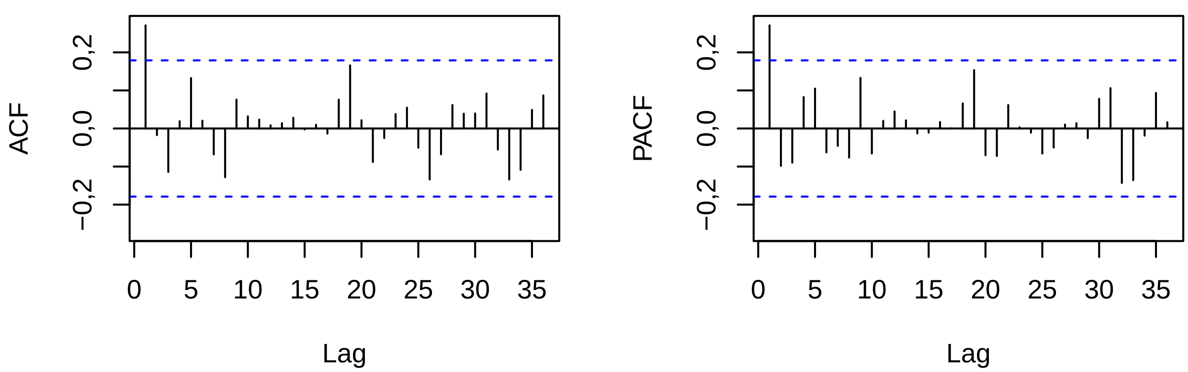

```r
modelo_ets <- ets(data_serie)

summary(modelo_ets)
```

```
## ETS(M,N,N)
##
## Call:
## ets(y = data_serie)
```

```
##
##   Smoothing parameters:
##     alpha = 0,9999
##
##   Initial states:
##     l = 1671,3768
##
##   sigma:  0,0326
##
##     AIC    AICc     BIC
## 1498,7 1498,9 1507,0
##
## Training set error measures:
##                   ME    RMSE     MAE      MPE    MAPE     MASE     ACF1
## Training set 1,1371 46,958 36,908 0,01362 2,5675 0,27148 0,27553
```

```
tsdisplay(modelo_ets$residuals)
```






```
Box.test(modelo_ets$residuals,lag=10)
```

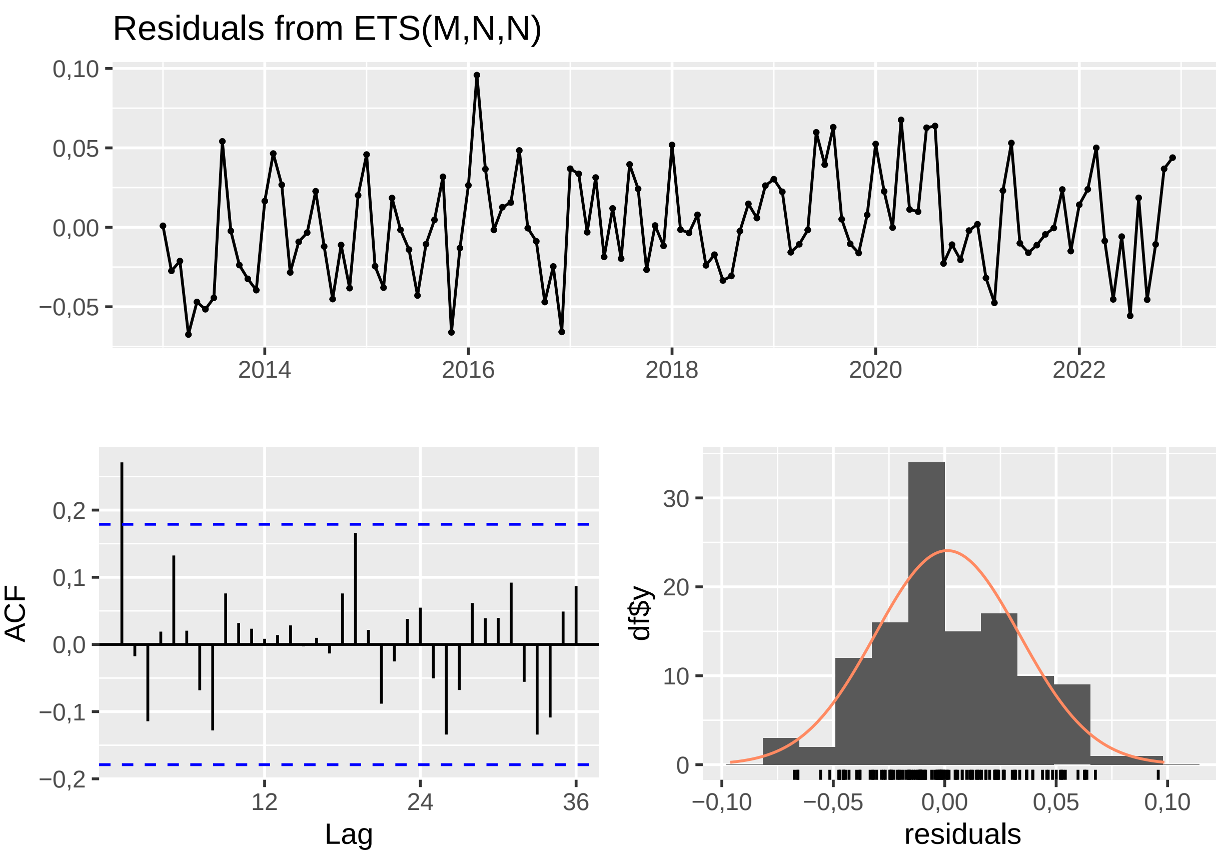
```
##
##  Box-Pierce test
##
## data:  modelo_ets$residuals
## X-squared = 16, df = 10, p-value = 0,1
```

```
modelo_ets$residuals
```

```
##              Jan         Feb         Mar         Apr         May         Jun
## 2013  0,00094668 -0,02739693 -0,02125497 -0,06746665 -0,04698367 -0,05156415
## 2014  0,01650173  0,04643099  0,02673752 -0,02839678 -0,00913951 -0,00335374
## 2015  0,04580829 -0,02449191 -0,03797003  0,01844891 -0,00160850 -0,01401190
## 2016  0,02644539  0,09579553  0,03665234 -0,00164782  0,01265276  0,01560778
```

```
## 2017  0,03687090  0,03364465 -0,00310416  0,03134042 -0,01861734  0,01190574
## 2018  0,05185993 -0,00149631 -0,00353883  0,00785466 -0,02393416 -0,01721277
## 2019  0,03029386  0,02234641 -0,01571768 -0,01066199 -0,00166985  0,05980610
## 2020  0,05243528  0,02262875 -0,00018271  0,06759995  0,01124199  0,00986470
## 2021  0,00195334 -0,03188253 -0,04753867  0,02308229  0,05305921 -0,01003084
## 2022  0,01420835  0,02390290  0,05003294 -0,00859506 -0,04534959 -0,00584745
##              Jul         Aug         Sep         Oct         Nov         Dec
## 2013 -0,04436542  0,05410956 -0,00231074 -0,02374253 -0,03245713 -0,03953852
## 2014  0,02272049 -0,01205271 -0,04517861 -0,01112089 -0,03828498  0,02012362
## 2015 -0,04292382 -0,01063987  0,00467324  0,03178645 -0,06610828 -0,01308685
## 2016  0,04837626 -0,00052826 -0,00880256 -0,04702106 -0,02463158 -0,06583971
## 2017 -0,01967258  0,03958083  0,02423824 -0,02668521  0,00113480 -0,01166756
## 2018 -0,03347088 -0,03060801 -0,00242030  0,01477143  0,00583069  0,02623111
## 2019  0,03944793  0,06299997  0,00509609 -0,01038508 -0,01616962  0,00783243
## 2020  0,06267861  0,06377342 -0,02275088 -0,01090543 -0,02046716 -0,00205149
## 2021 -0,01600320 -0,01119634 -0,00446457 -0,00041138  0,02380673 -0,01494657
## 2022 -0,05570024  0,01856147 -0,04551514 -0,01074358  0,03681739  0,04386768
```

```
checkresiduals(modelo_ets)
```

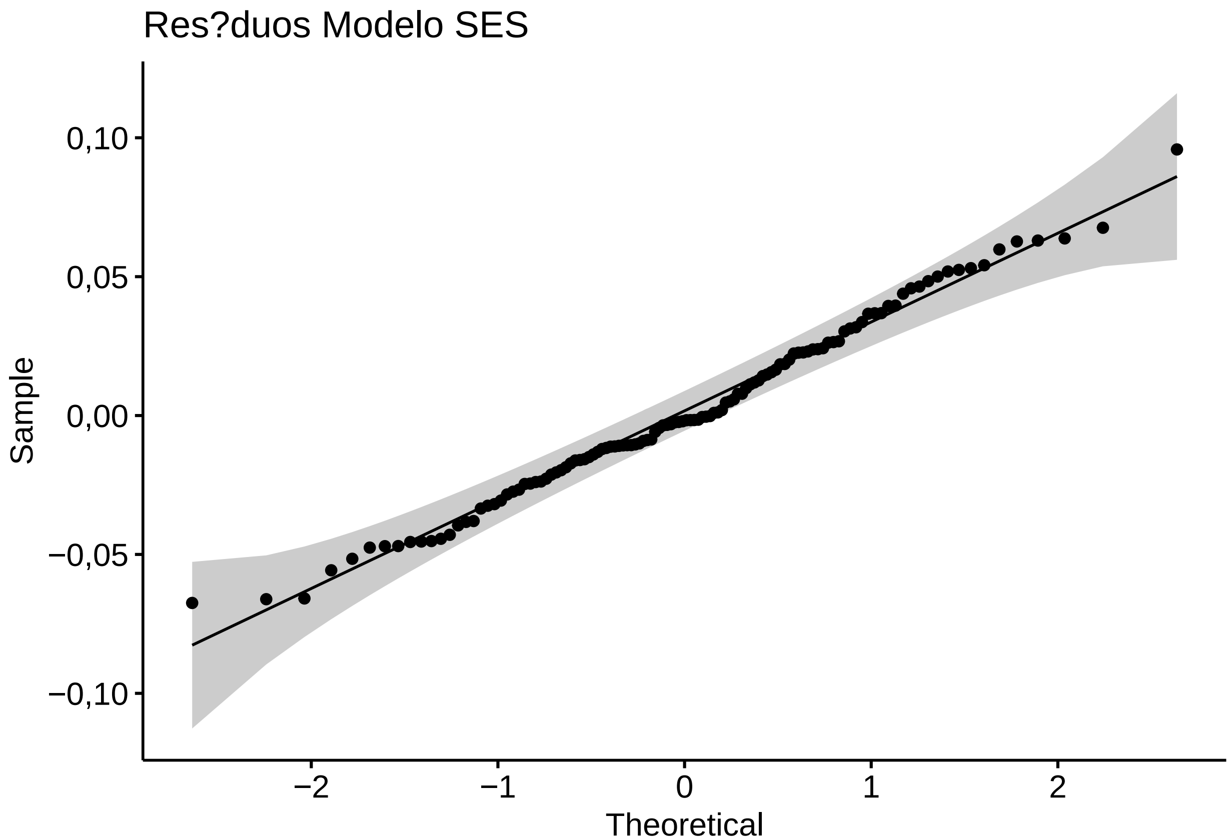



```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(M,N,N)
## Q* = 23,7, df = 24, p-value = 0,48
##
## Model df: 0.   Total lags used: 24
```

```
ggqqplot(modelo_ets$residuals)+ggtitle("Res?duos Modelo SES")
```

```
## Don't know how to automatically pick scale for object of type <ts>. Defaulting
```

```
## to continuous.
## Don't know how to automatically pick scale for object of type <ts>. Defaulting
## to continuous.
## Don't know how to automatically pick scale for object of type <ts>. Defaulting
## to continuous.
```



1 Introdução

```r
# verificar - Sazonalidade, raiz unitaria e tendencia

source("functions.R")


tend_determ(data_serie)
```

```
## $CS
##
##  Cox Stuart test
##
## data:  ts
## statistic = 47, n = 60, p-value = 0,000012
## alternative hypothesis: non randomness
##
##
## $CeST
##
##  Cox and Stuart Trend test
##
## data:  ts
```

```
## z = 5,38, n = 120, p-value = 0,000000076
## alternative hypothesis: monotonic trend
##
##
## $MannKT
##
##  Mann-Kendall trend test
##
## data:  ts
## z = 7,32, n = 120, p-value = 0,00000000000024
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##            S         varS          tau
##   3230,00000 194366,66667      0,45238
##
##
## $MannK
## tau = 0,452, 2-sided pvalue =<0,0000000000000002
##
## $KPSST
##
##  KPSS Test for Trend Stationarity
##
## data:  ts
## KPSS Trend = 0,444, Truncation lag parameter = 4, p-value = 0,01
##
##
## $Tabela
##                 Testes            H0 p_valor Conclusao
## 1           Cox Stuart NAO tendencia    0,00 Tendencia
## 2 Cox and Stuart Trend NAO tendencia    0,00 Tendencia
## 3   Mann-Kendall Trend NAO tendencia    0,00 Tendencia
## 4         Mann-Kendall NAO tendencia    0,00 Tendencia
## 5  KPSS Test for Trend NAO tendencia    0,01 Tendencia
```

```r
raiz_unit(data_serie)
```

```
## $ADF
##
##  Augmented Dickey-Fuller Test
##
## data:  ts
## Dickey-Fuller = -2,53, Lag order = 4, p-value = 0,36
## alternative hypothesis: stationary
##
##
## $PP
##
##  Phillips-Perron Unit Root Test
##
## data:  ts
## Dickey-Fuller Z(alpha) = -10,2, Truncation lag parameter = 4, p-value =
## 0,53
## alternative hypothesis: stationary
##
##
## $KPSSL
```

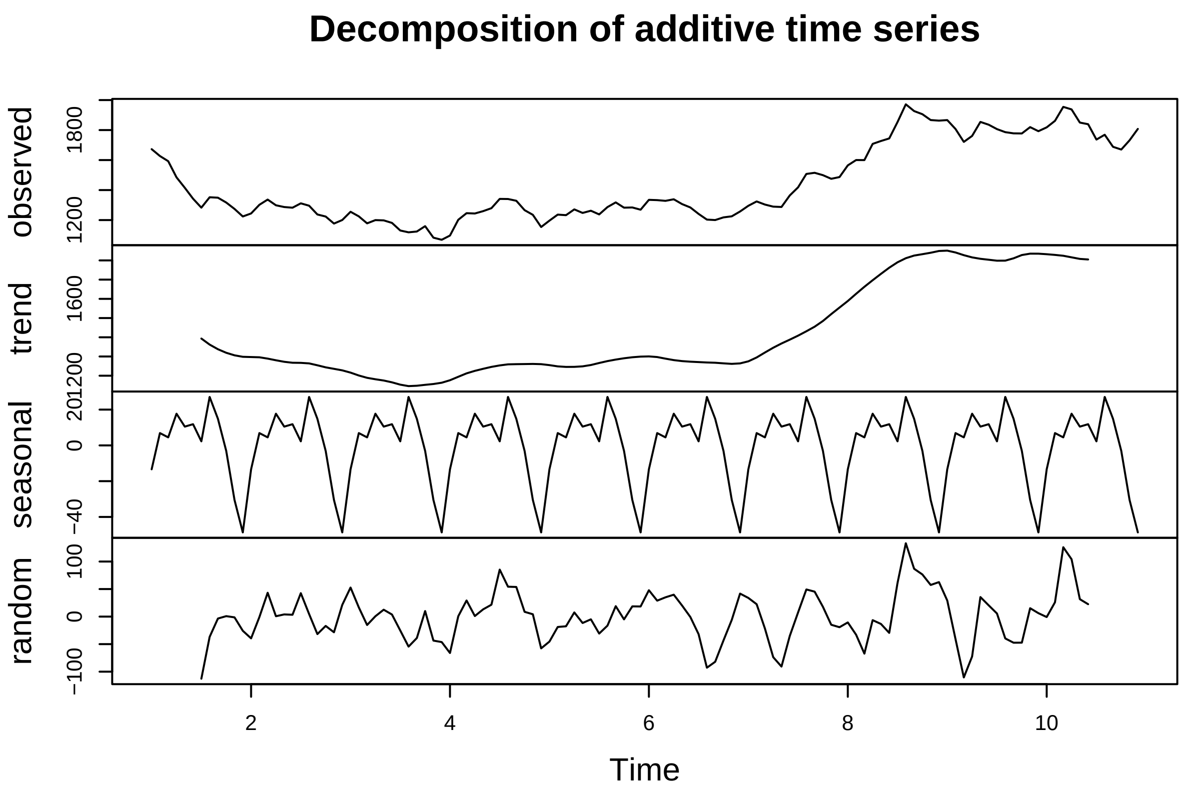
```
##
##  KPSS Test for Level Stationarity
##
## data:  ts
## KPSS Level = 1,65, Truncation lag parameter = 4, p-value = 0,01
##
##
## $Tabela
##                       Testes            H0 p_valor Conclusao
## 1   Augmented Dickey-Fuller     Tendencia  0,3553 Tendencia
## 2 Phillips-Perron Unit Root     Tendencia  0,5252 Tendencia
## 3       KPSS Test for Level NAO tendencia  0,0100 Tendencia
```

```
sazonalidade(data_serie)
```

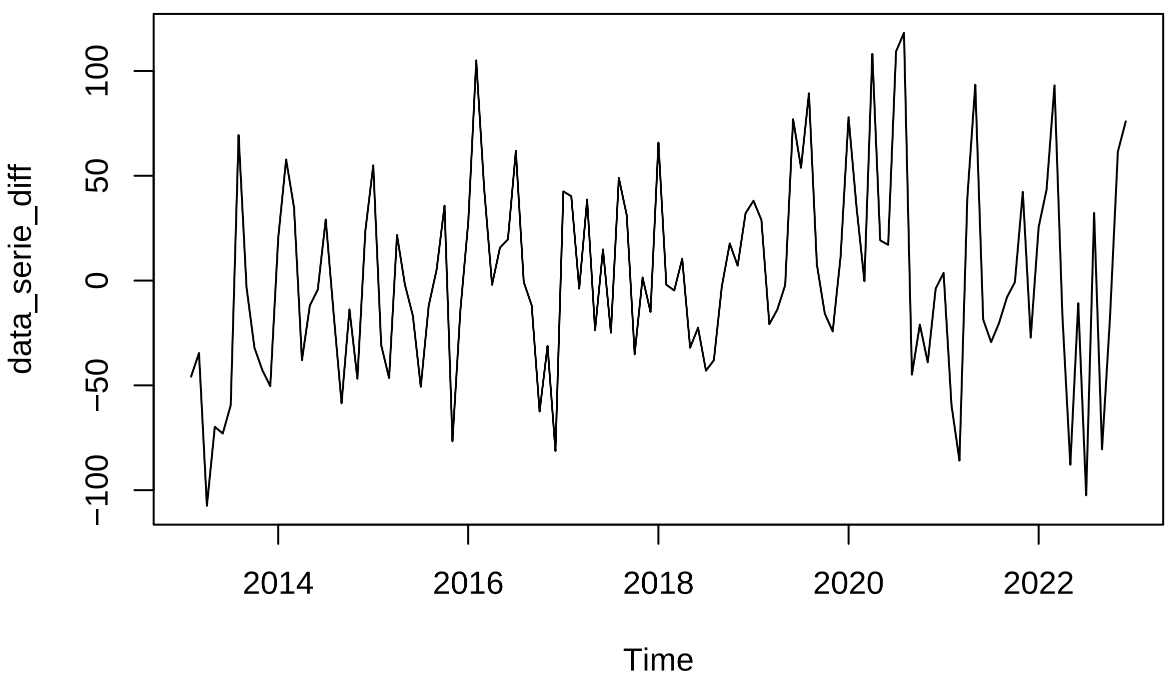
```
## $KrusW
## Test used:  Kruskall Wallis
##
## Test statistic:  1,78
## P-value:  0,99913
##
## $Fried
## Test used:  Friedman rank
##
## Test statistic:  6,26
## P-value:  0,85536
##
## $Tabela
##            Testes          H0 p_valor   Conclusao
## 1 Kruskall Wallis NAO Sazonal  0,9991 NAO Sazonal
## 2   Friedman rank NAO Sazonal  0,8554 NAO Sazonal
```

```
# resultado -
```

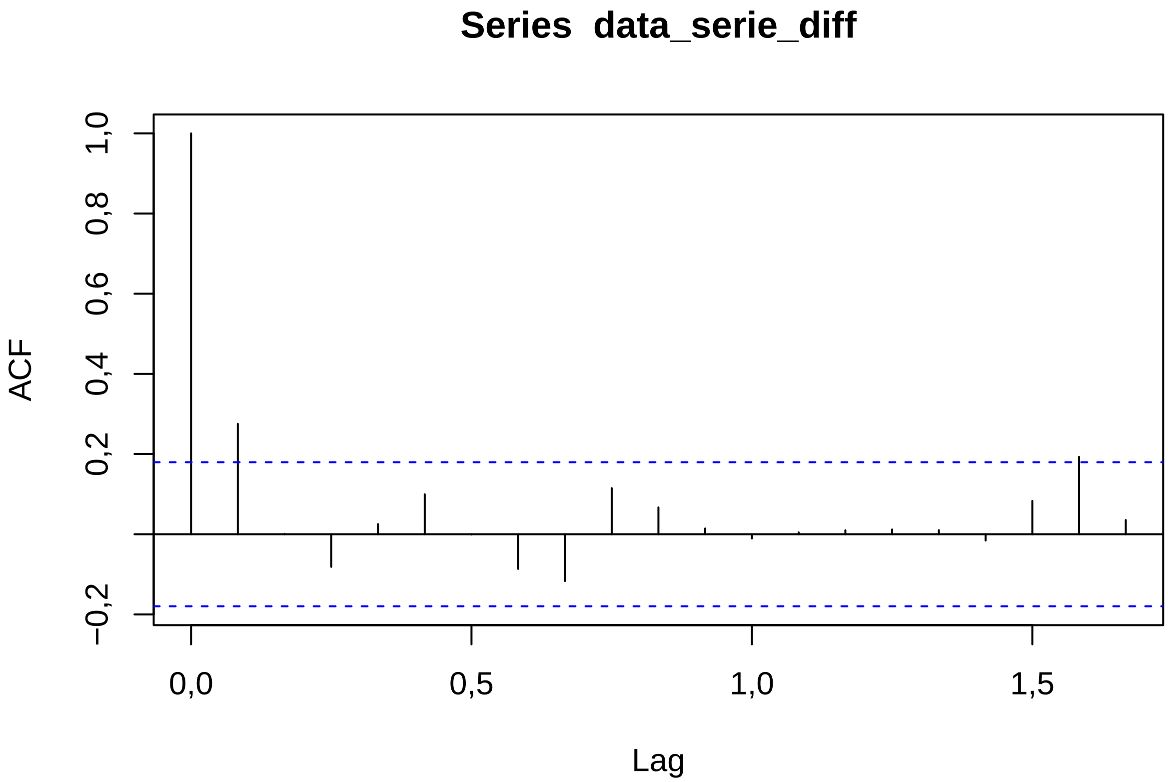
```
decomposicao <- decompose(ts(data_serie, frequency = 12))

plot(decomposicao)
```




```r
# diferenciação

data_serie_diff<-diff(data_serie,differences = 1)
plot(data_serie_diff)
```




```r
acf(data_serie_diff)
```




```r
adf.test(data_serie_diff, alternative = "stationary")
```

```
## Warning in adf.test(data_serie_diff, alternative = "stationary"): p-value
## smaller than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  data_serie_diff
## Dickey-Fuller = -4,69, Lag order = 4, p-value = 0,01
## alternative hypothesis: stationary
```

```r
tend_determ(data_serie_diff)
```

```
## $CS
##
##  Cox Stuart test
##
## data:  ts
## statistic = 39, n = 59, p-value = 0,018
## alternative hypothesis: non randomness
##
##
## $CeST
##
##  Cox and Stuart Trend test
##
## data:  ts
## z = 1,96, n = 119, p-value = 0,05
## alternative hypothesis: monotonic trend
##
##
## $MannKT
```

```
##
##  Mann-Kendall trend test
##
## data:  ts
## z = 2,06, n = 119, p-value = 0,039
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##            S         varS          tau
##    899,00000 189567,00000      0,12804
##
##
## $MannK
## tau = 0,128, 2-sided pvalue =0,0392
##
## $KPSST
##
##  KPSS Test for Trend Stationarity
##
## data:  ts
## KPSS Trend = 0,112, Truncation lag parameter = 4, p-value = 0,1
##
##
## $Tabela
##                 Testes            H0 p_valor     Conclusao
## 1           Cox Stuart NAO tendencia  0,0183     Tendencia
## 2 Cox and Stuart Trend NAO tendencia  0,0502 NAO tendencia
## 3   Mann-Kendall Trend NAO tendencia  0,0392     Tendencia
## 4         Mann-Kendall NAO tendencia  0,0392     Tendencia
## 5  KPSS Test for Trend NAO tendencia  0,1000 NAO tendencia
```

```r
raiz_unit(data_serie_diff)
```

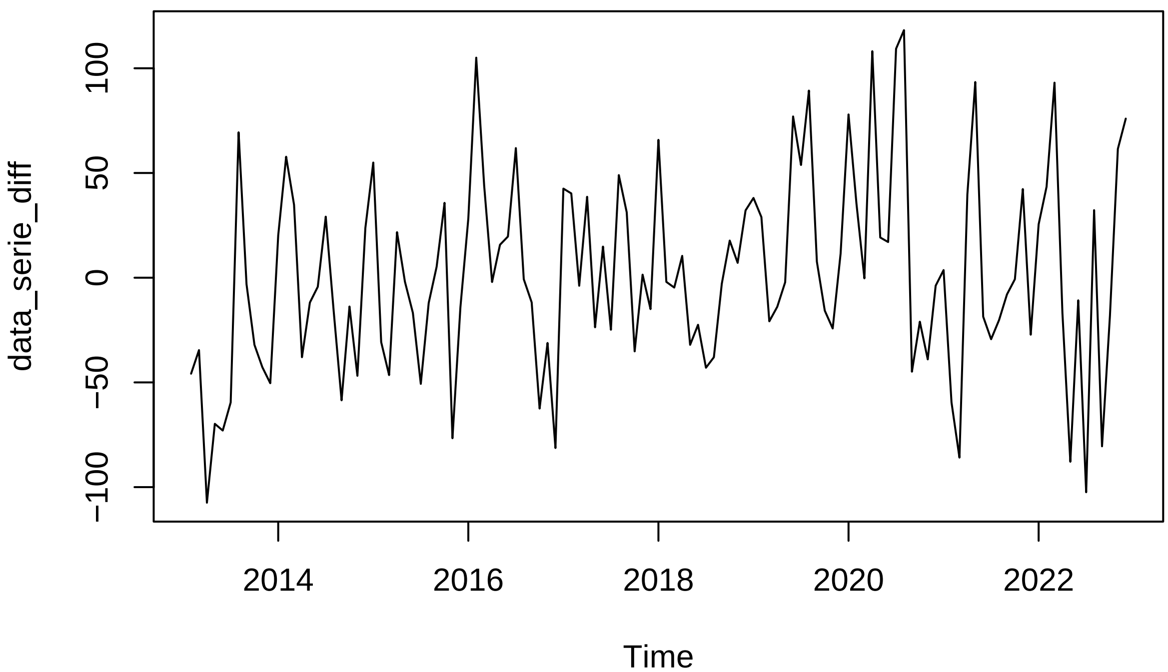
```
## $ADF
##
##  Augmented Dickey-Fuller Test
##
## data:  ts
## Dickey-Fuller = -4,69, Lag order = 4, p-value = 0,01
## alternative hypothesis: stationary
##
##
## $PP
##
##  Phillips-Perron Unit Root Test
##
## data:  ts
## Dickey-Fuller Z(alpha) = -78,8, Truncation lag parameter = 4, p-value =
## 0,01
## alternative hypothesis: stationary
##
##
## $KPSSL
##
##  KPSS Test for Level Stationarity
##
## data:  ts
## KPSS Level = 0,392, Truncation lag parameter = 4, p-value = 0,081
```

```
##
##
## $Tabela
##                        Testes            H0 p_valor     Conclusao
## 1   Augmented Dickey-Fuller     Tendencia  0,0100 NAO tendencia
## 2 Phillips-Perron Unit Root     Tendencia  0,0100 NAO tendencia
## 3       KPSS Test for Level NAO tendencia  0,0807 NAO tendencia
```

```r
sazonalidade(data_serie_diff)
```

```
## $KrusW
## Test used:  Kruskall Wallis
##
## Test statistic:  16,51
## P-value:  0,12312
##
## $Fried
## Test used:  Friedman rank
##
## Test statistic:  14,59
## P-value:  0,20206
##
## $Tabela
##             Testes          H0 p_valor   Conclusao
## 1 Kruskall Wallis NAO Sazonal  0,1231 NAO Sazonal
## 2   Friedman rank NAO Sazonal  0,2021 NAO Sazonal
```

```r
plot(data_serie_diff)
```

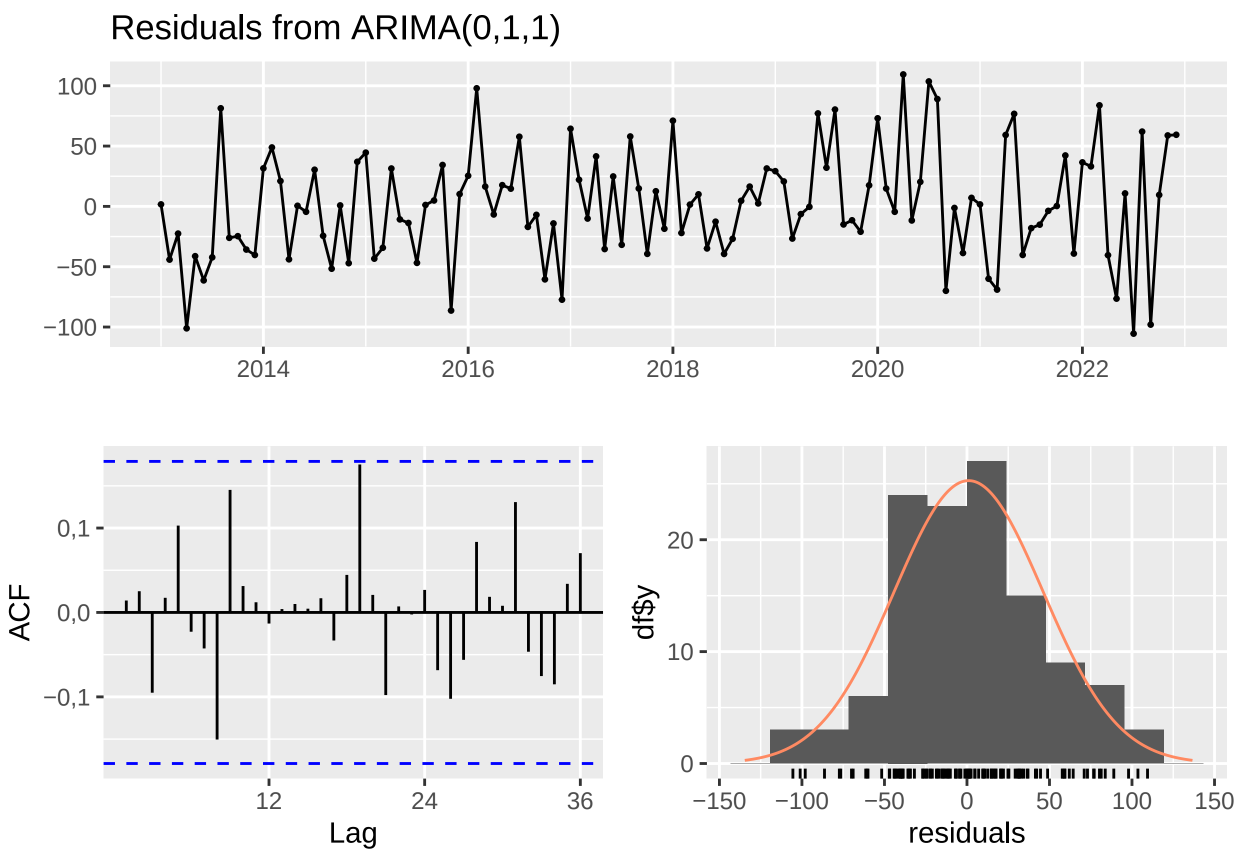



```r
arima_model<-auto.arima(data_serie)

summary(arima_model)
```

```
## Series: data_serie
## ARIMA(0,1,1)
##
## Coefficients:
```

```
##         ma1
##       0,282
## s.e.  0,083
##
## sigma^2 = 2062:  log likelihood = -622,48
## AIC=1249   AICc=1249,1   BIC=1254,5
##
## Training set error measures:
##                  ME    RMSE    MAE      MPE   MAPE    MASE     ACF1
## Training set 1,0079 45,034 35,547 0,023366 2,4696 0,26147 0,014123
```

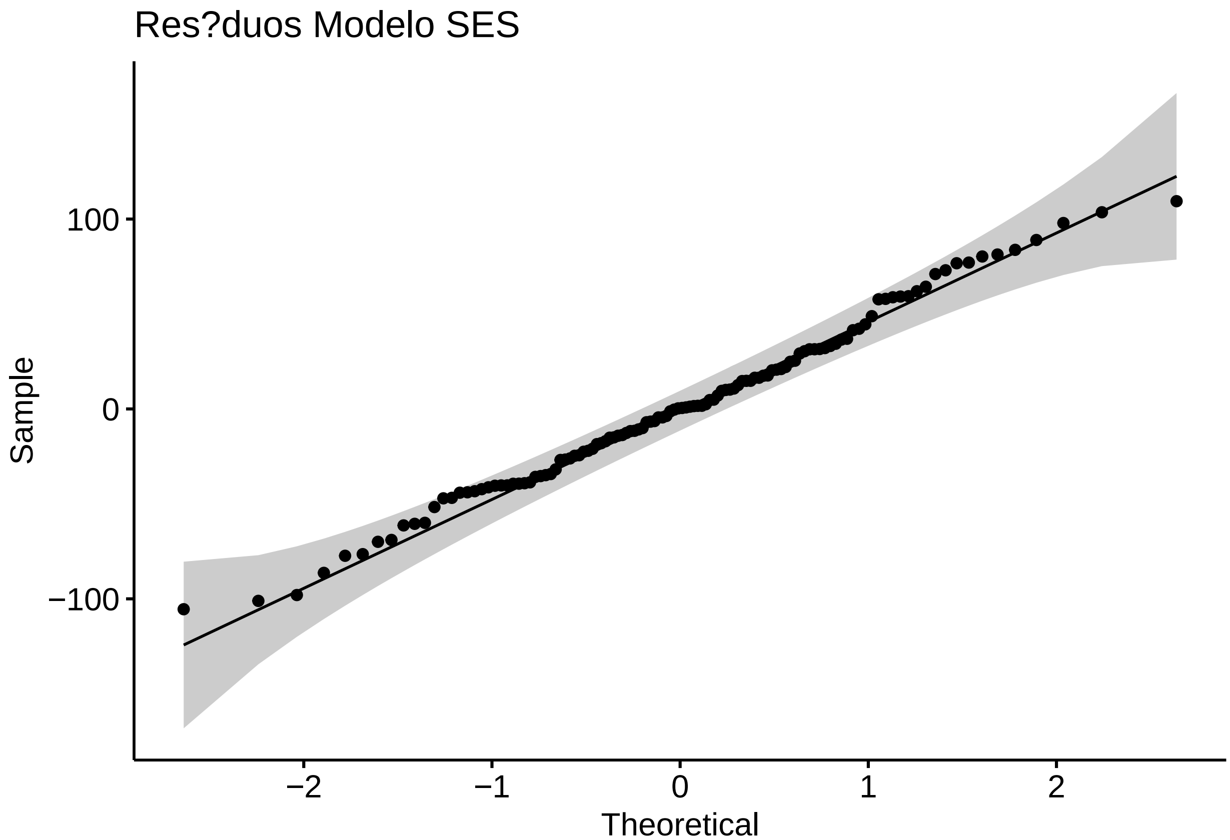
```
checkresiduals(arima_model)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,1,1)
## Q* = 15,4, df = 23, p-value = 0,88
##
## Model df: 1.   Total lags used: 24
```

```
ggqqplot(arima_model$residuals)+ggtitle("Res?duos Modelo SES")
```

```
## Don't know how to automatically pick scale for object of type <ts>. Defaulting
## to continuous.
## Don't know how to automatically pick scale for object of type <ts>. Defaulting
## to continuous.
## Don't know how to automatically pick scale for object of type <ts>. Defaulting
## to continuous.
```


Res?duos Modelo SES
Sample
100
0
−100
−2
−1
0
1
2
Theoretical