Spatio-Temporal Data Analysis Project

2020-04-26

Patterns in foreign sims connected to OpenWiFi-Milan

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1 Introduction & Motivation

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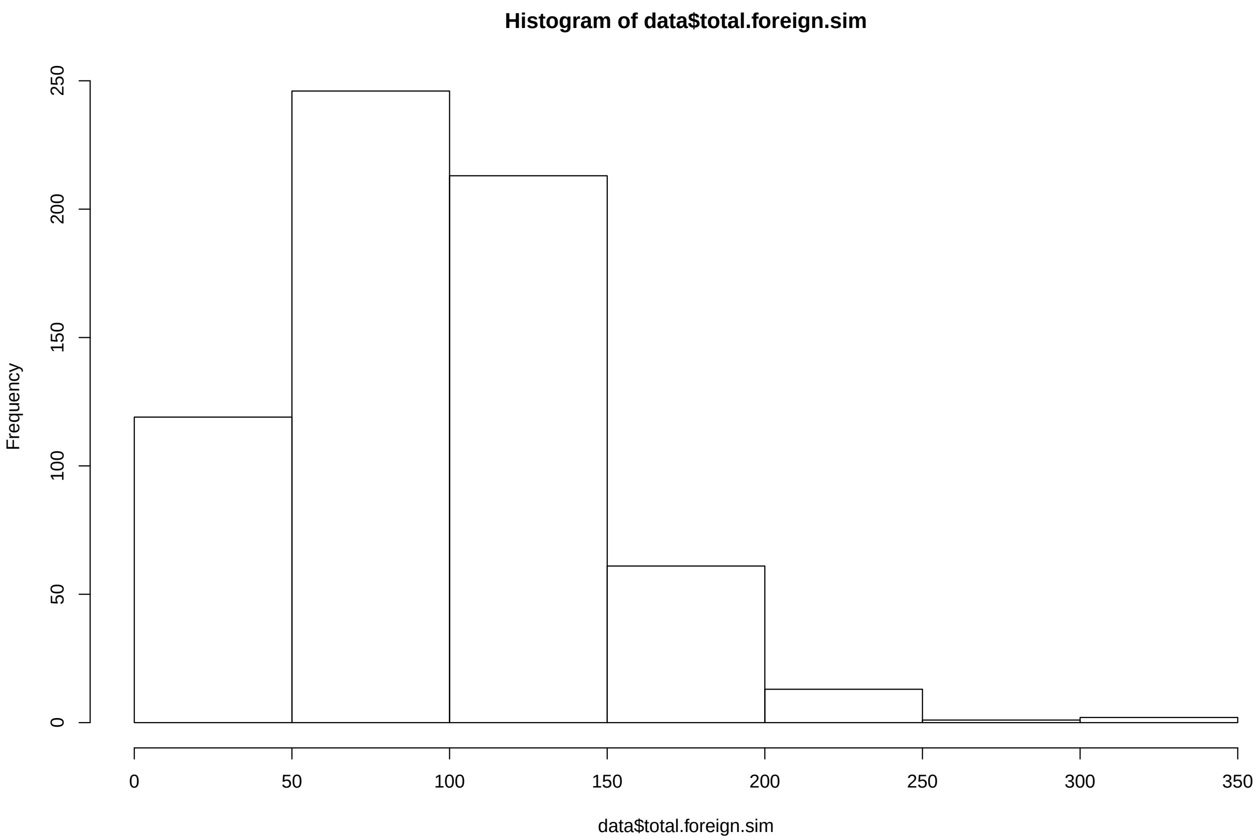
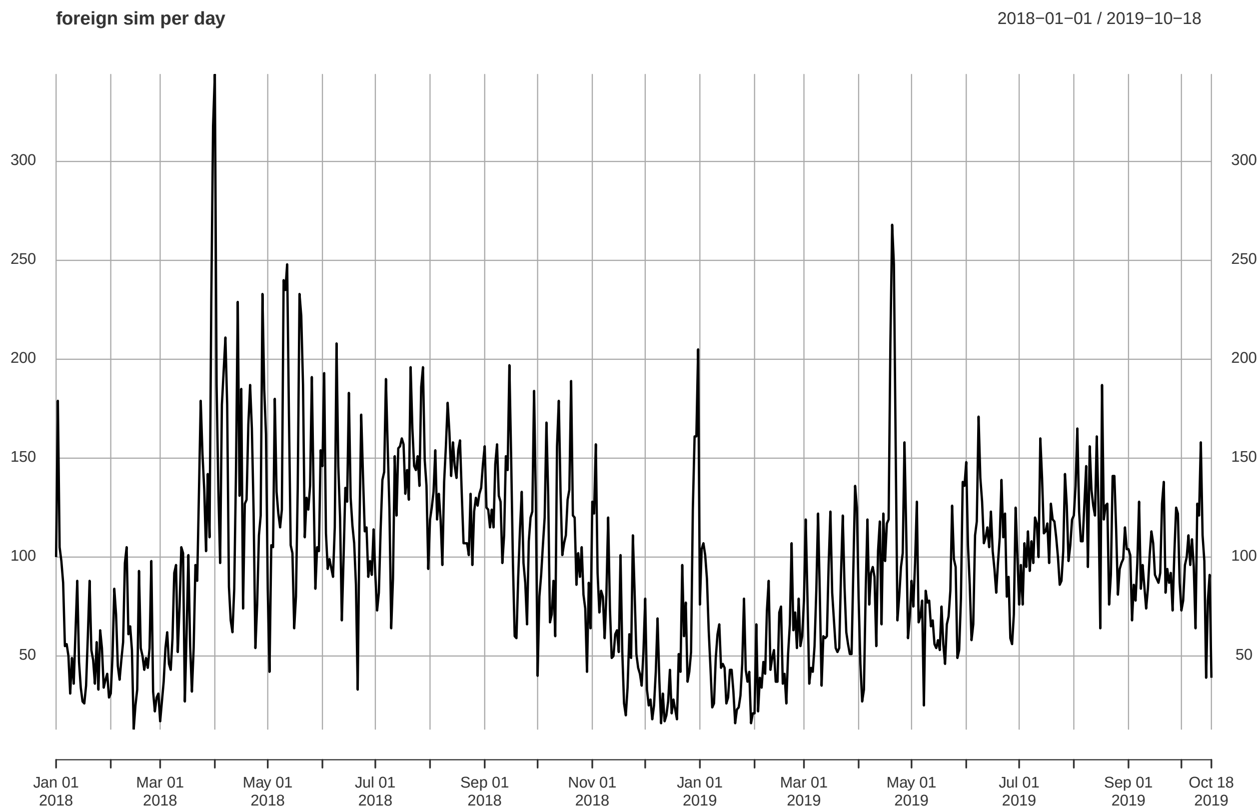
3 Exploration of the Data

```
## [1] "minimum, lower-hinge, median, upper-hinge, maximum)"
```

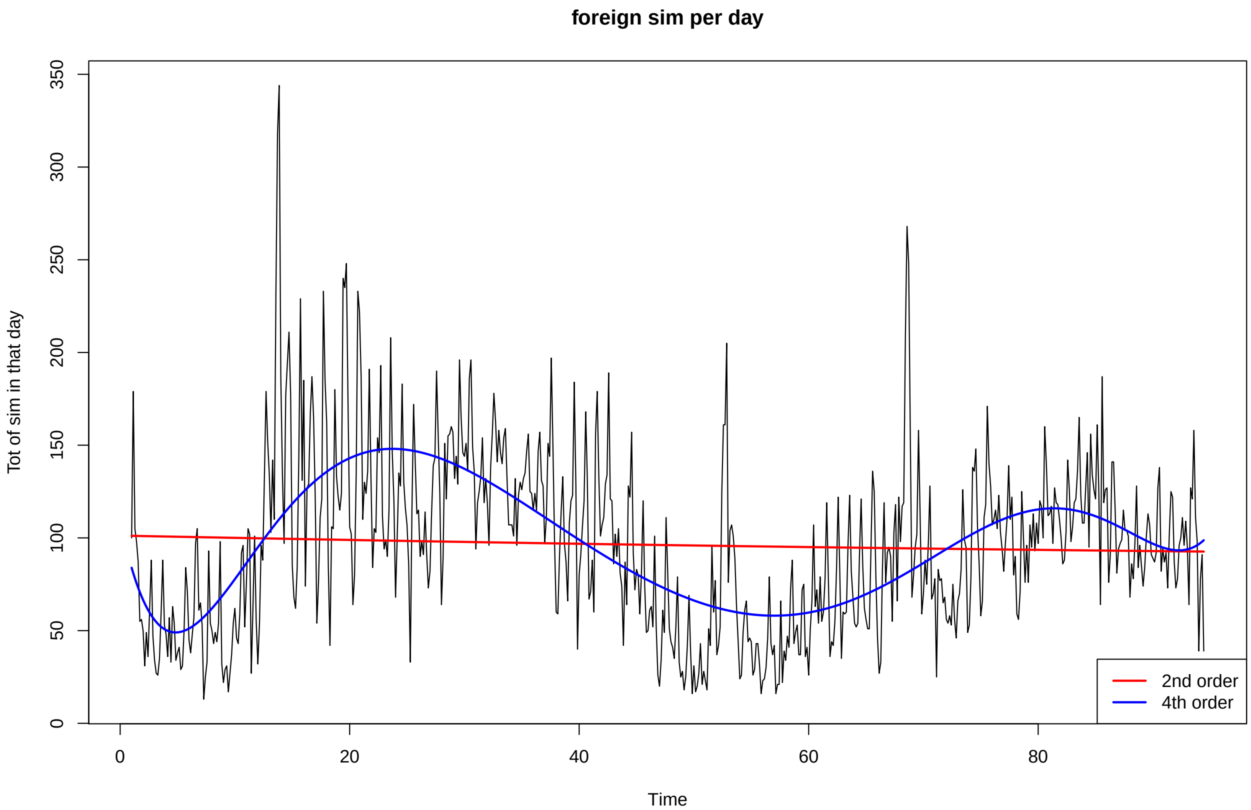
```
## [1]  13  59  95 124 344
```



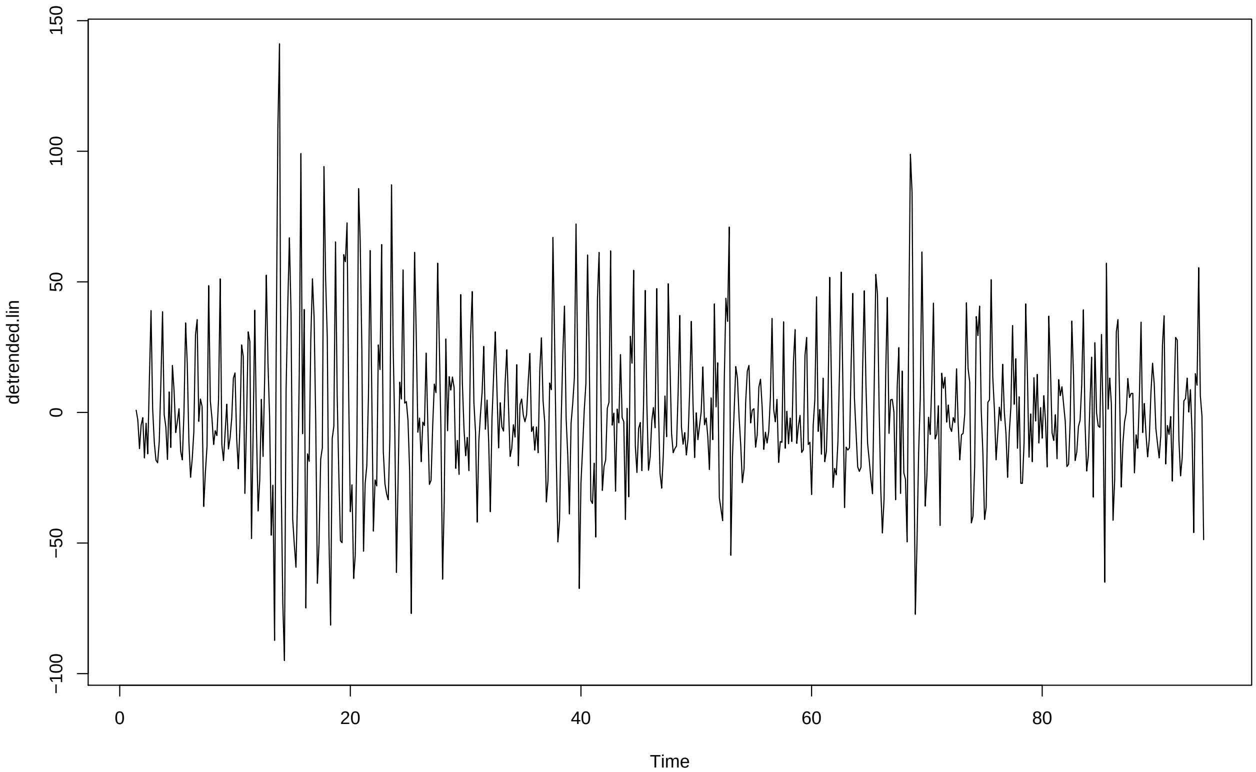
We loaded the dataset from the various datasets aggregating into only one dataset with 655 rows representing 2 years of data gathered. Starting from 01.01.2018 to 30.10.2019. Data is here sette


foreign sim per day
2018−01−01 / 2019−10−18
300
250
200
150
100
50
Jan 01 2018
Mar 01 2018
May 01 2018
Jul 01 2018
Sep 01 2018
Nov 01 2018
Jan 01 2019
Mar 01 2019
May 01 2019
Jul 01 2019
Sep 01 2019
Oct 18 2019

4 Trend recognition

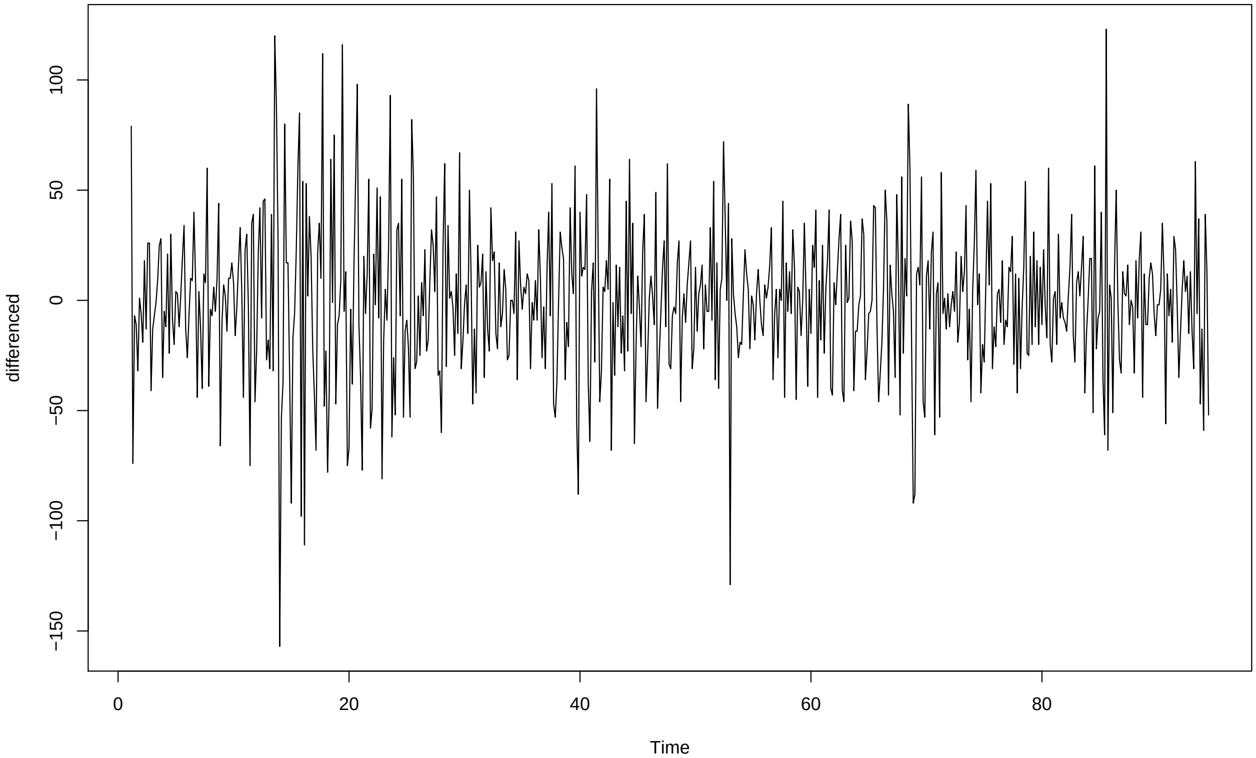


4.1 Detrending using LM

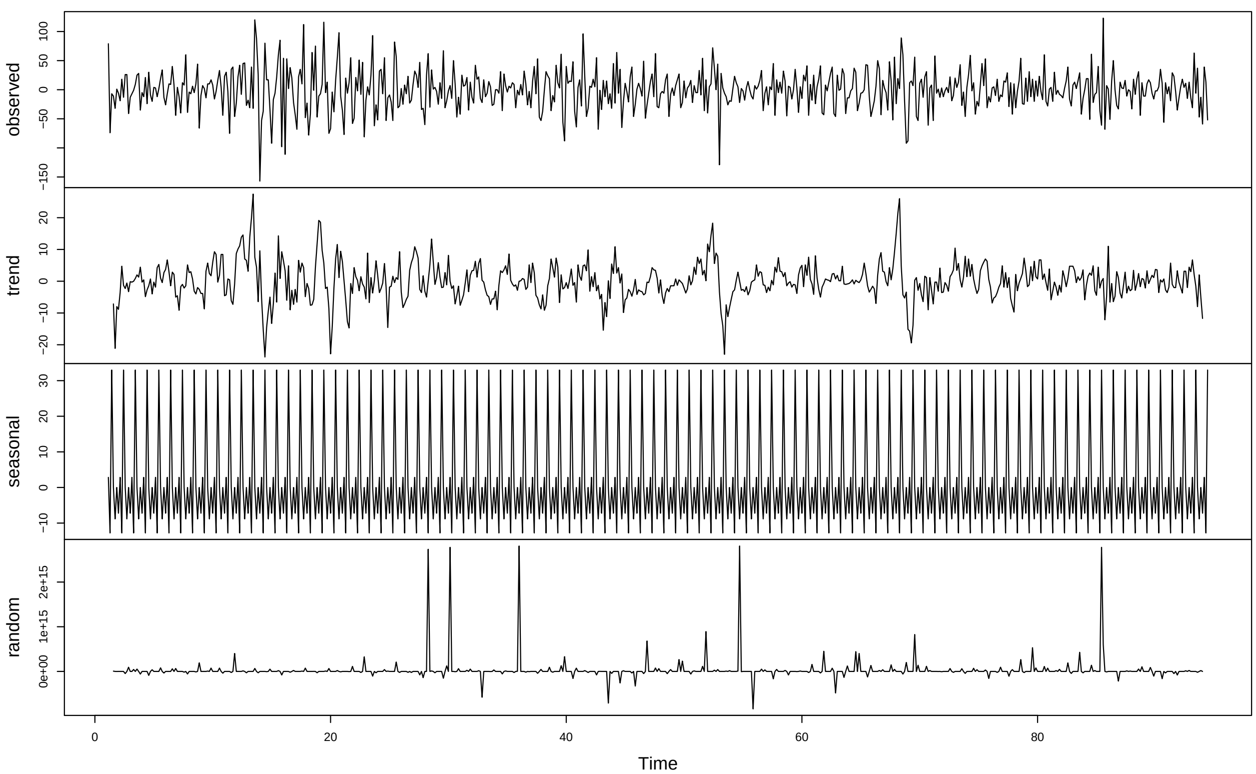


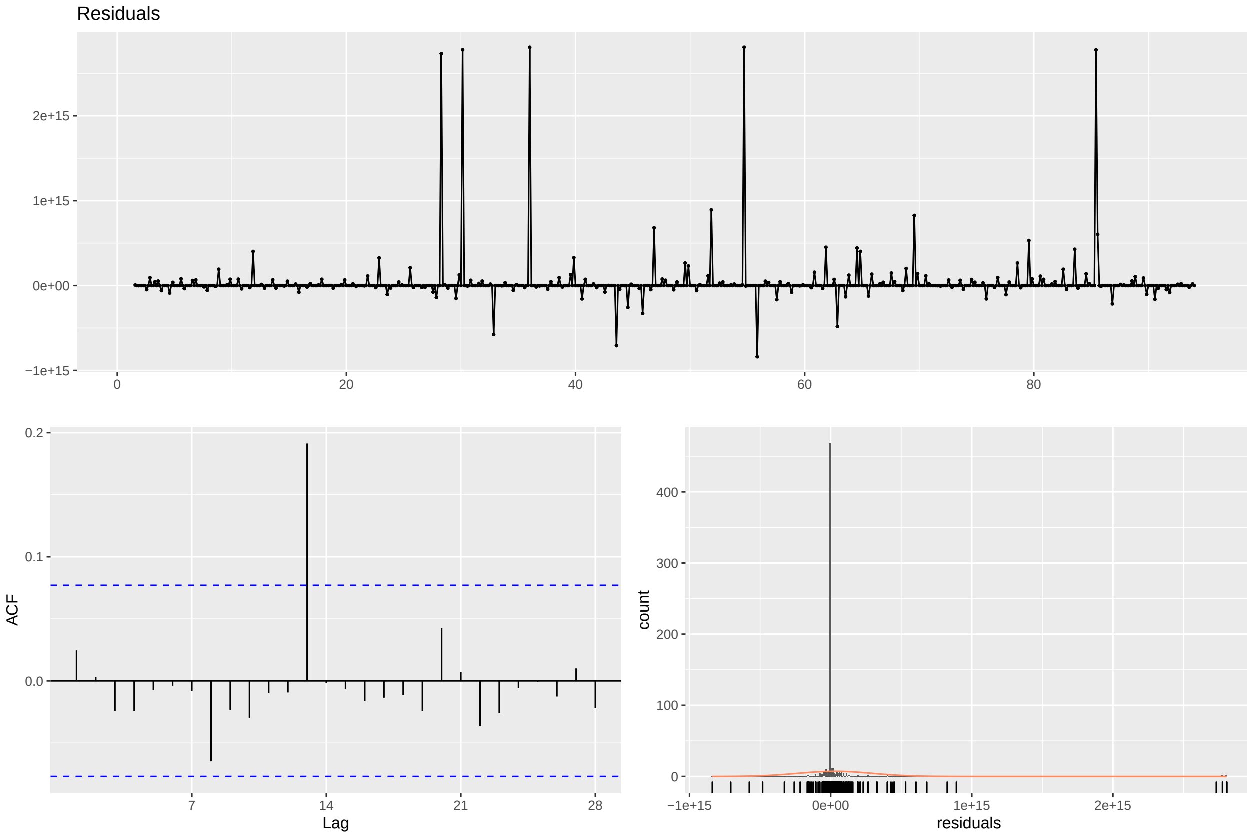
5 Removing seasonality

A good idea is to differenciate before decomposing. With the multiplicative model



Decomposition of multiplicative time series

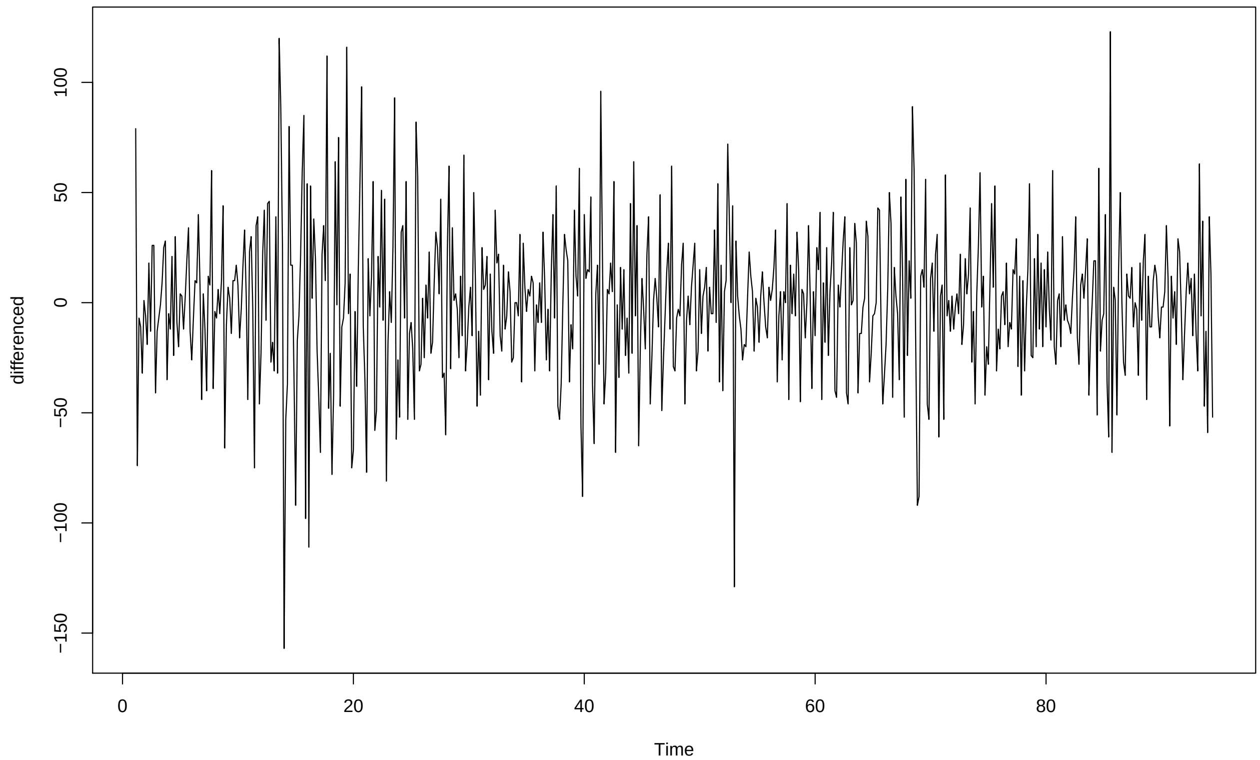


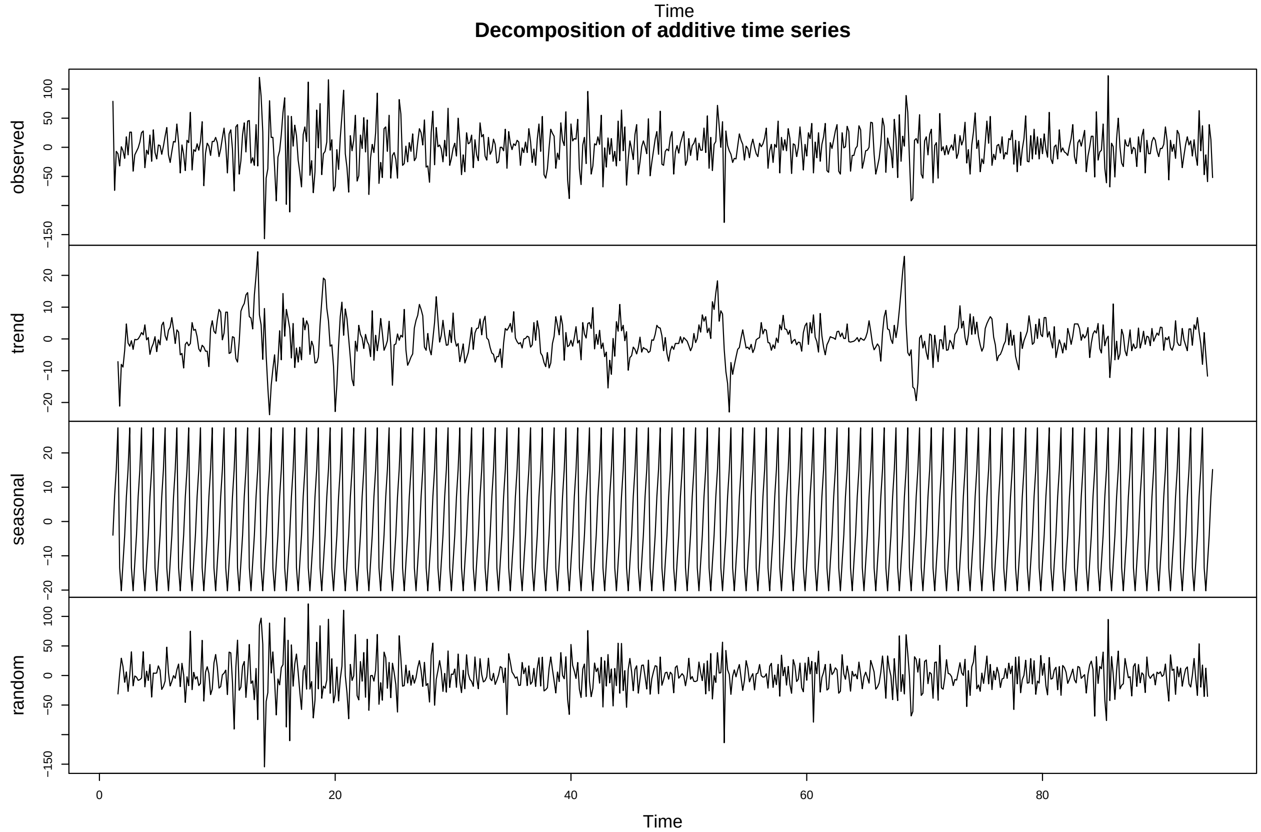


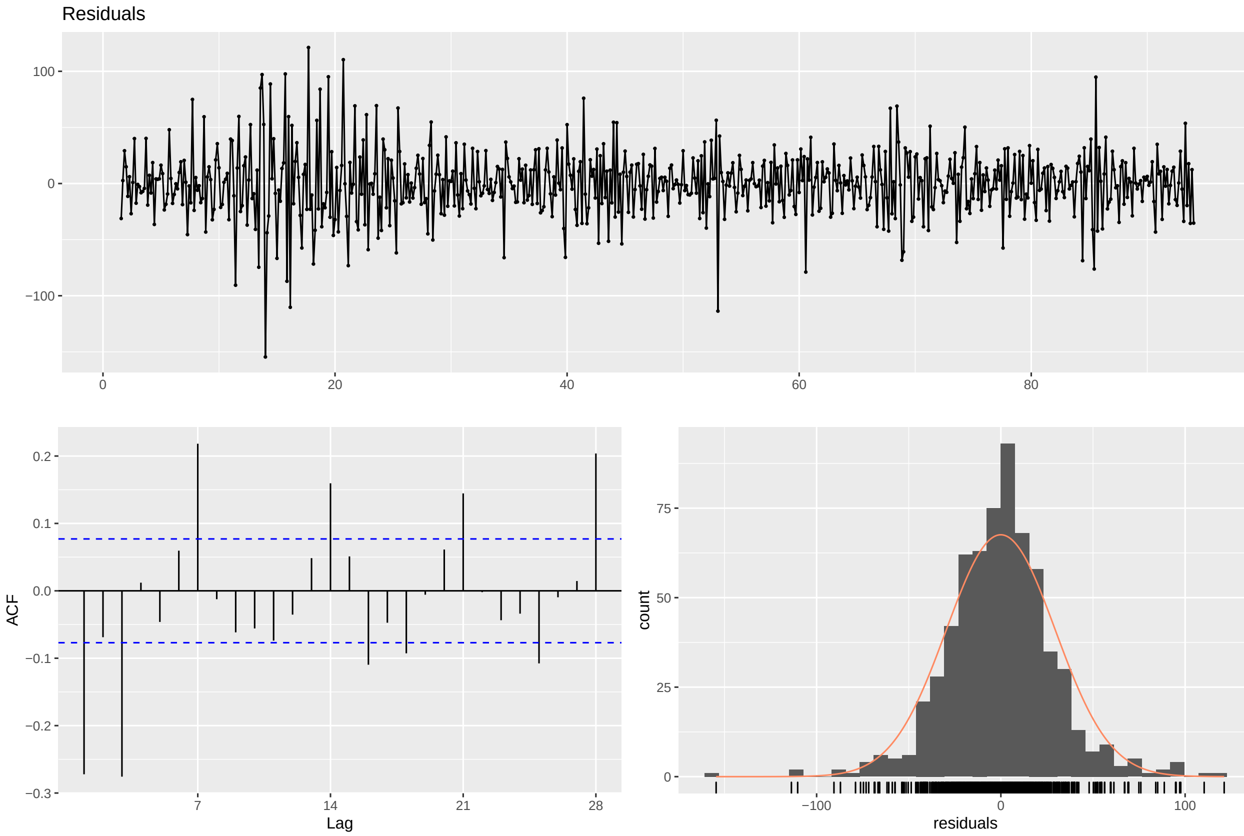

```
##
##  Box-Pierce test
##
## data:  decomposed$random
## X-squared = 1.1981, df = 5, p-value = 0.9451
```

```
##
##  Box-Ljung test
##
## data:  decomposed$random
## X-squared = 1.2068, df = 5, p-value = 0.9442
```

With the additive model This model doesn’t work at all


differenced
Time
100
50
0
−50
−100
−150
0
20
40
60
80

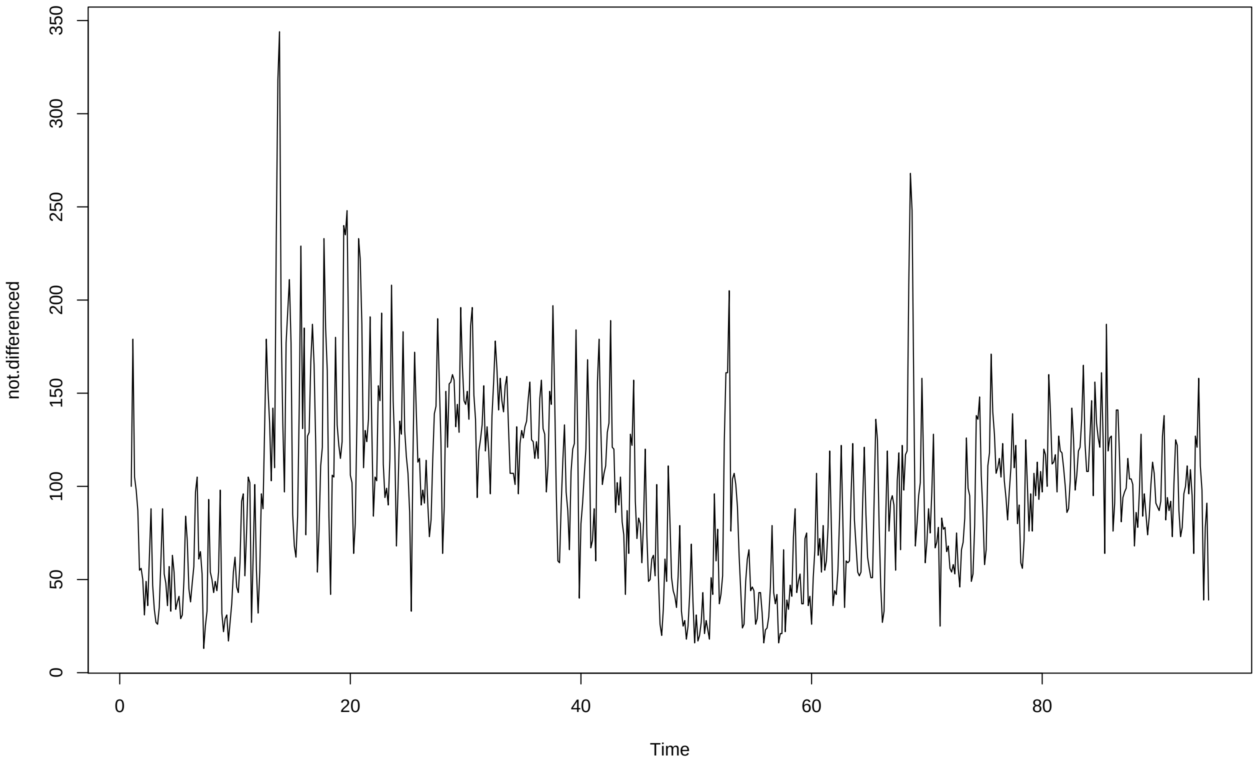

Decomposition of additive time series
observed
trend
seasonal
random
Time

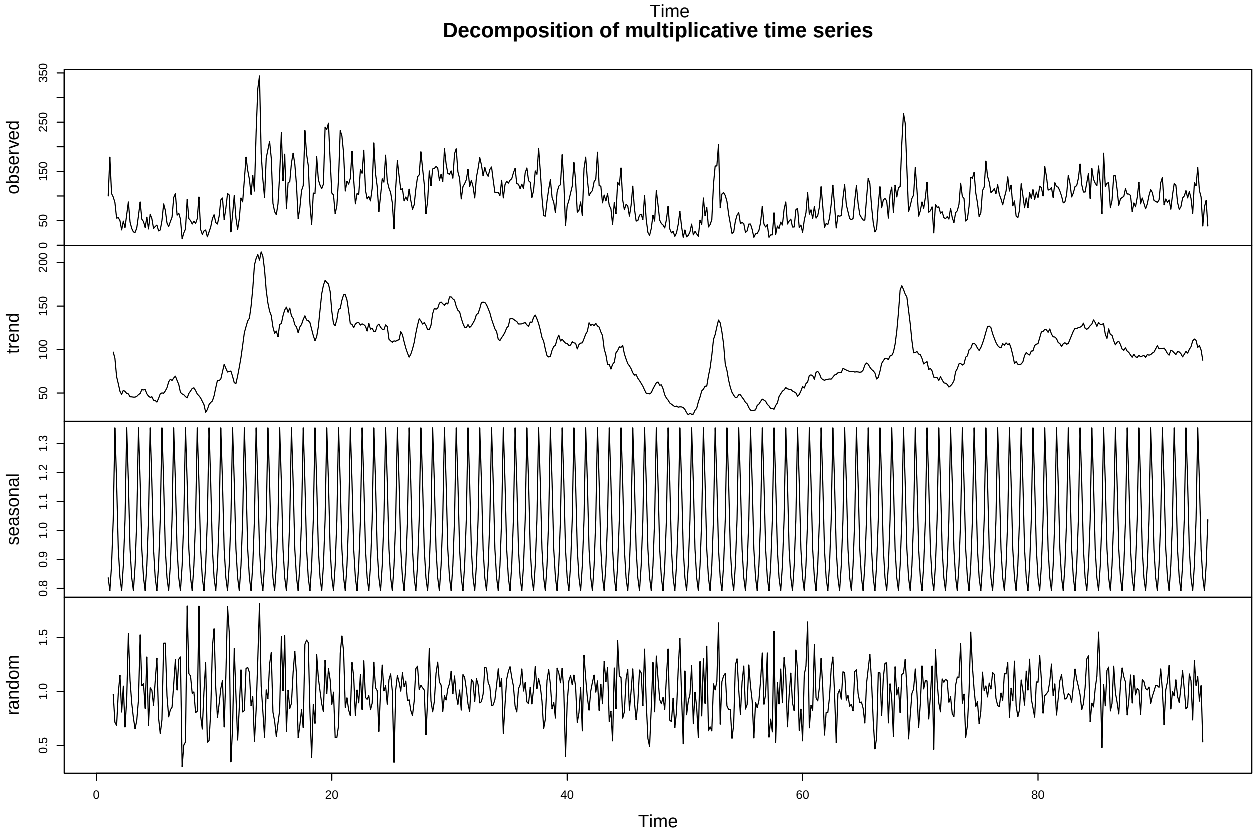


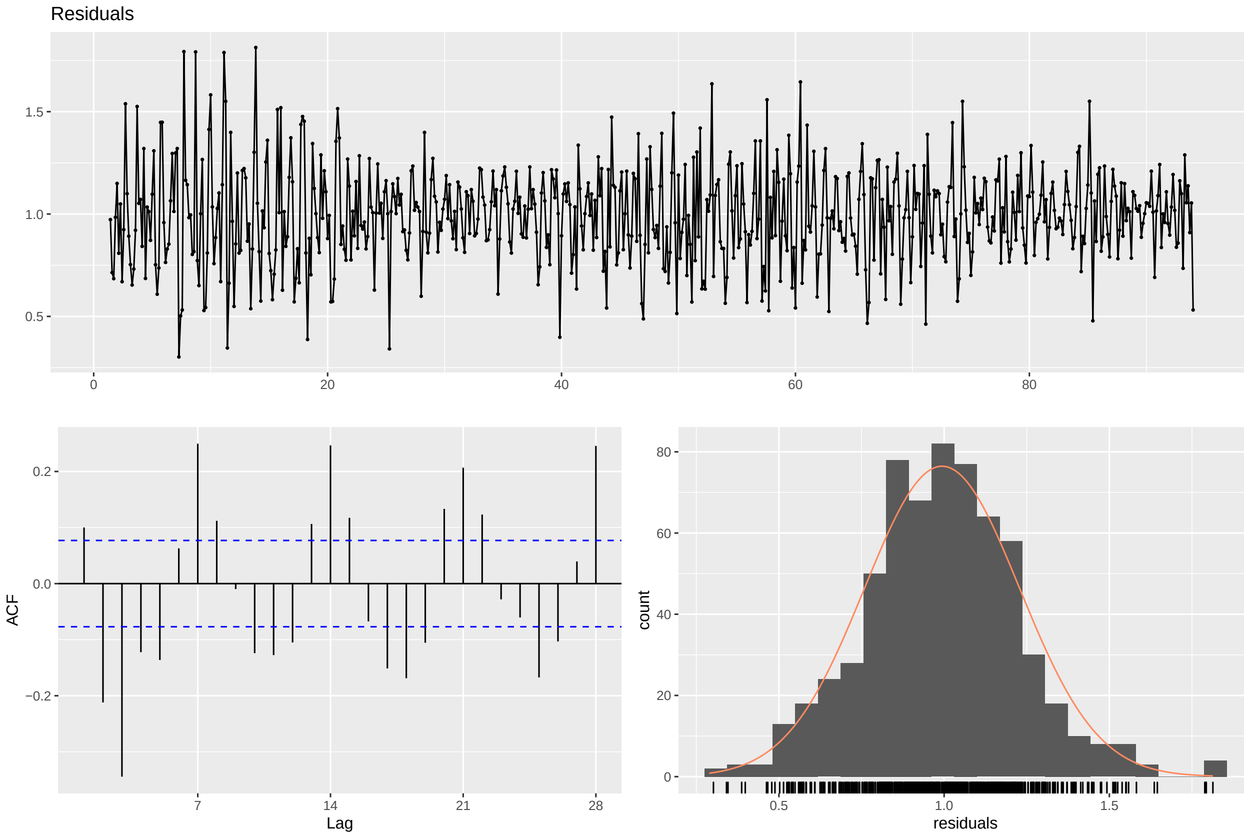

```
##
##  Box-Pierce test
##
## data:  decomposed$random
## X-squared = 101.8, df = 5, p-value < 2.2e-16
```

```
##
##  Box-Ljung test
##
## data:  decomposed$random
## X-squared = 102.44, df = 5, p-value < 2.2e-16
```

Without the first differentiation the result will have been much worse:


not.differenced
Time
0
50
100
150
200
250
300
350
0
20
40
60
80


Decomposition of multiplicative time series
observed
trend
seasonal
random
Time

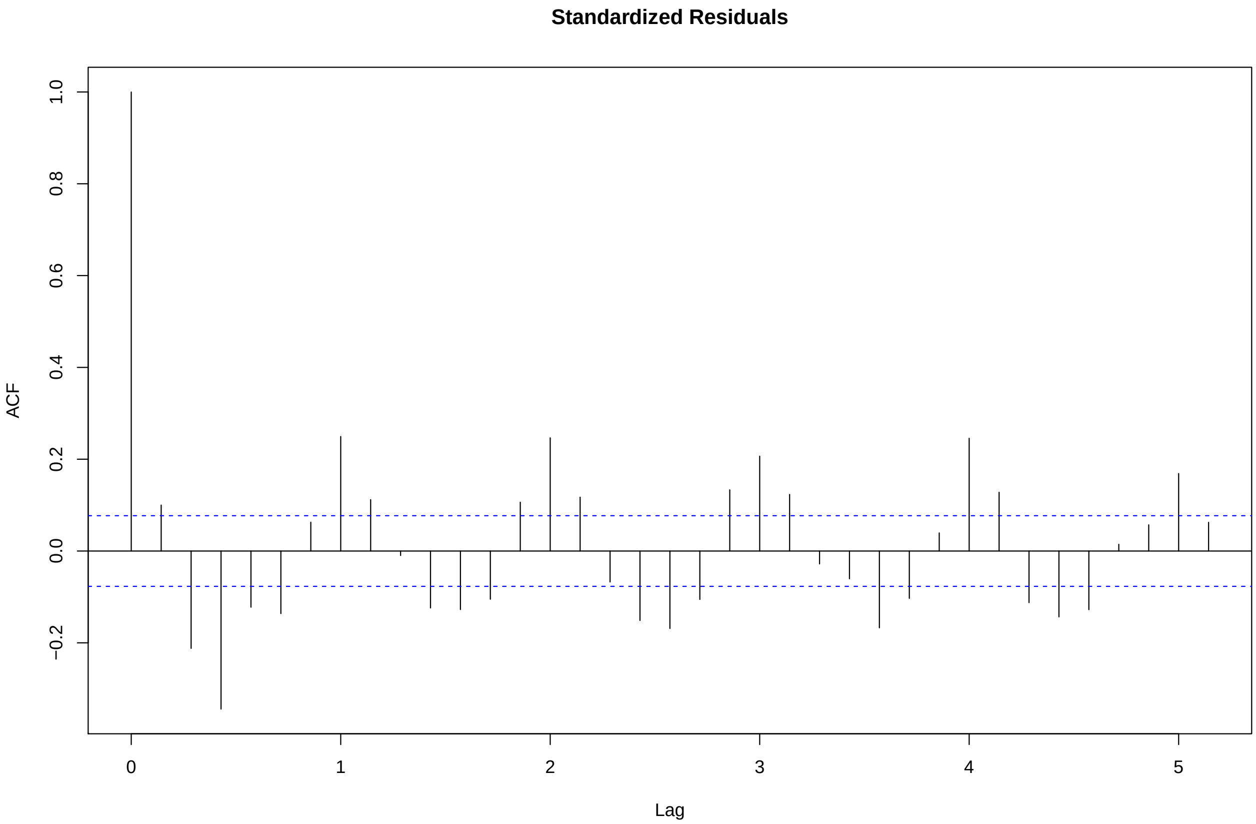


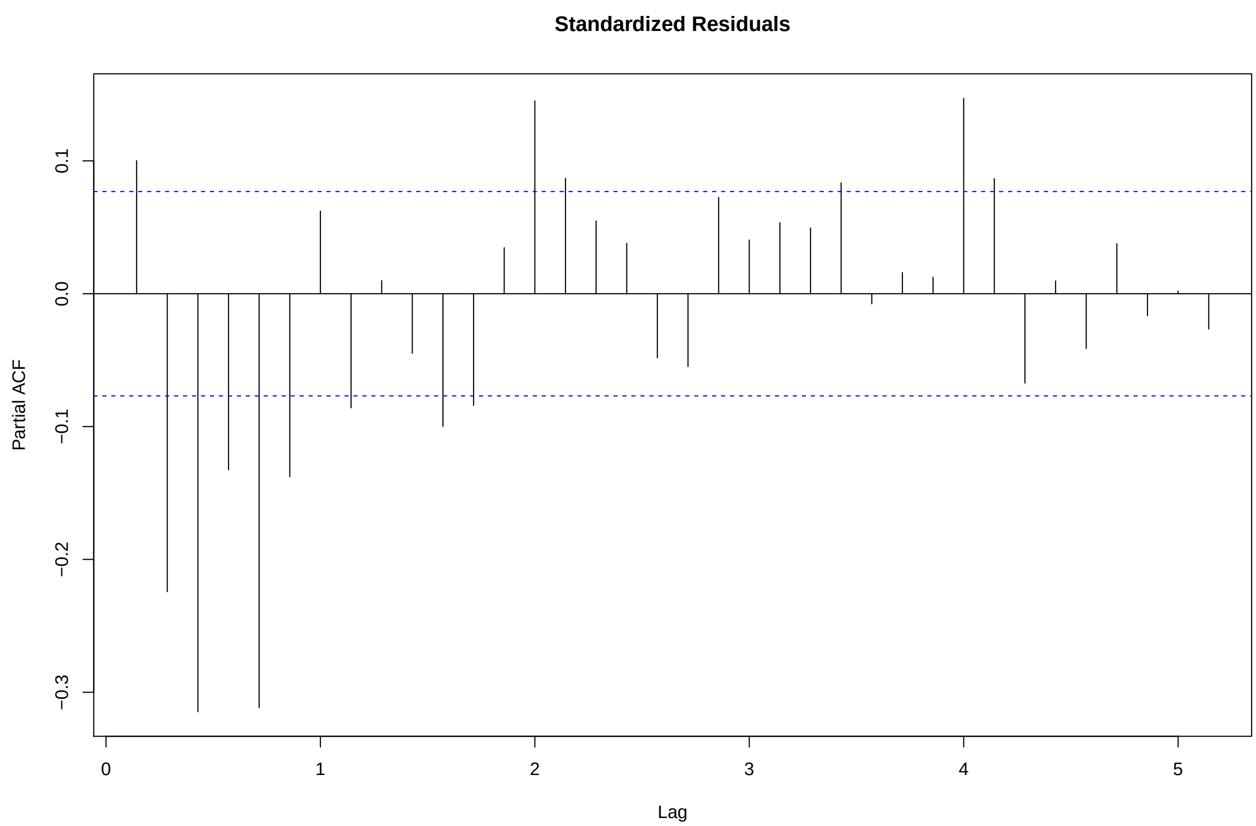

```
##
##  Box-Pierce test
##
## data:  decomposed$random
## X-squared = 134.37, df = 5, p-value < 2.2e-16
```

```
##
##  Box-Ljung test
##
## data:  decomposed$random
## X-squared = 135.4, df = 5, p-value < 2.2e-16
```

Every 7 lags the peak recurs

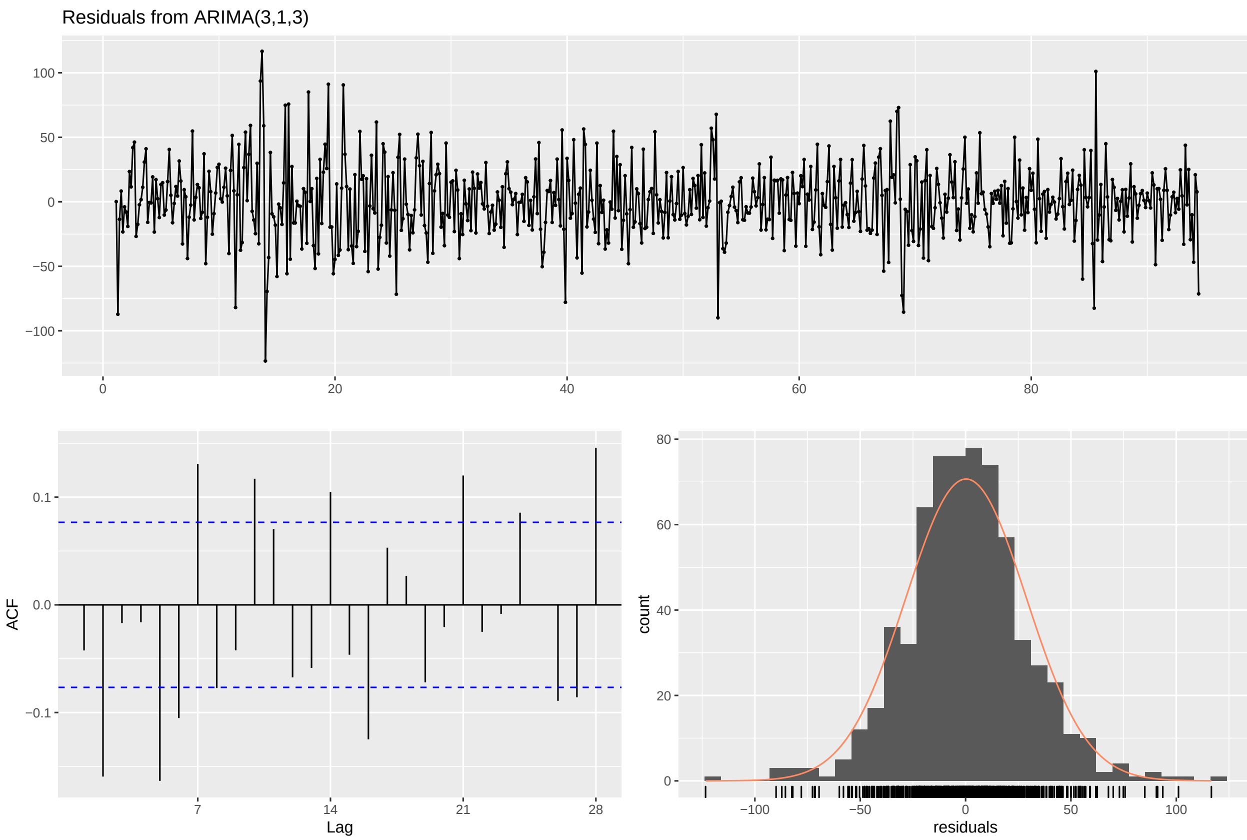
6 Check Residuals





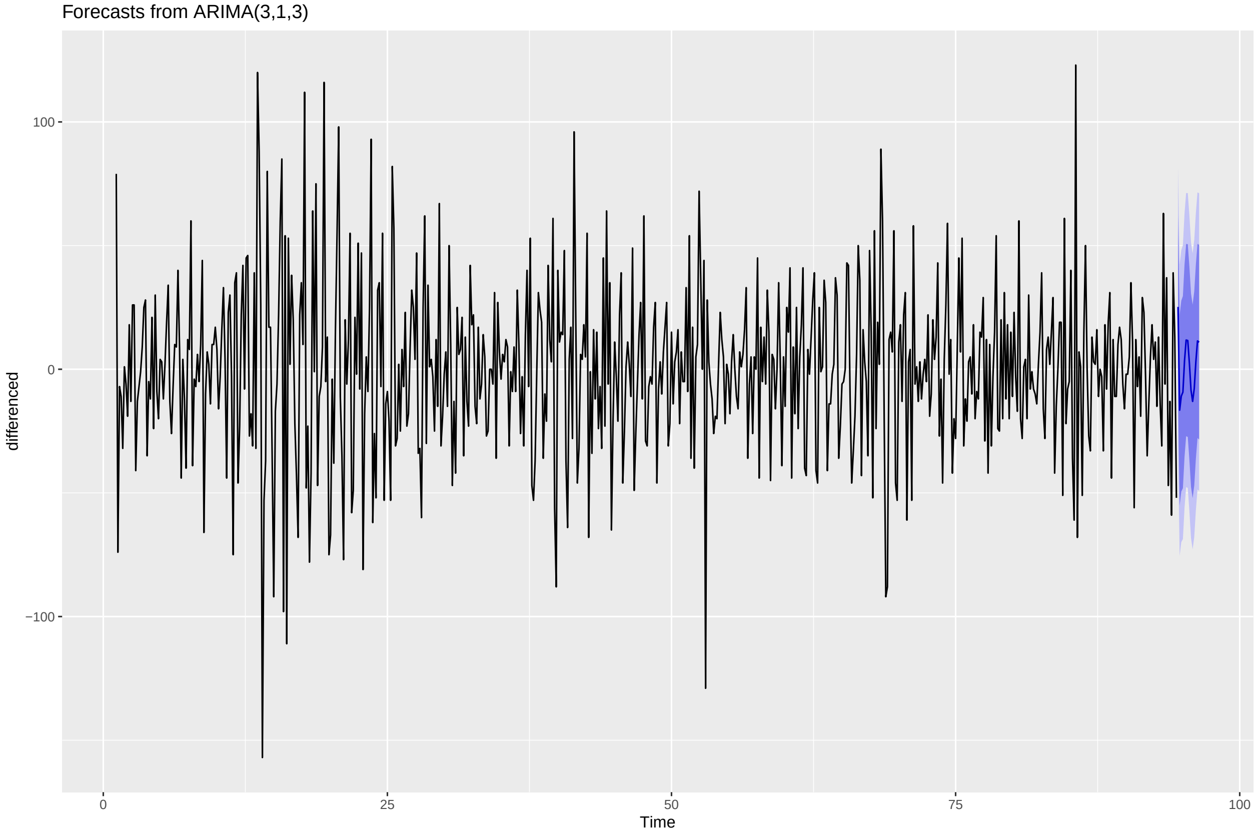
7 Arima

```
## Series: differenced
## ARIMA(3,1,3)
##
## Coefficients:
##          ar1      ar2      ar3      ma1     ma2      ma3
##       0.8858  -0.5556  -0.3444  -2.1937  2.0793  -0.8856
## s.e.  0.0407   0.0494   0.0389   0.0211  0.0424   0.0267
##
## sigma^2 estimated as 825:  log likelihood=-3120.88
## AIC=6255.75   AICc=6255.93   BIC=6287.12
##
## Training set error measures:
##                     ME     RMSE      MAE MPE MAPE      MASE        ACF1
## Training set 0.2368323 28.56859 21.52922 NaN  Inf 0.7603388 -0.04237868
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(3,1,3)
## Q* = 84.817, df = 8, p-value = 5.218e-15
##
```

```
## Model df: 6.   Total lags used: 14
```

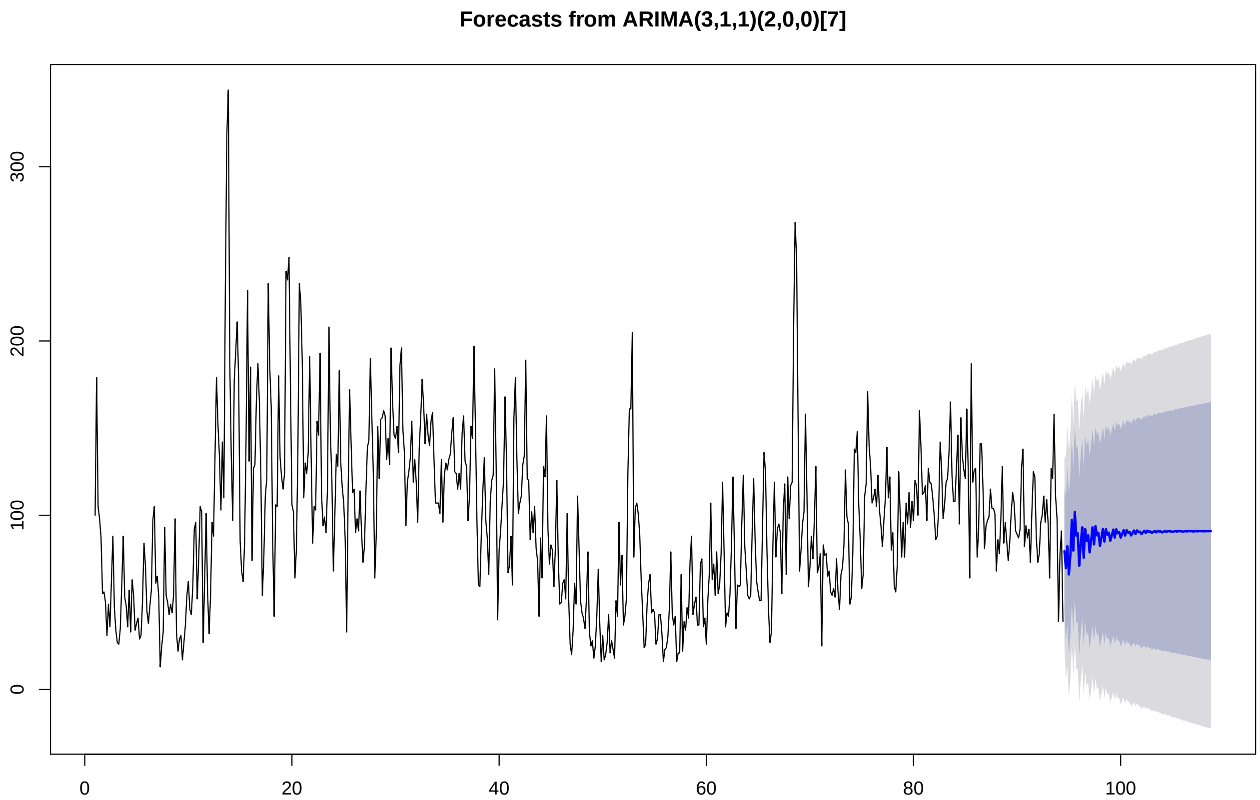


8 Auto Arima

```
##
##  Fitting models using approximations to speed things up...
##
##  ARIMA(2,1,2)(1,0,1)[7] with drift         : Inf
##  ARIMA(0,1,0)           with drift         : 6473.005
##  ARIMA(1,1,0)(1,0,0)[7] with drift         : 6346.759
##  ARIMA(0,1,1)(0,0,1)[7] with drift         : 6395.033
##  ARIMA(0,1,0)                              : 6466.527
##  ARIMA(1,1,0)           with drift         : 6469
##  ARIMA(1,1,0)(2,0,0)[7] with drift         : 6306.944
##  ARIMA(1,1,0)(2,0,1)[7] with drift         : Inf
##  ARIMA(1,1,0)(1,0,1)[7] with drift         : Inf
##  ARIMA(0,1,0)(2,0,0)[7] with drift         : 6343.017
##  ARIMA(2,1,0)(2,0,0)[7] with drift         : 6312.557
##  ARIMA(1,1,1)(2,0,0)[7] with drift         : 6244.129
##  ARIMA(1,1,1)(1,0,0)[7] with drift         : 6286.522
##  ARIMA(1,1,1)(2,0,1)[7] with drift         : Inf
##  ARIMA(1,1,1)(1,0,1)[7] with drift         : Inf
```

```
##  ARIMA(0,1,1)(2,0,0)[7] with drift         : 6298.145
##  ARIMA(2,1,1)(2,0,0)[7] with drift         : 6238.386
##  ARIMA(2,1,1)(1,0,0)[7] with drift         : 6264.384
##  ARIMA(2,1,1)(2,0,1)[7] with drift         : Inf
##  ARIMA(2,1,1)(1,0,1)[7] with drift         : Inf
##  ARIMA(3,1,1)(2,0,0)[7] with drift         : 6234.382
##  ARIMA(3,1,1)(1,0,0)[7] with drift         : 6258.62
##  ARIMA(3,1,1)(2,0,1)[7] with drift         : Inf
##  ARIMA(3,1,1)(1,0,1)[7] with drift         : Inf
##  ARIMA(3,1,0)(2,0,0)[7] with drift         : 6300.76
##  ARIMA(4,1,1)(2,0,0)[7] with drift         : Inf
##  ARIMA(3,1,2)(2,0,0)[7] with drift         : 6240.819
##  ARIMA(2,1,2)(2,0,0)[7] with drift         : 6243.815
##  ARIMA(4,1,0)(2,0,0)[7] with drift         : 6291.779
##  ARIMA(4,1,2)(2,0,0)[7] with drift         : Inf
##  ARIMA(3,1,1)(2,0,0)[7]                    : 6227.929
##  ARIMA(3,1,1)(1,0,0)[7]                    : 6252.359
##  ARIMA(3,1,1)(2,0,1)[7]                    : Inf
##  ARIMA(3,1,1)(1,0,1)[7]                    : Inf
##  ARIMA(2,1,1)(2,0,0)[7]                    : 6232.056
##  ARIMA(3,1,0)(2,0,0)[7]                    : 6294.277
##  ARIMA(4,1,1)(2,0,0)[7]                    : 6234.823
##  ARIMA(3,1,2)(2,0,0)[7]                    : 6234.373
##  ARIMA(2,1,0)(2,0,0)[7]                    : 6306.074
##  ARIMA(2,1,2)(2,0,0)[7]                    : 6237.558
##  ARIMA(4,1,0)(2,0,0)[7]                    : 6285.297
##  ARIMA(4,1,2)(2,0,0)[7]                    : Inf
##
##  Now re-fitting the best model(s) without approximations...
##
##  ARIMA(3,1,1)(2,0,0)[7]                    : 6244.074
##
##  Best model: ARIMA(3,1,1)(2,0,0)[7]
```

```
## Series: data.ts
## ARIMA(3,1,1)(2,0,0)[7]
##
## Coefficients:
##          ar1     ar2      ar3      ma1    sar1    sar2
##       0.5742  0.1332  -0.1068  -0.9754  0.3347  0.2233
## s.e.  0.0404  0.0473   0.0411   0.0128  0.0402  0.0416
##
## sigma^2 estimated as 769.1:  log likelihood=-3099.35
## AIC=6212.69   AICc=6212.87   BIC=6244.07
```

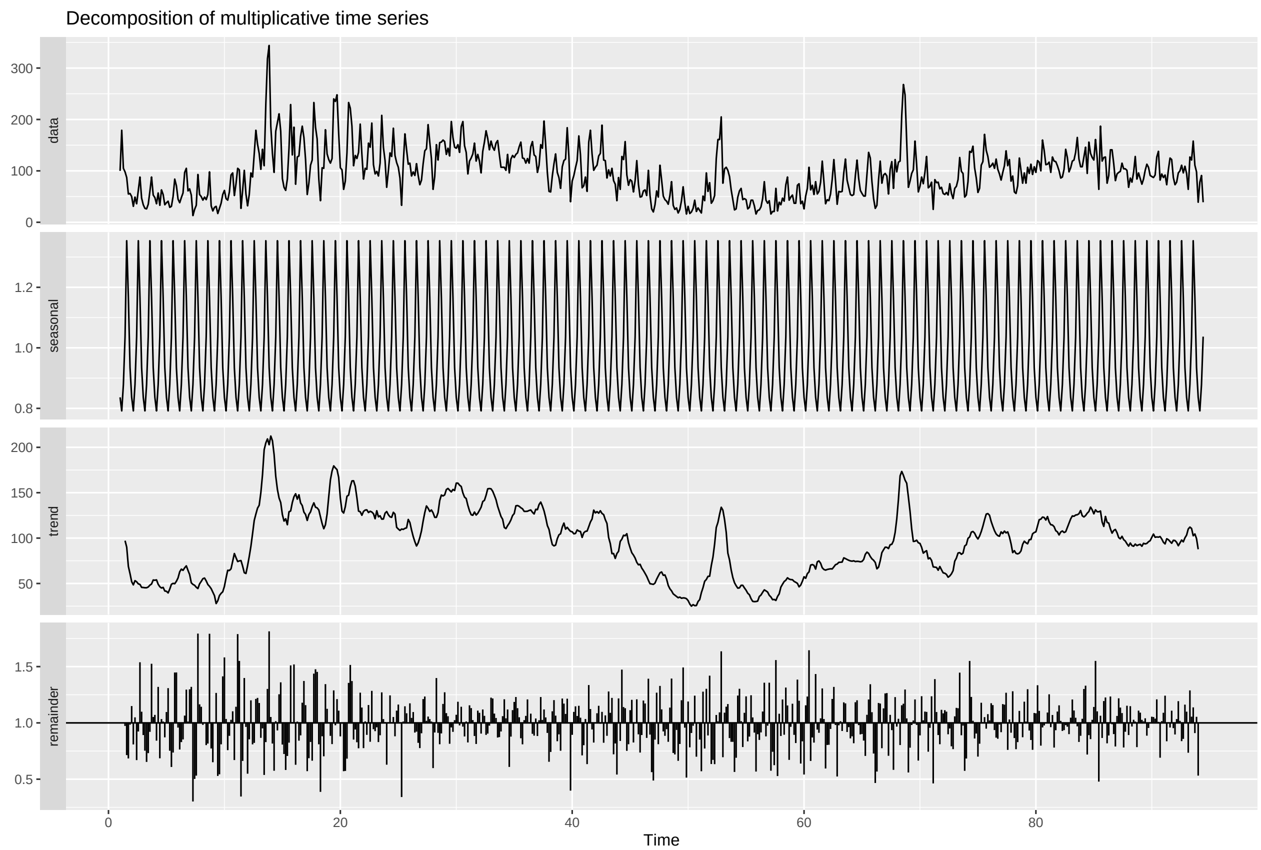


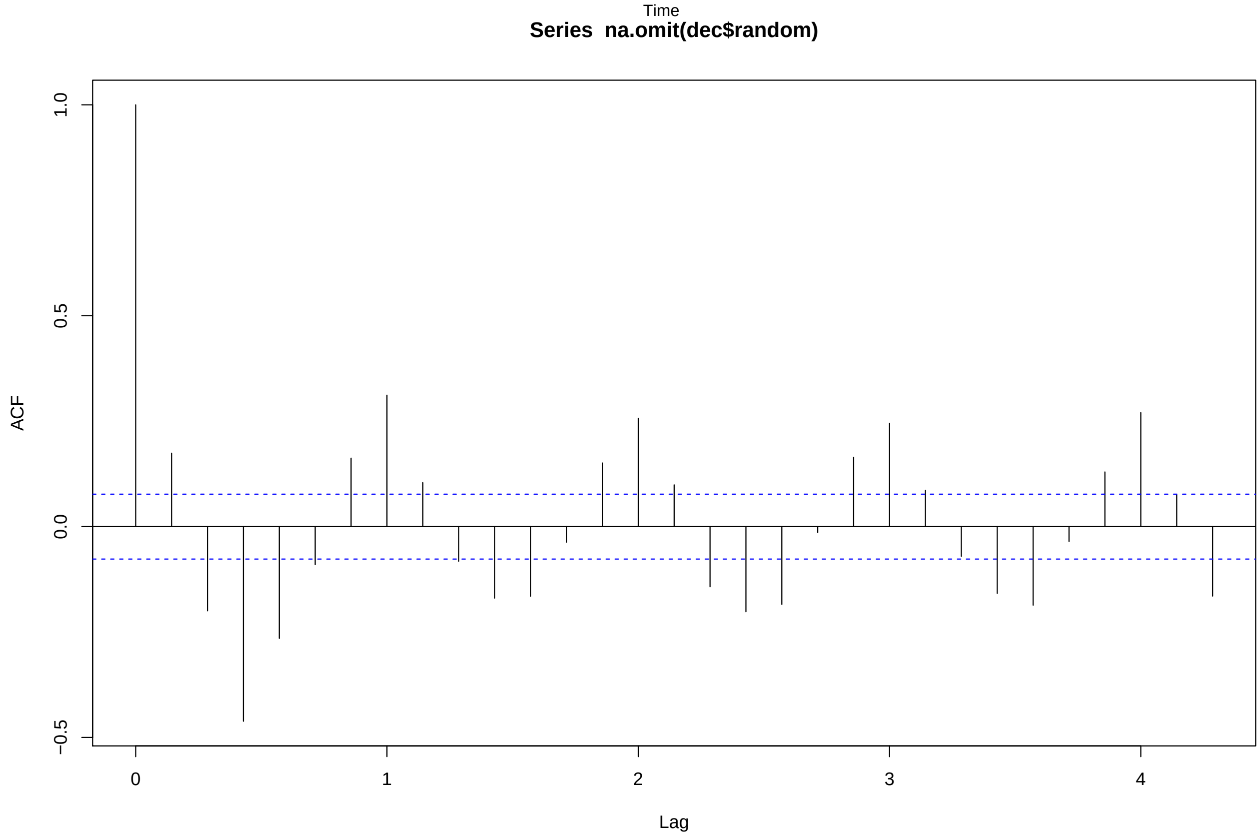
The plot is not good but AIC and BIC are very high, we should try with a multi seasonal decomposition

```
## [1] 7
```

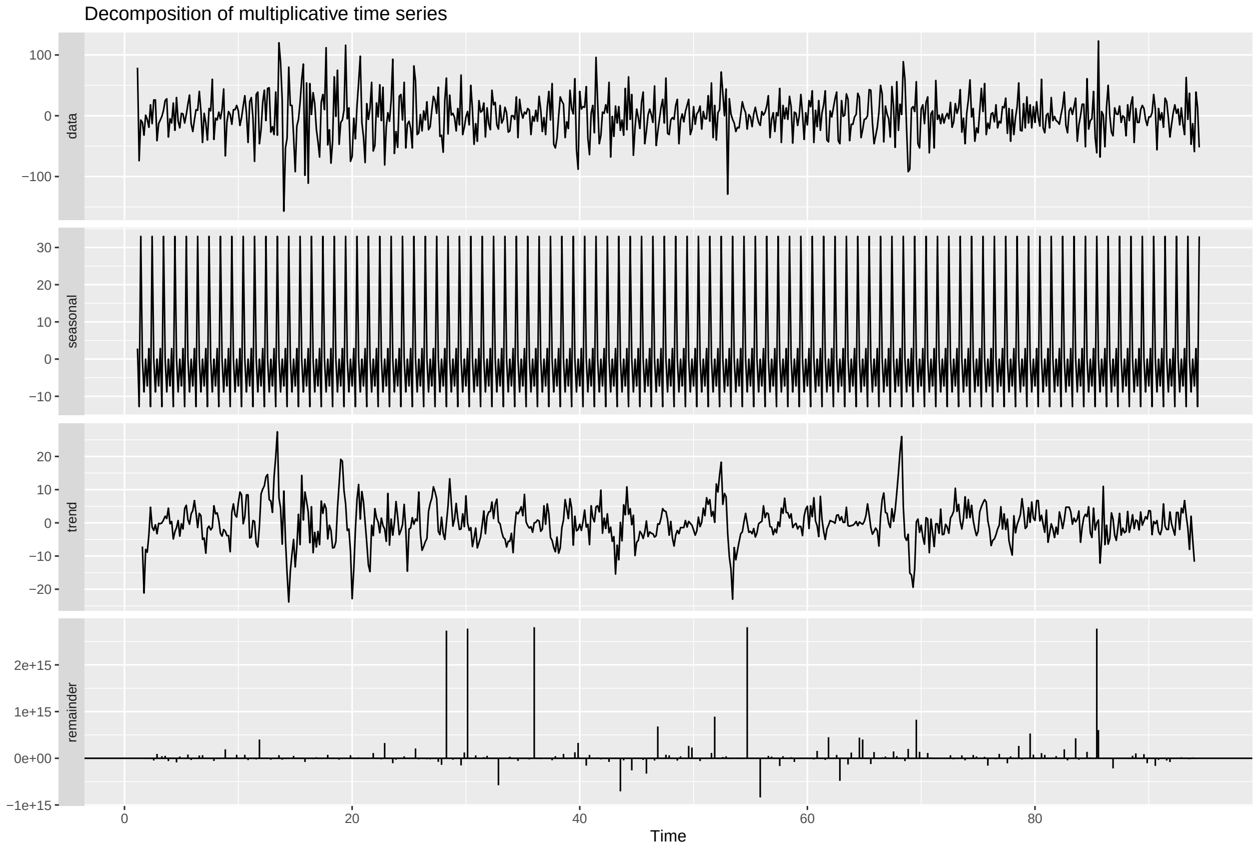
9 Searching for multi seasonalities

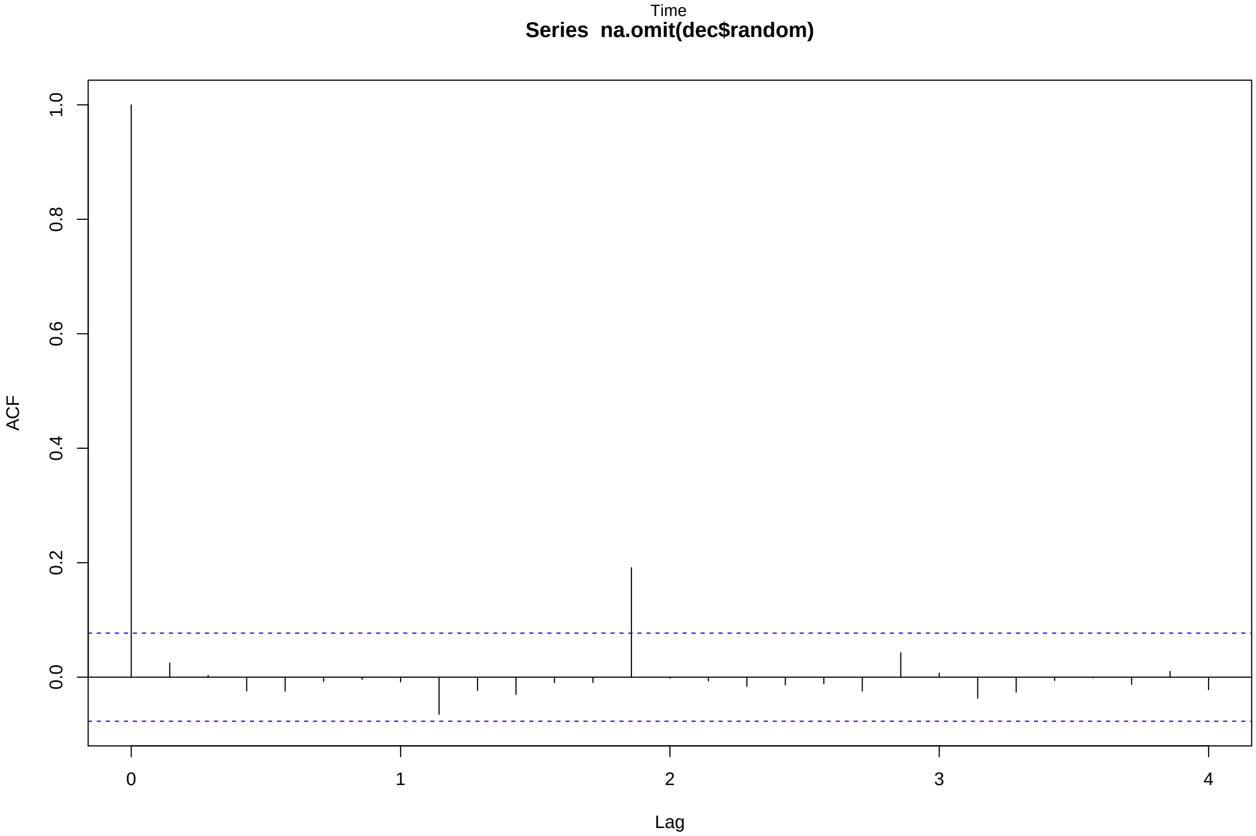
without differentiation residuals looks pretty bad





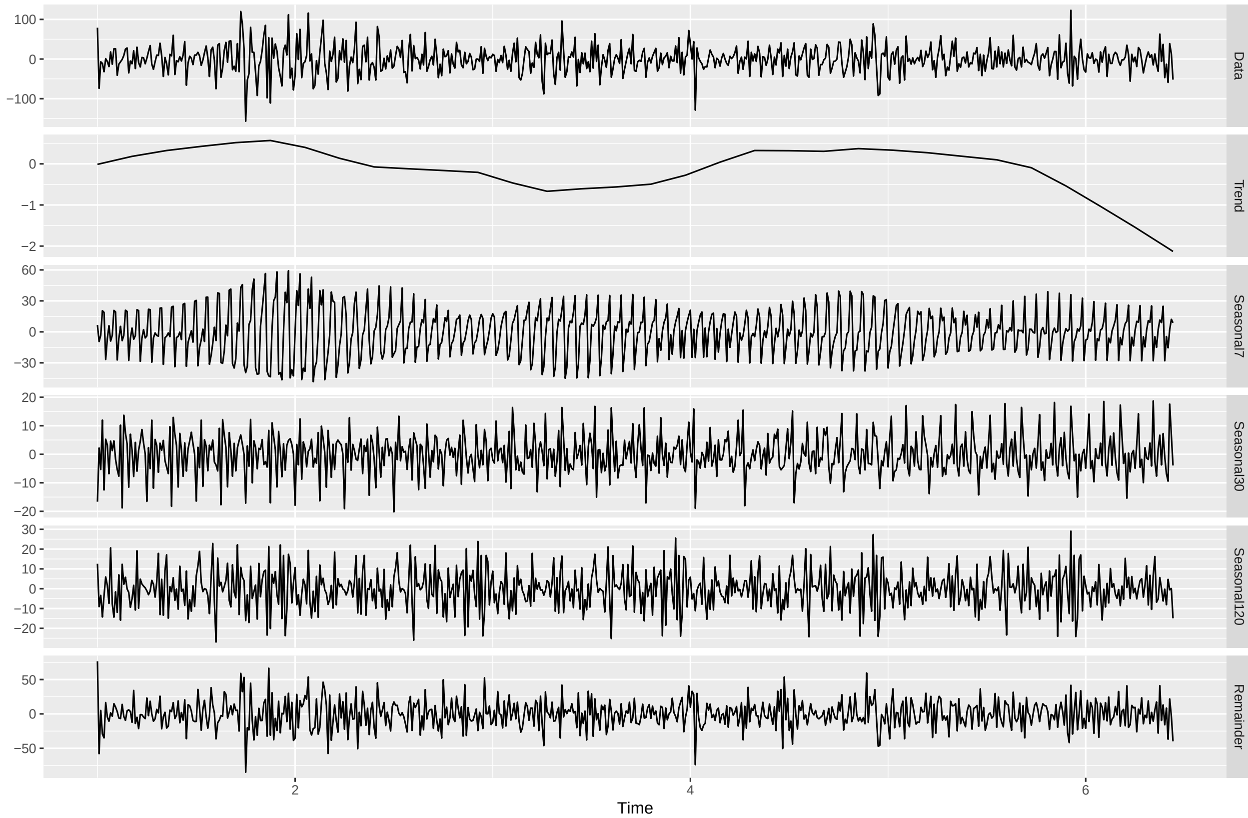
trying with differentiation and a multiplicative model:

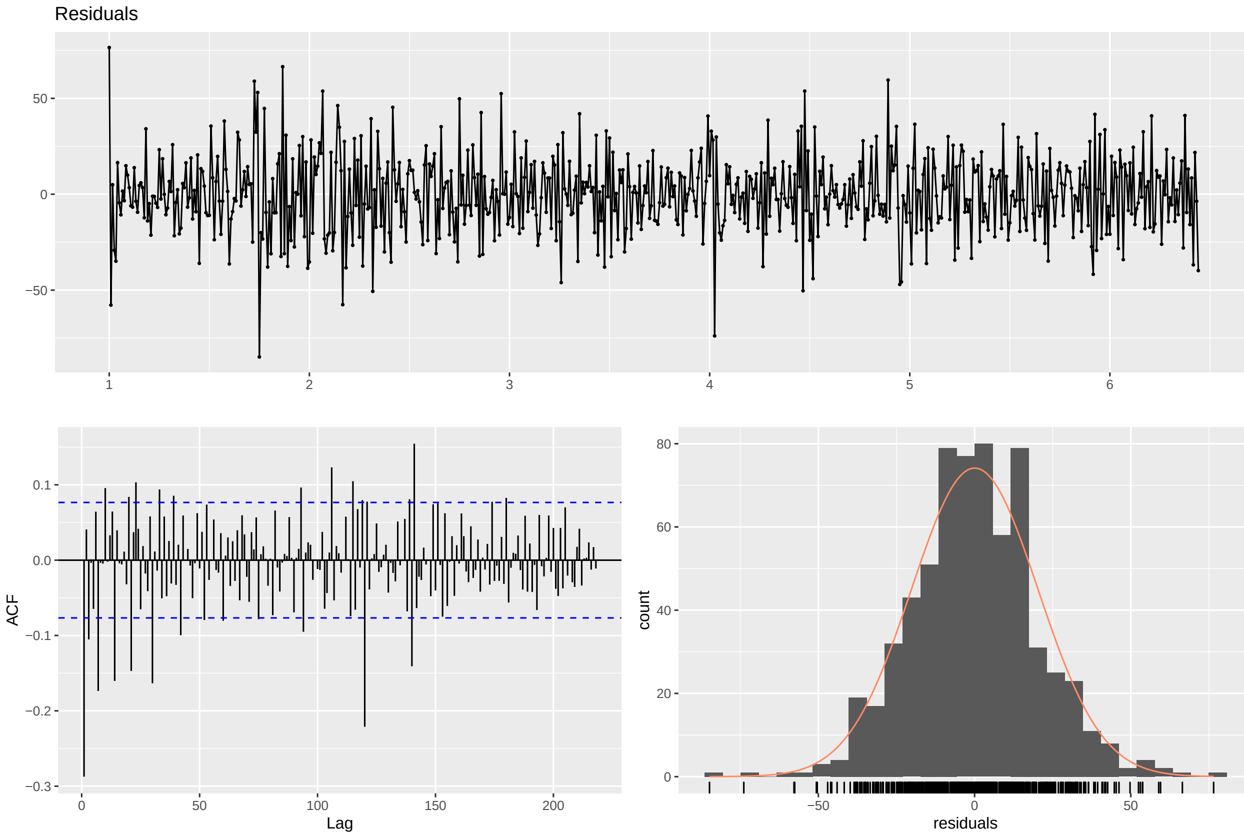




Looks better than before but we can still see every 5(*7) a seasonality/trend left. 5*7 is about a month, probably there is a monthly seasonality

10 Transforming into msts






```
##
##  Box-Pierce test
##
## data:  remainder(decomposed)
## X-squared = 65.062, df = 5, p-value = 1.088e-12
```

```
##
##  Box-Ljung test
##
## data:  remainder(decomposed)
## X-squared = 65.402, df = 5, p-value = 9.248e-13
```

11 Conclusions

It was really interesting!

12 TODO

prima diff, poi prima diff seasonal, check acf pacf, check no trend(trend se con decadono a 0 velocemente) identificare i picchi identificare l estate doppia seasonality una settimanale e una annuale ARCH GARCH VAR<—- stabilizzare con trasformazioni