Spatio-Temporal Data Analysis Project

2020-04-25

1 Patterns in foreign sims connected to OpenWiFi-Milan

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2 Loading the Data

```r
setwd("~/Documents/GitHub/STDA-project-proposal")
set.seed(25061997)

require(zoo)
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```r
require(xts)
```

```
## Loading required package: xts
```

```r
data <- read.csv("sims2018milan.csv",sep = ";")
data <- rbind(data, read.csv("foreignsim_2019-11-07.csv",sep = ";"))

data$prefix <- NULL
data$country <- NULL
data$num <- NULL
data$total.ita.sim <- NULL

ll <- aggregate.data.frame(data$total.foreign.sim,by=list(data$date),FUN=mean)
names(ll)[2] <- "total.foreign.sim"
names(ll)[1] <- "Date"
data <- ll

data <- data[-c(656,657,658), ]
```

3 Exploration of the Data

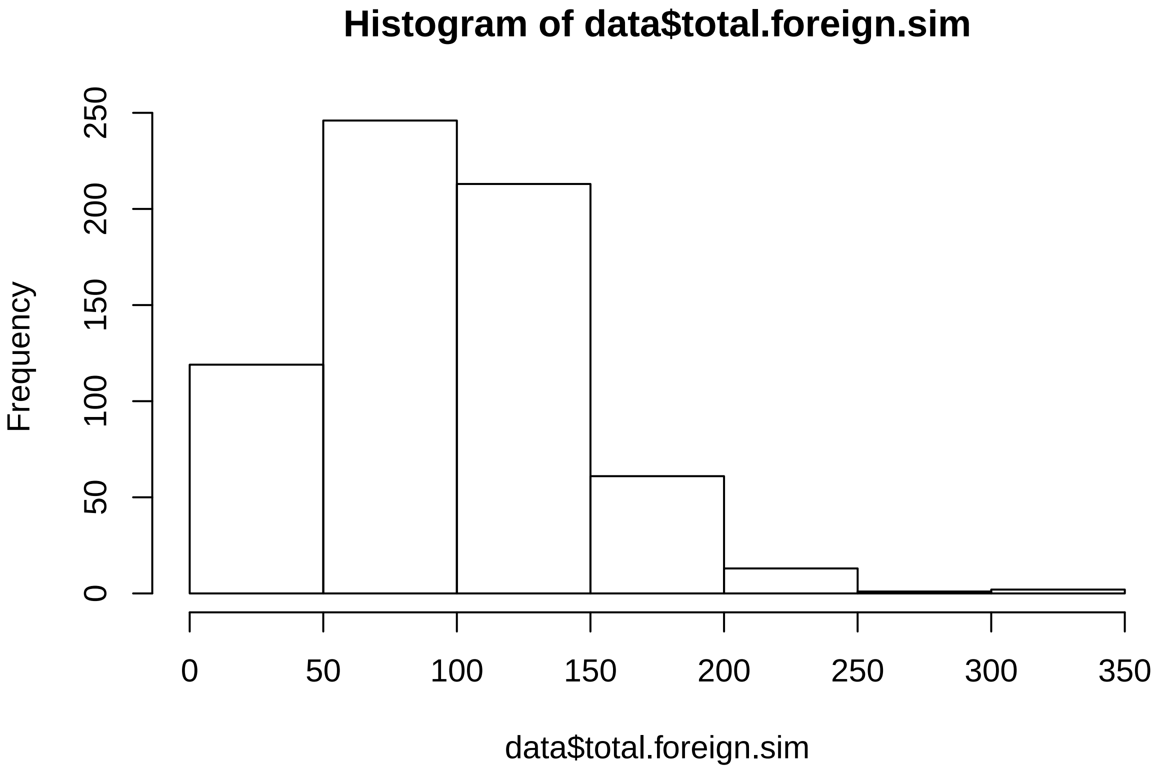
```r
print("minimum, lower-hinge, median, upper-hinge, maximum)")
```

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

```r
fivenum(data$total.foreign.sim)
```

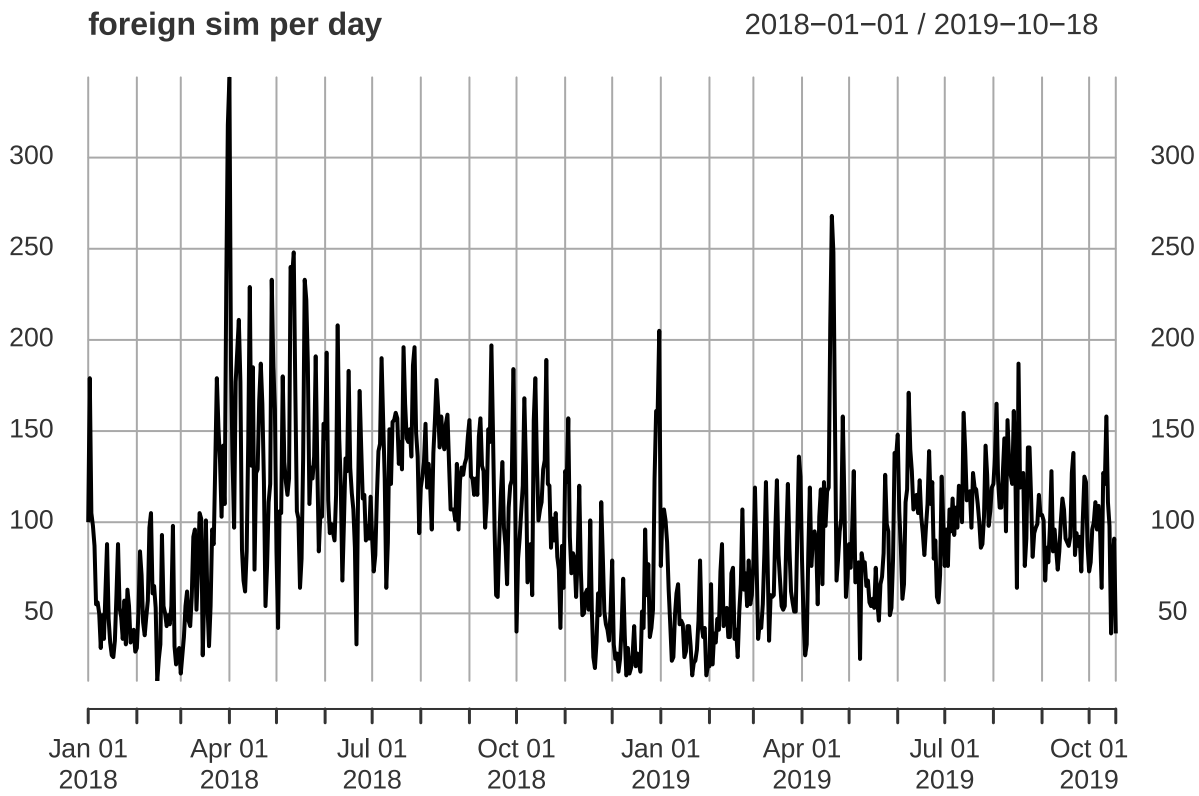
```
## [1]  13  59  95 124 344
```

```r
hist(data$total.foreign.sim)
```



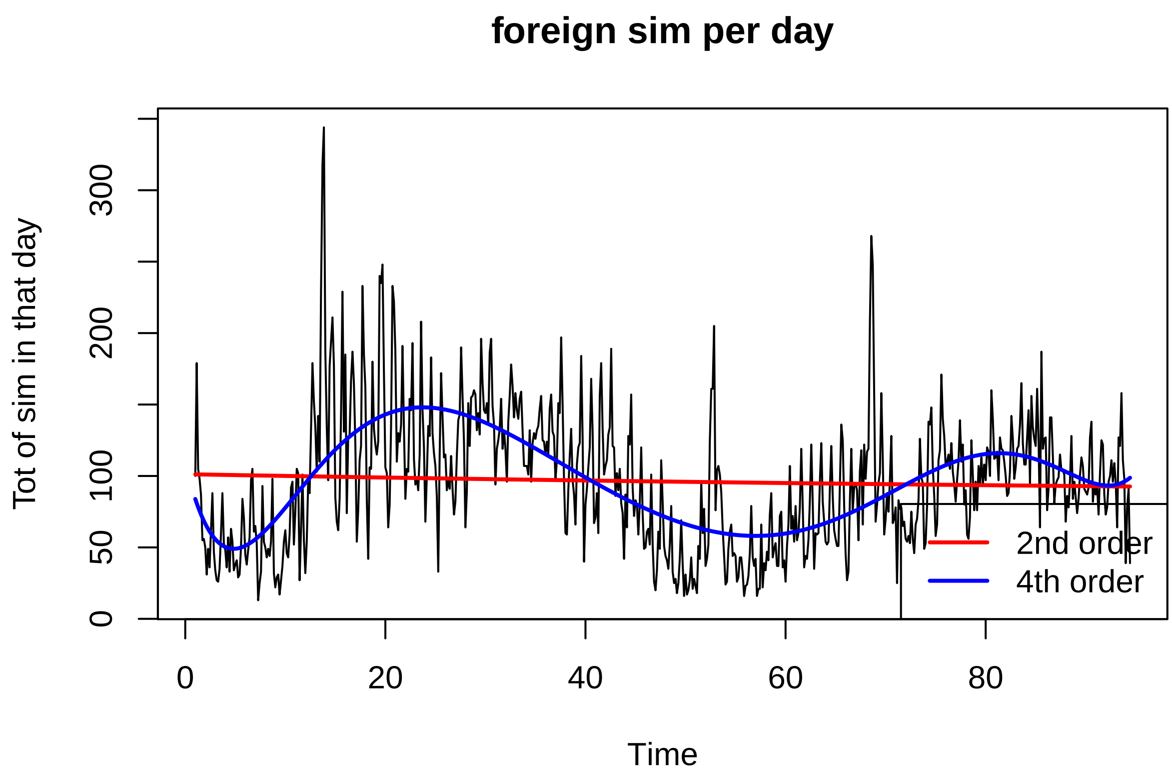
We loaded the dataset from the various datasets aggregating into only one dataset with 655 rows representing 2 years of data gathered. Starting from 01.01.2018 to 30.10.2019. Data is here sette

```
data$Date <- as.Date(data$Date, format = "%Y-%m-%d")
#typeof(data$date[1])
data.xts <- xts(data$total.foreign.sim, order.by=data$Date, frequency = 7)
data.ts <- ts(data$total.foreign.sim, frequency = 7)

main <- "foreign sim per day"
ylab<-"Tot of sim in that day"
plot(data.xts,ylab=ylab,main=main)
```



4 Trend recognition

```
tt<-as.numeric(time(data.ts))
fit2<-lm(data.ts~poly(tt,degree=2,raw=TRUE))
fit4<-lm(data.ts~poly(tt,degree=8,raw=TRUE))

main <- "foreign sim per day"
plot(data.ts,ylab=ylab,main=main)
lines(tt,predict(fit2),col='red',lwd=2)
lines(tt,predict(fit4),col='blue',lwd=2)
legend("bottomright",legend = c("2nd order","4th order"),lwd=2,lty=1,col=c("red","blue"))
```

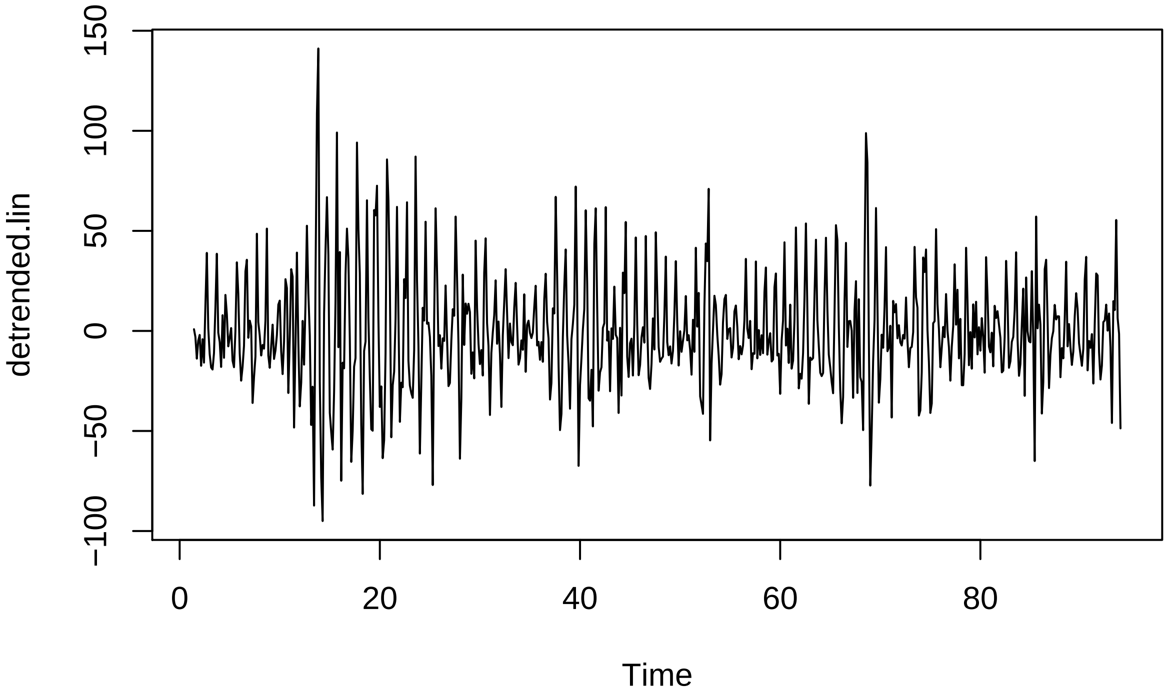


4.1 Detrending using LM

```
require(fpp)
```

```
## Loading required package: fpp

## Loading required package: forecast

## Warning: package 'forecast' was built under R version 3.6.2

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

## Loading required package: fma

## Loading required package: expsmooth

## Loading required package: lmtest

## Loading required package: tseries
```

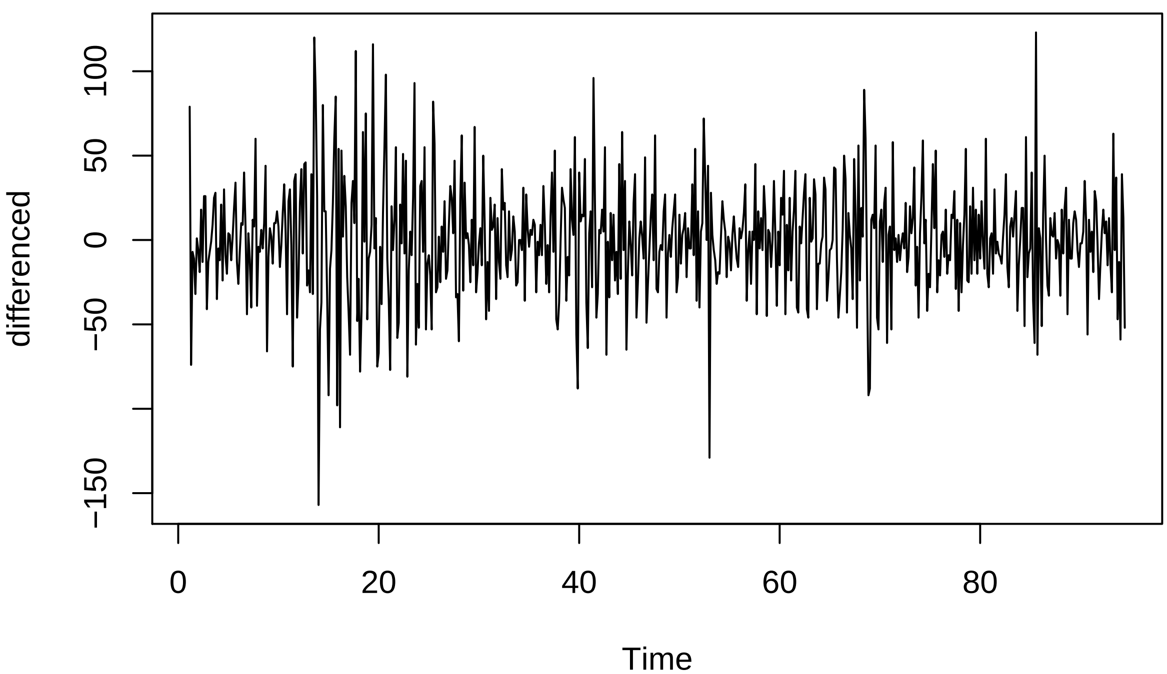
```
detrended.lin <- data.ts - ma(data.ts, order = 7, centre = T)
#detrended.lin <- data.ts - predict(fit4)
plot(detrended.lin)
```



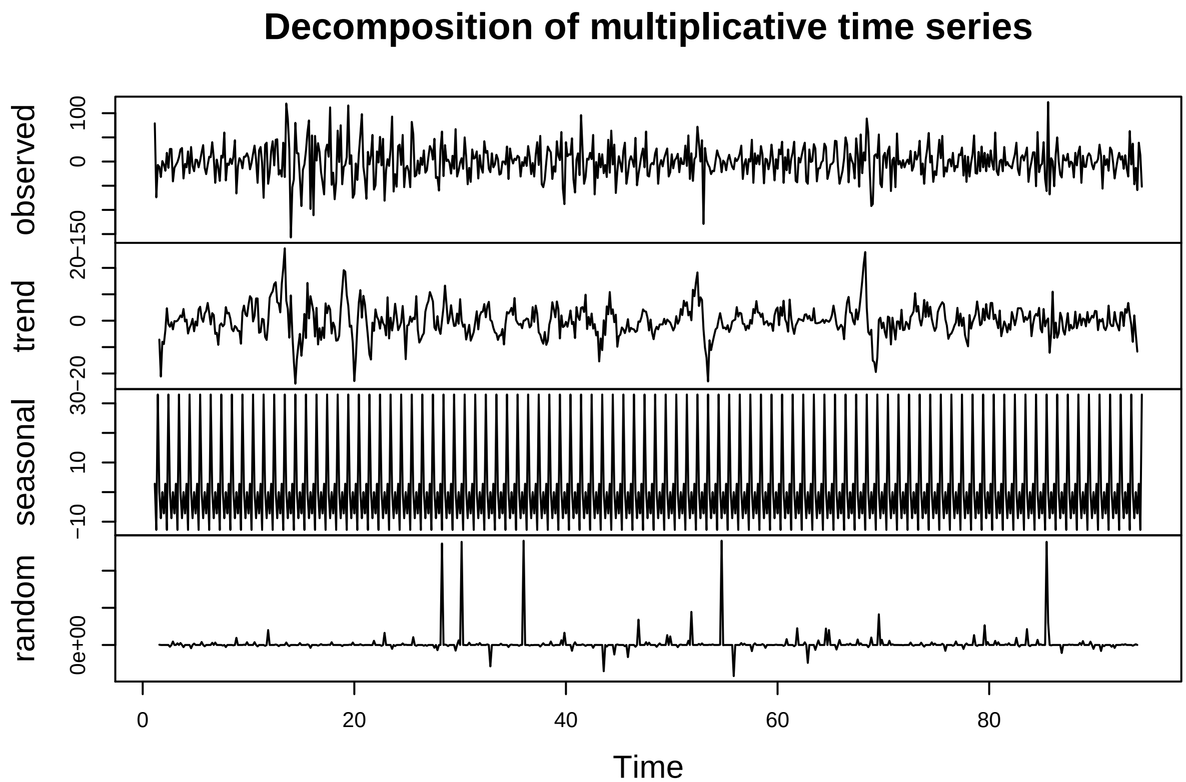
5 Removing seasonality

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

```
differenced <- diff(data.ts)
plot(differenced)
```

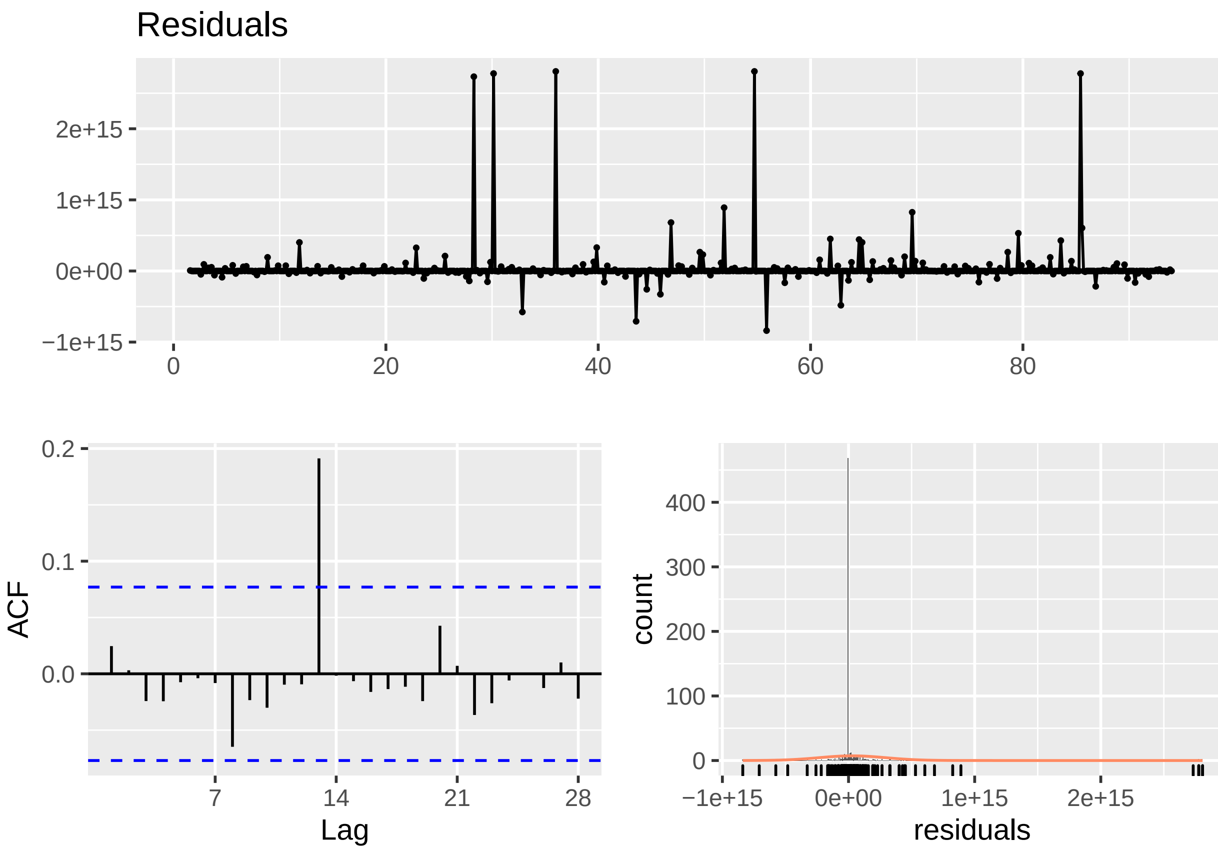



```
decomposed <- decompose(differenced,type = "multiplicative")
plot(decomposed)
```




```
checkresiduals(decomposed$random)
```

```
## Warning in modeldf.default(object): Could not find appropriate degrees of
## freedom for this model.
```




```r
Box.test(decomposed$random, lag=5, fitdf=0)
```

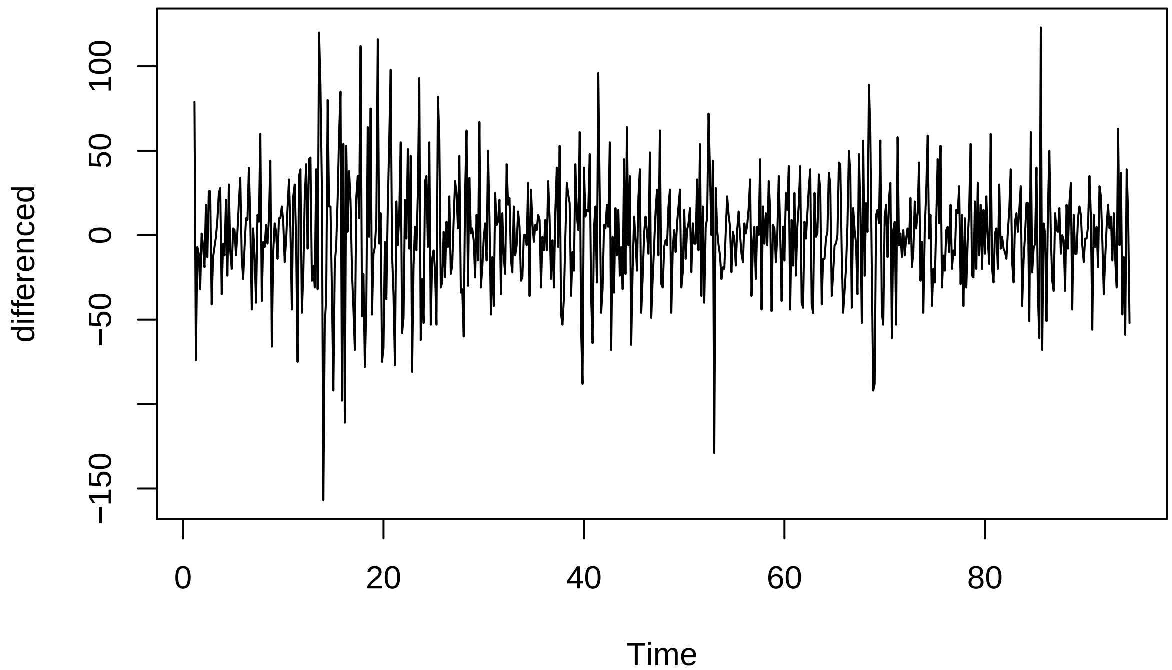
```
##
##  Box-Pierce test
##
## data:  decomposed$random
## X-squared = 1.1981, df = 5, p-value = 0.9451
```

```r
Box.test(decomposed$random, lag=5, fitdf=0, type="Lj")
```

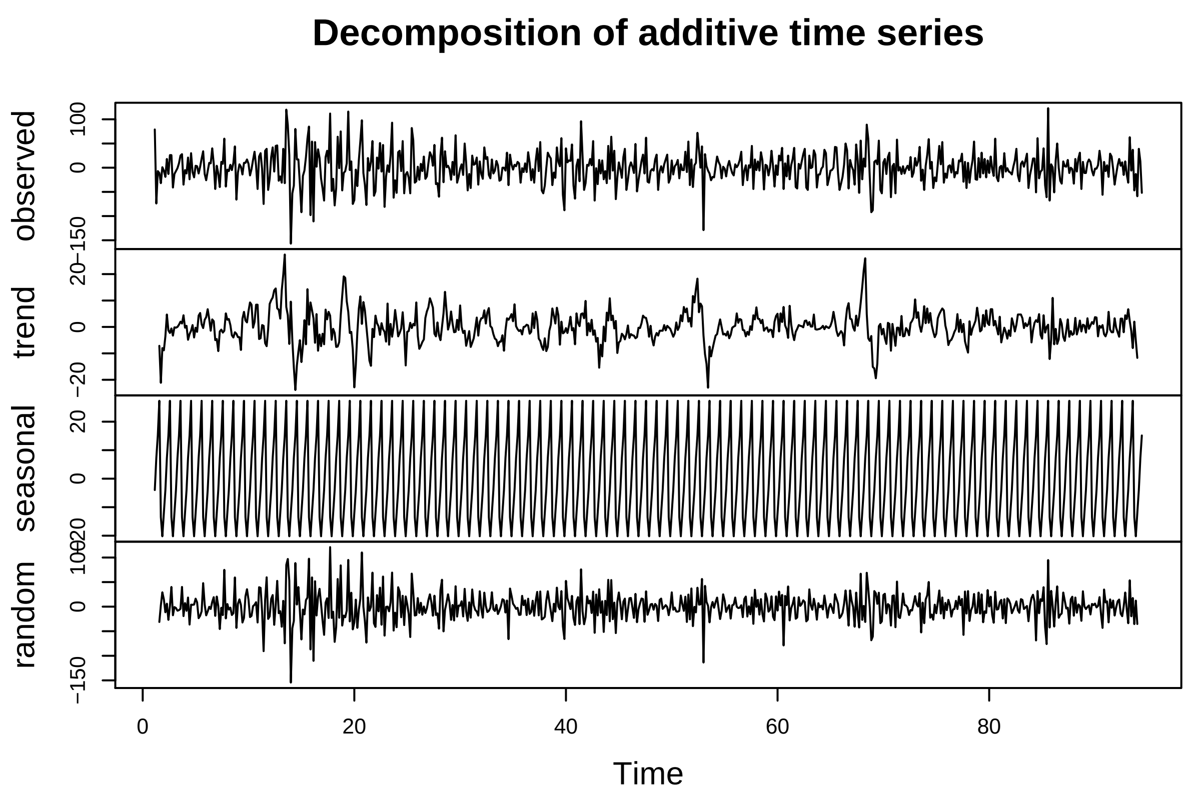
```
##
##  Box-Ljung test
##
## data:  decomposed$random
## X-squared = 1.2068, df = 5, p-value = 0.9442
```

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

```r
differenced <- diff(data.ts)
plot(differenced)
```

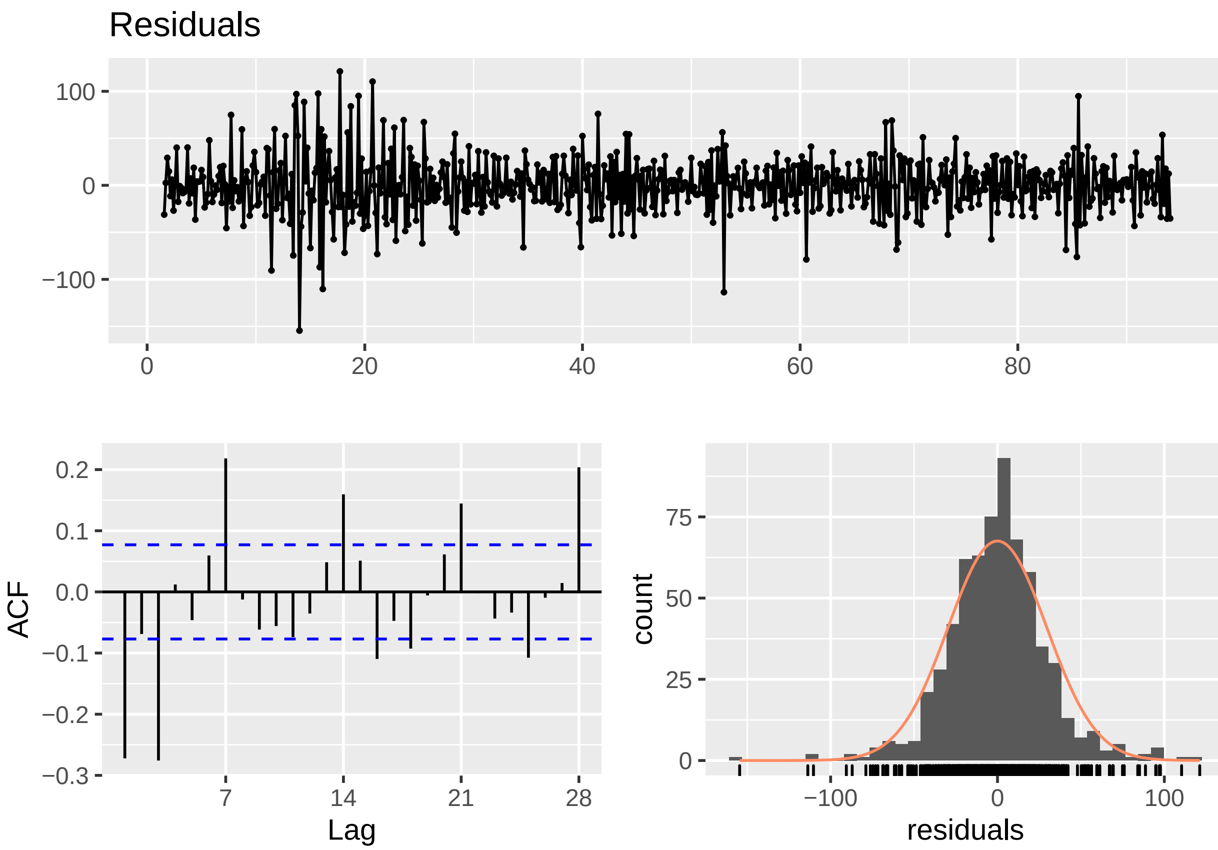



```r
decomposed <- decompose(differenced,type = "additive")
plot(decomposed)
```




```r
checkresiduals(decomposed$random)
```

```
## Warning in modeldf.default(object): Could not find appropriate degrees of
## freedom for this model.
```




```
Box.test(decomposed$random, lag=5, fitdf=0)
```

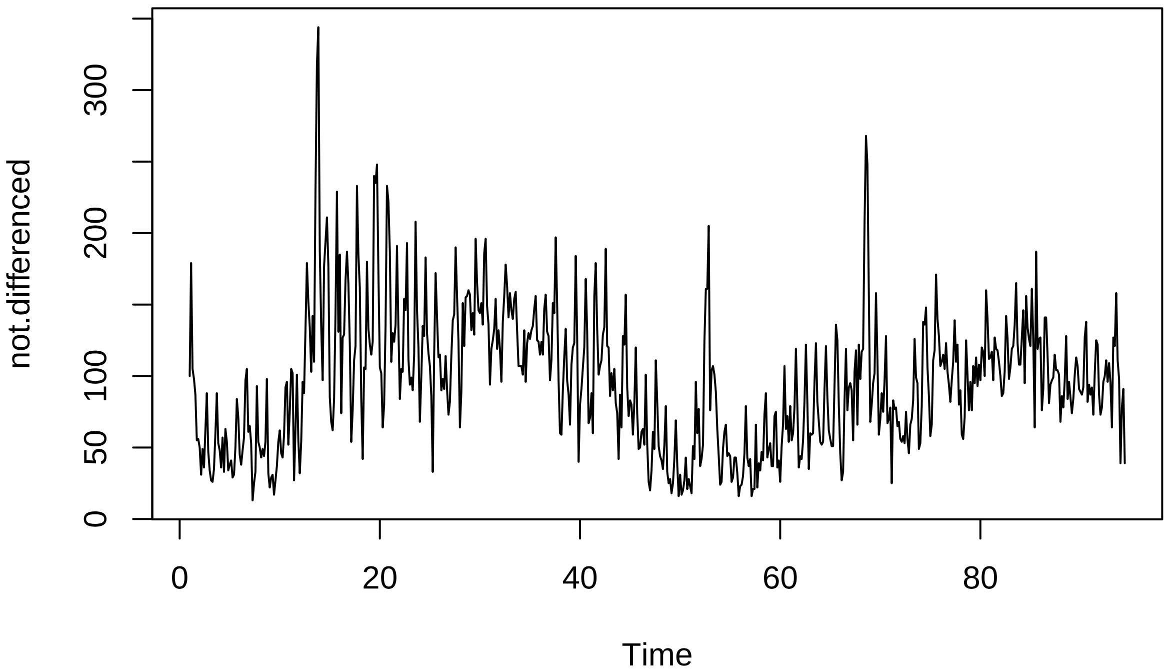
```
##
##  Box-Pierce test
##
## data:  decomposed$random
## X-squared = 101.8, df = 5, p-value < 2.2e-16
```

```
Box.test(decomposed$random, lag=5, fitdf=0, type="Lj")
```

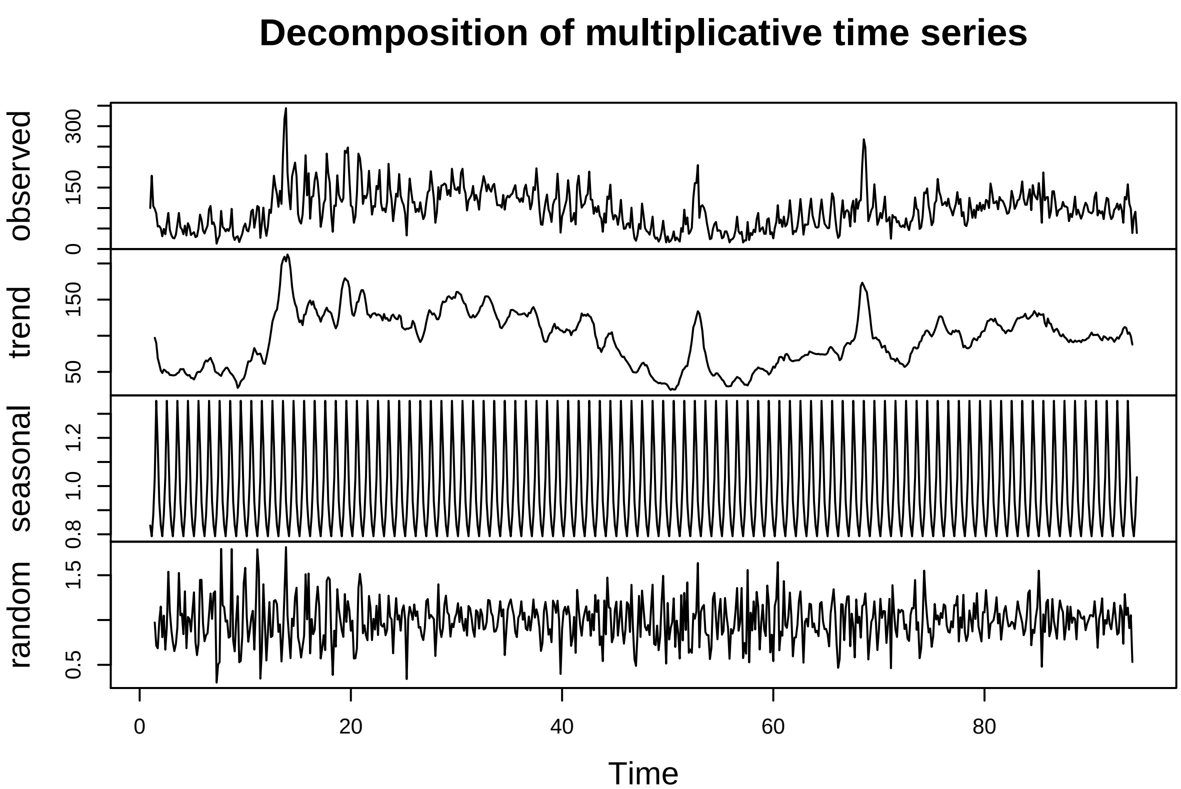
```
##
##  Box-Ljung test
##
## data:  decomposed$random
## X-squared = 102.44, df = 5, p-value < 2.2e-16
```

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

```
not.differenced <- data.ts
plot(not.differenced)
```

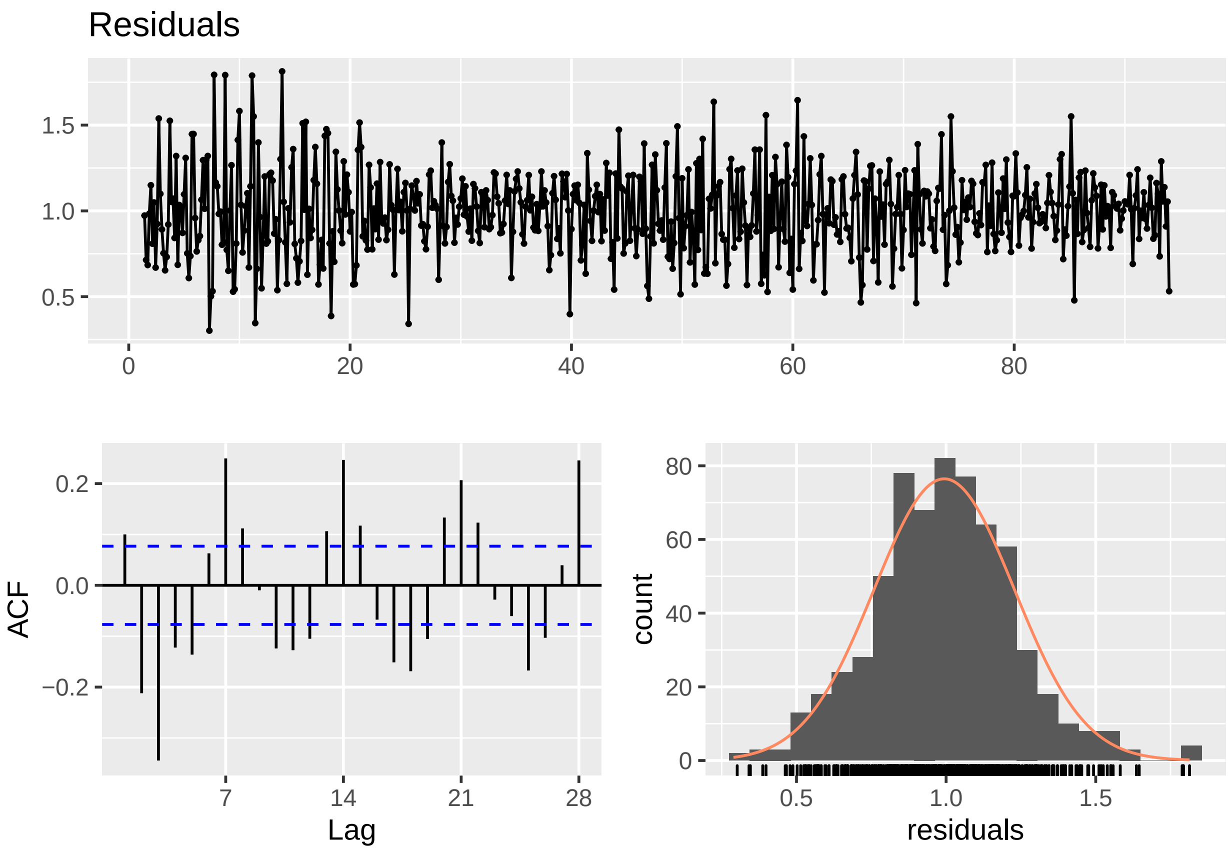



```r
decomposed <- decompose(not.differenced,type = "multiplicative")
plot(decomposed)
```




```r
checkresiduals(decomposed$random)
```

```
## Warning in modeldf.default(object): Could not find appropriate degrees of
## freedom for this model.
```




```
Box.test(decomposed$random, lag=5, fitdf=0)
```

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

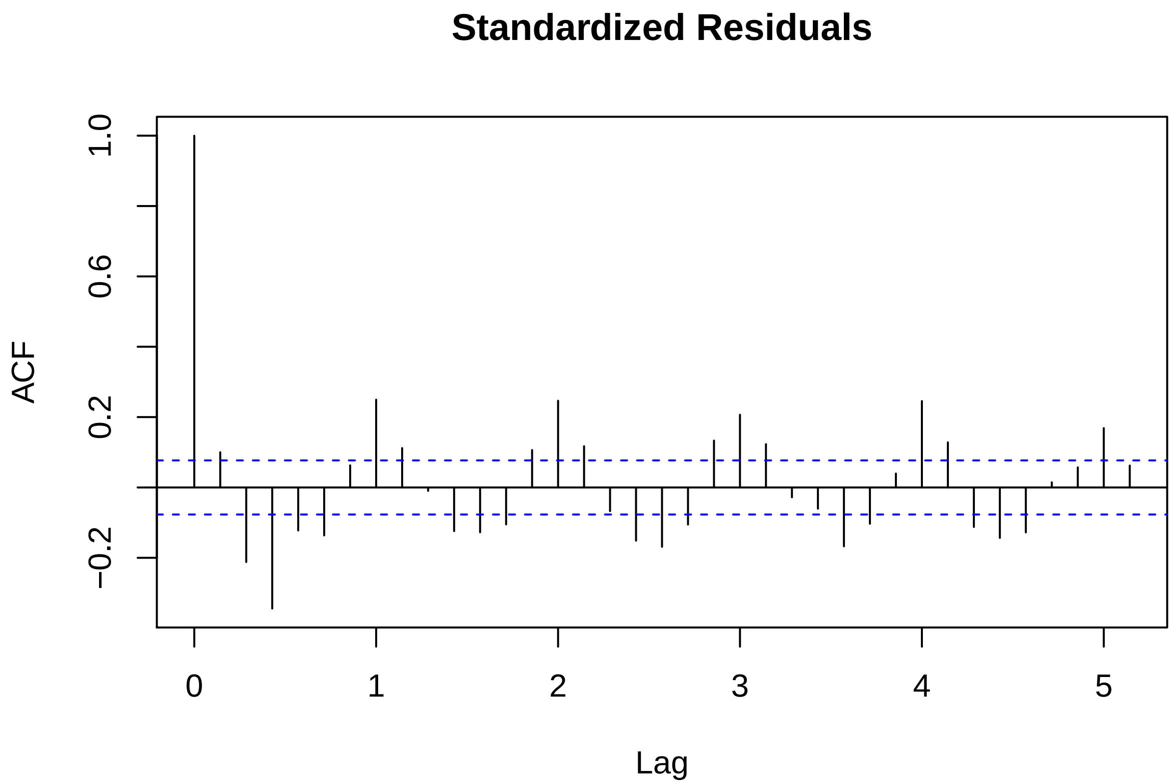
```
Box.test(decomposed$random, lag=5, fitdf=0, type="Lj")
```

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

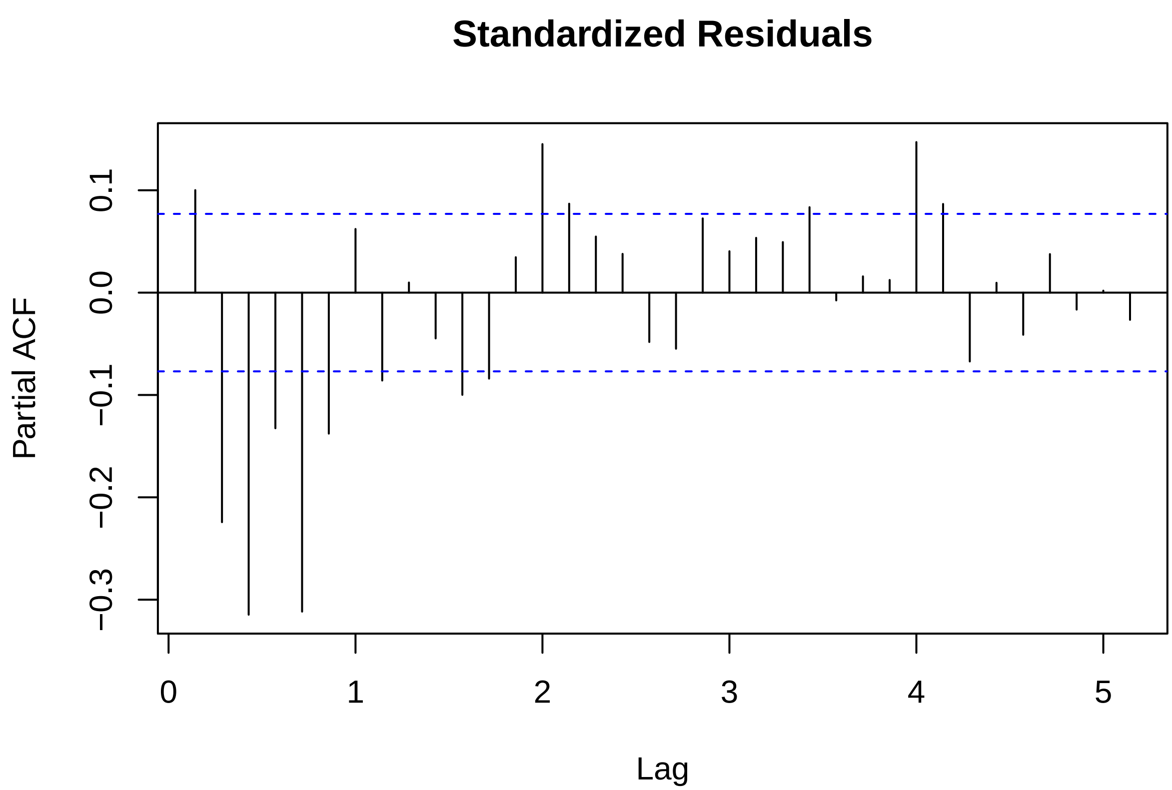
Every 7 lags the peak recurs

6 Check Residuals

```
acf(na.omit(decomposed$random), main = "Standardized Residuals", 36)
```




```r
pacf(na.omit(decomposed$random), main = "Standardized Residuals", 36)
```

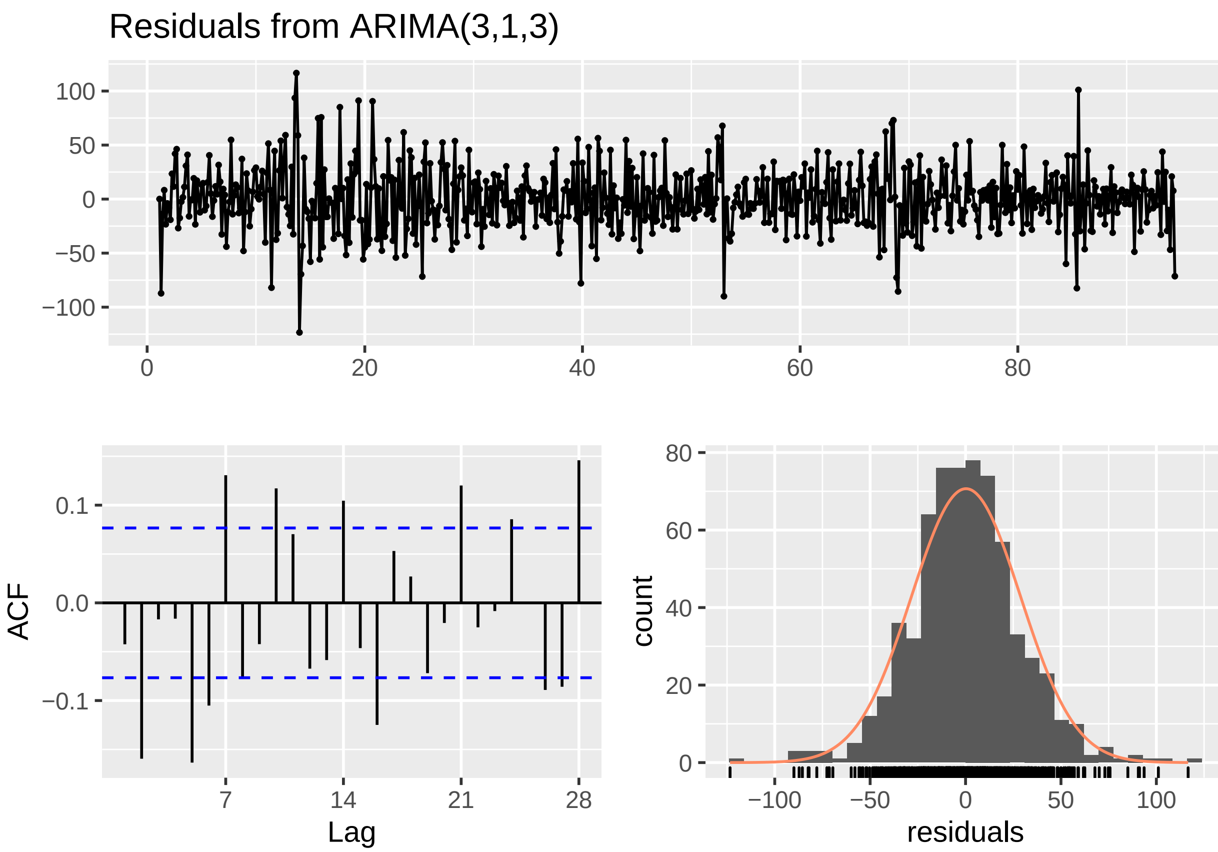


7 Arima

```r
require(fpp)
fit <- Arima(differenced, order=c(3,1,3))
summary(fit)
```

```
## 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
```

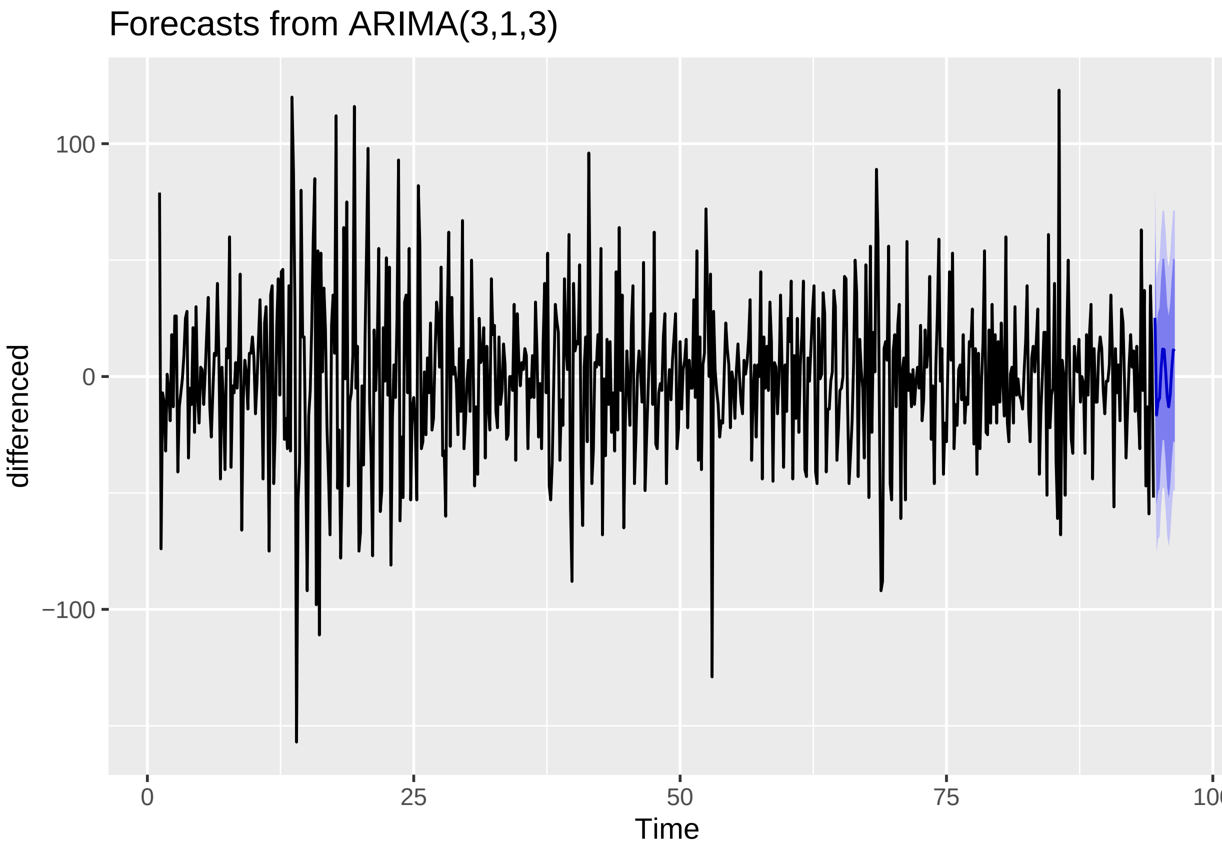
```r
checkresiduals(fit)
```




```
##
##  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
```

```r
autoplot(forecast(fit))
```



8 Auto Arima

```r
require(fpp)
auto.arima(data.ts,stepwise=TRUE,trace=TRUE,ic = "bic")
```

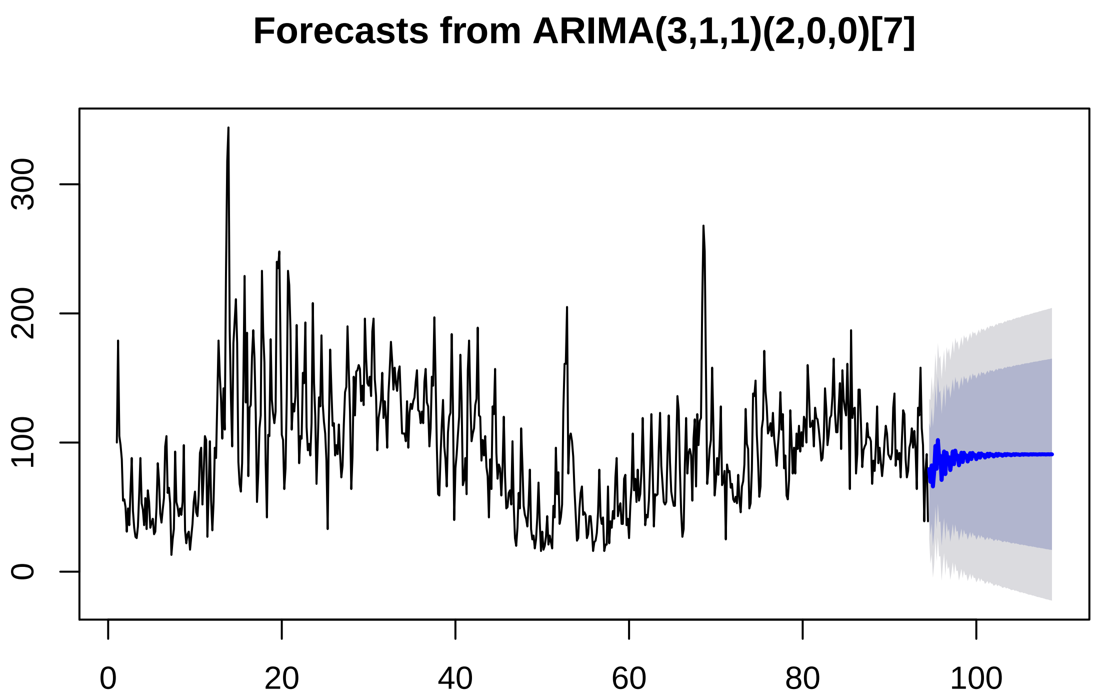
```
##
##  Fitting models using approximations to speed things up...
##
##  ARIMA(2,1,2)(1,0,1)[7] with drift         : Inf
##  ARIMA(0,1,0)           with drift         : 6473.005
##  ARIMA(1,1,0)(1,0,0)[7] with drift         : 6346.759
##  ARIMA(0,1,1)(0,0,1)[7] with drift         : 6395.033
##  ARIMA(0,1,0)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

```r
aa <- Arima(order = c(3,1,1), seasonal = c(2,0,0), y = data.ts)
```

```r
plot(forecast(aa,data.ts))
```



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

```r
frequency(data.ts)
```

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

9 Searching for multi seasonalities

without differentiation residuals looks pretty bad

```r
library(lubridate)
```

```
## Warning: package 'lubridate' was built under R version 3.6.2
```

```
##
## Attaching package: 'lubridate'
```

```
## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```r
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:lubridate':
##
##     intersect, setdiff, union
```

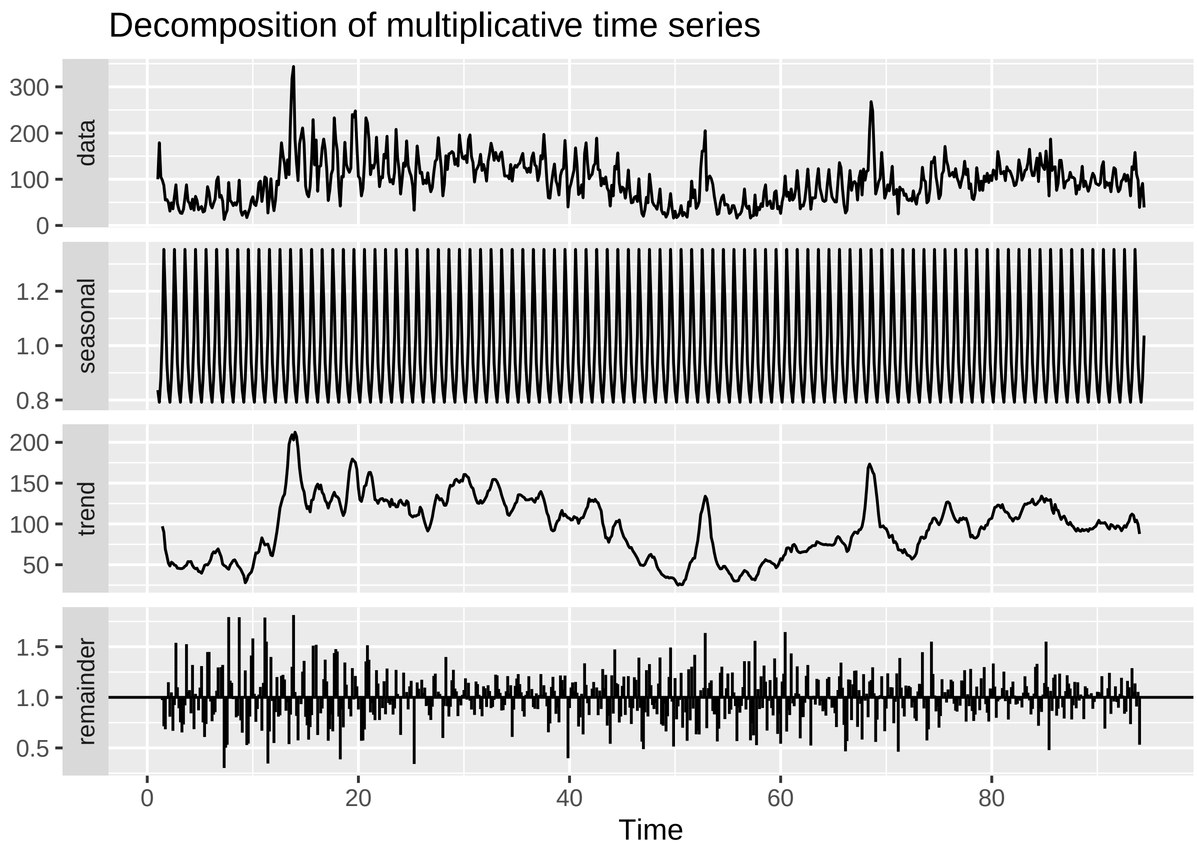
```
## The following objects are masked from 'package:xts':
##
##     first, last
```

```
## The following objects are masked from 'package:stats':
##
```

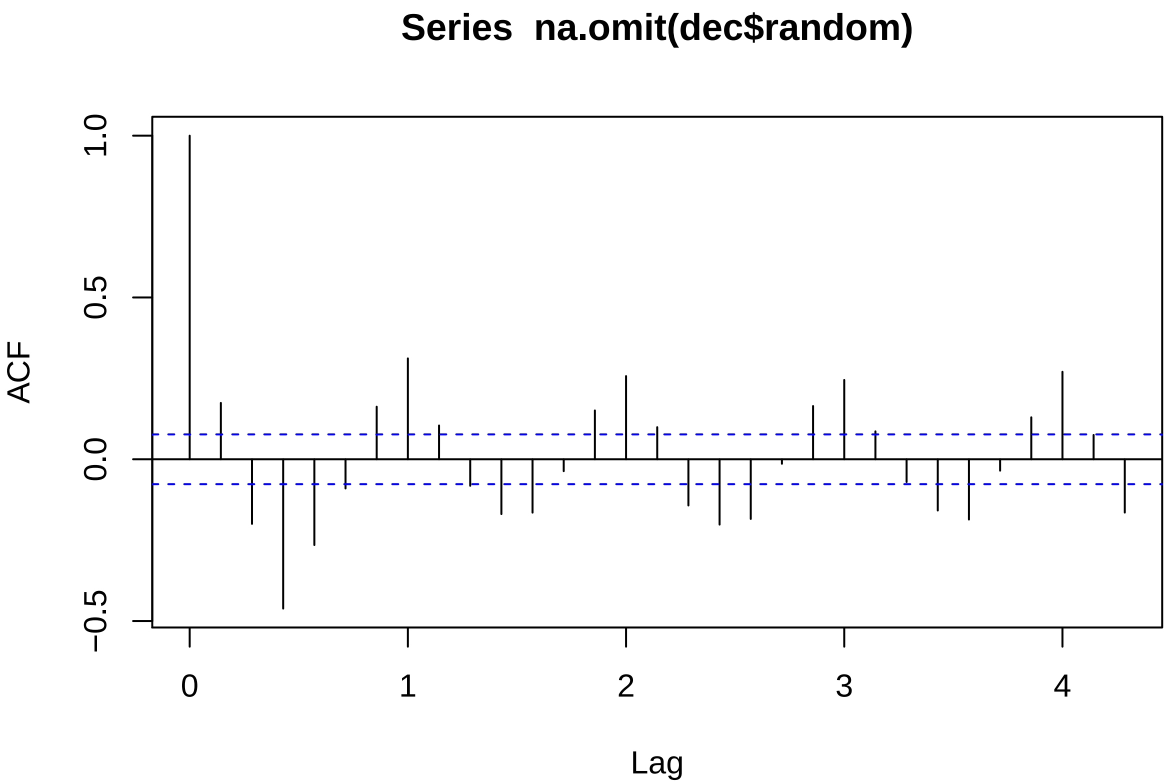
```
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(forecast)
library(ggplot2)
library(scales)

data.ts %>% decompose(type="multiplicative") %>% autoplot()
```

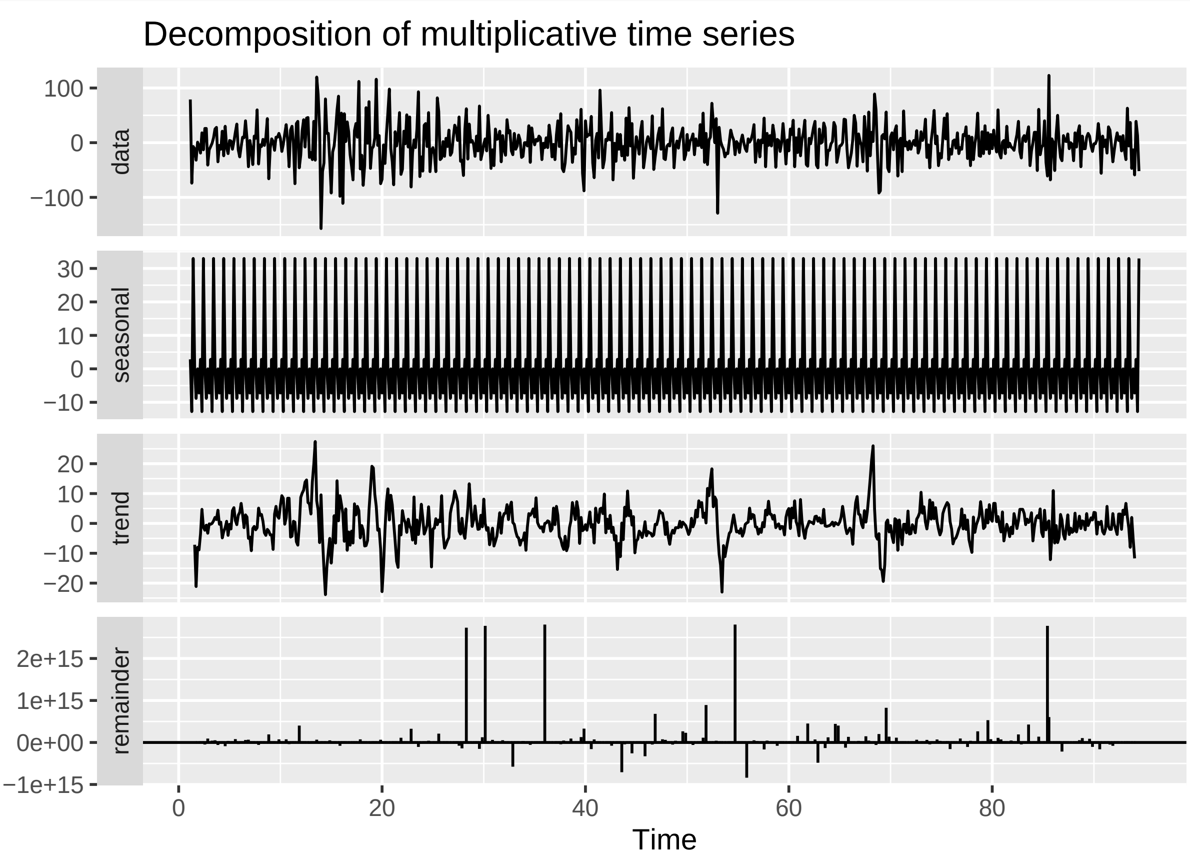



```
dec <- decompose(data.ts)
acf(na.omit(dec$random), lag.max = 30)
```

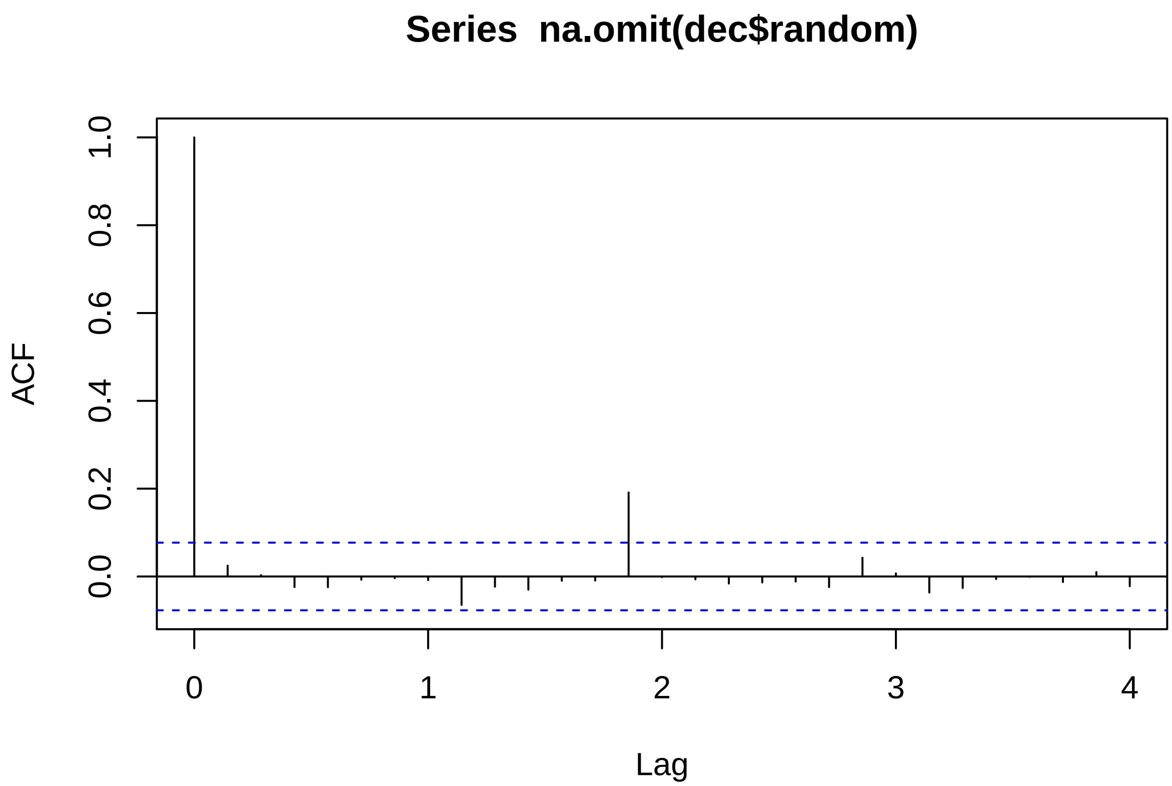


trying with differentiation and a multiplicative model:

```
differenced %>% decompose(type="multiplicative") %>% autoplot()
```



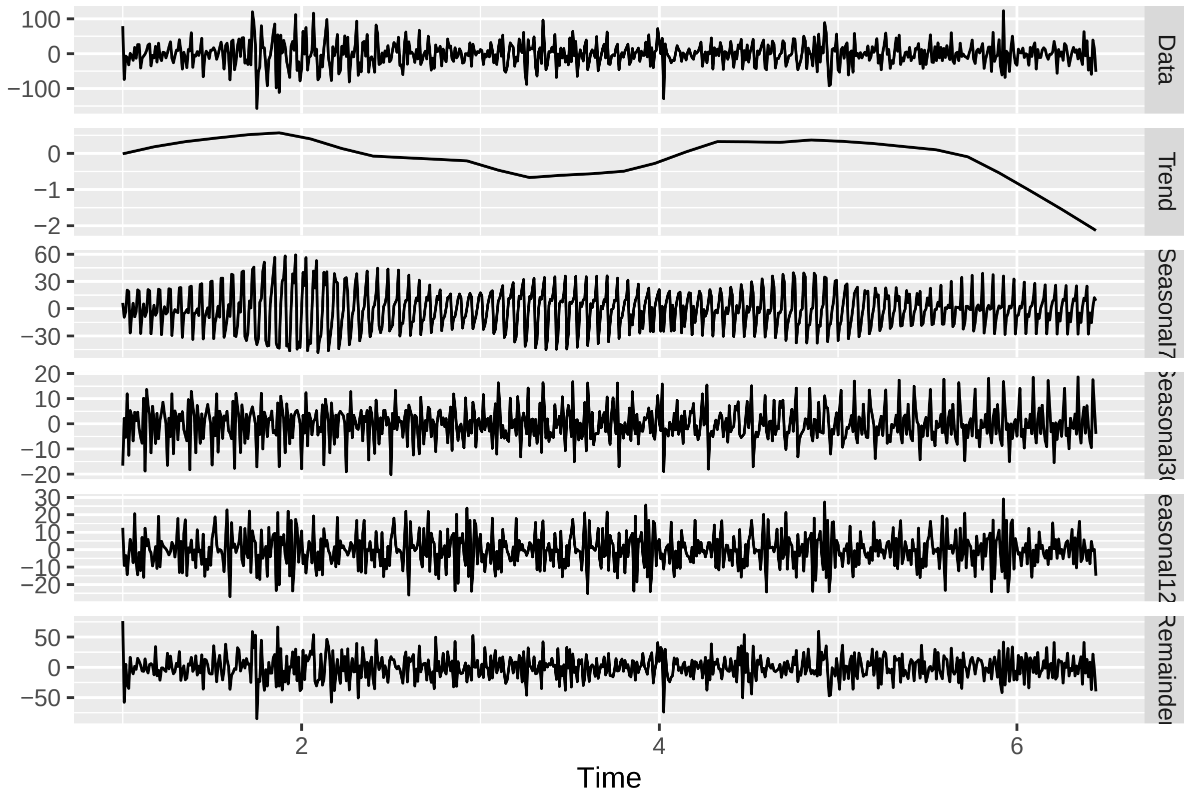
```r
dec <- decompose(differenced,type="multiplicative")
acf(na.omit(dec$random))
```



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

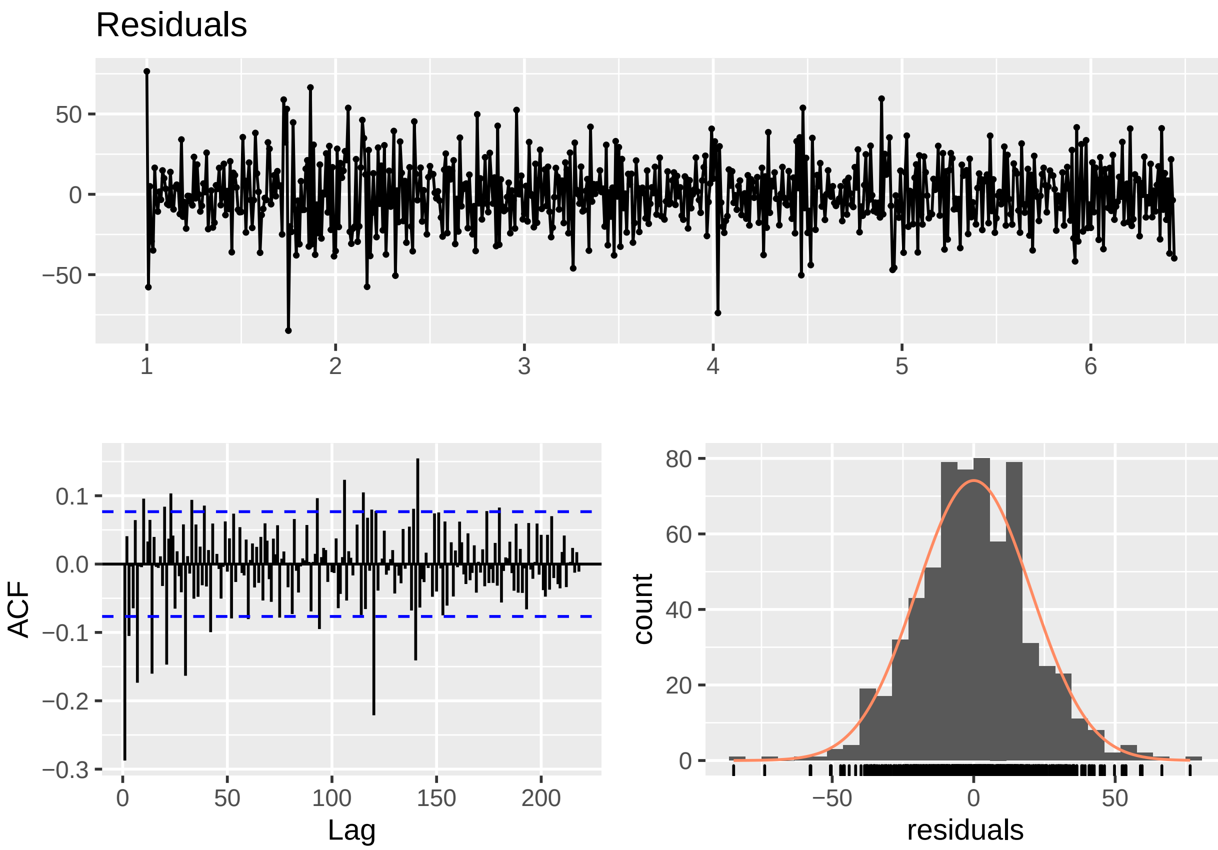
```r
require(forecast)
msts_cons <- msts(as.data.frame(diff(data.ts)), seasonal.periods = c(7, 30, 4*30))
msts_cons %>% mstl() %>% autoplot()
```




```
decomposed <- mstl(msts_cons)
```

```
checkresiduals(remainder(decomposed))
```

```
## Warning in modeldf.default(object): Could not find appropriate degrees of
## freedom for this model.
```




```r
Box.test(remainder(decomposed), lag=5, fitdf=0)
```

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

```r
Box.test(remainder(decomposed), lag=5, fitdf=0, type="Lj")
```

```
##
##  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