# Timeseries analysis

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# loading file

```
df <-  read.csv("C:/Users/patel/Downloads/TV_by_network_daypart.csv")

str(df)
```

```
## 'data.frame':    2640 obs. of  4 variables:
##  $ date    : int  201401 201401 201401 201401 201401 201401 201401 201401 201401
201401 ...
##  $ network: Factor w/ 5 levels "A","B","C","D",..: 1 2 3 4 5 1 2 3 4 5 ...
##  $ daypart: Factor w/ 11 levels "M,T,W,R,F 1:00 PM - 4:00 PM",..: 11 11 11 11 11
10 10 10 10 10 ...
##  $ viewers: int  275 423 1046 215 521 133 0 326 146 0 ...
```

```
library(dplyr)
```

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

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

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

```
library(forecast)
```

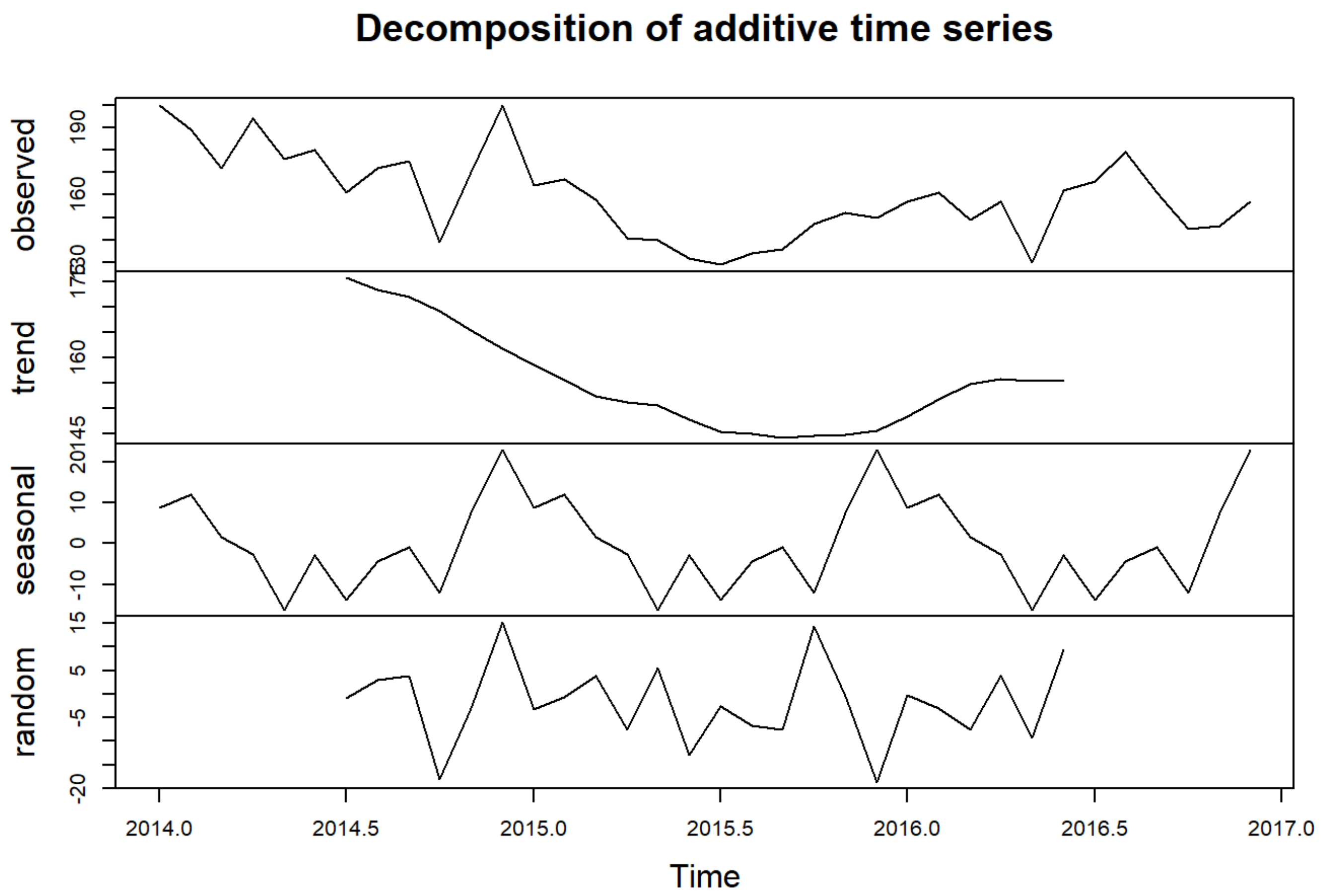
# spiltting by daypart

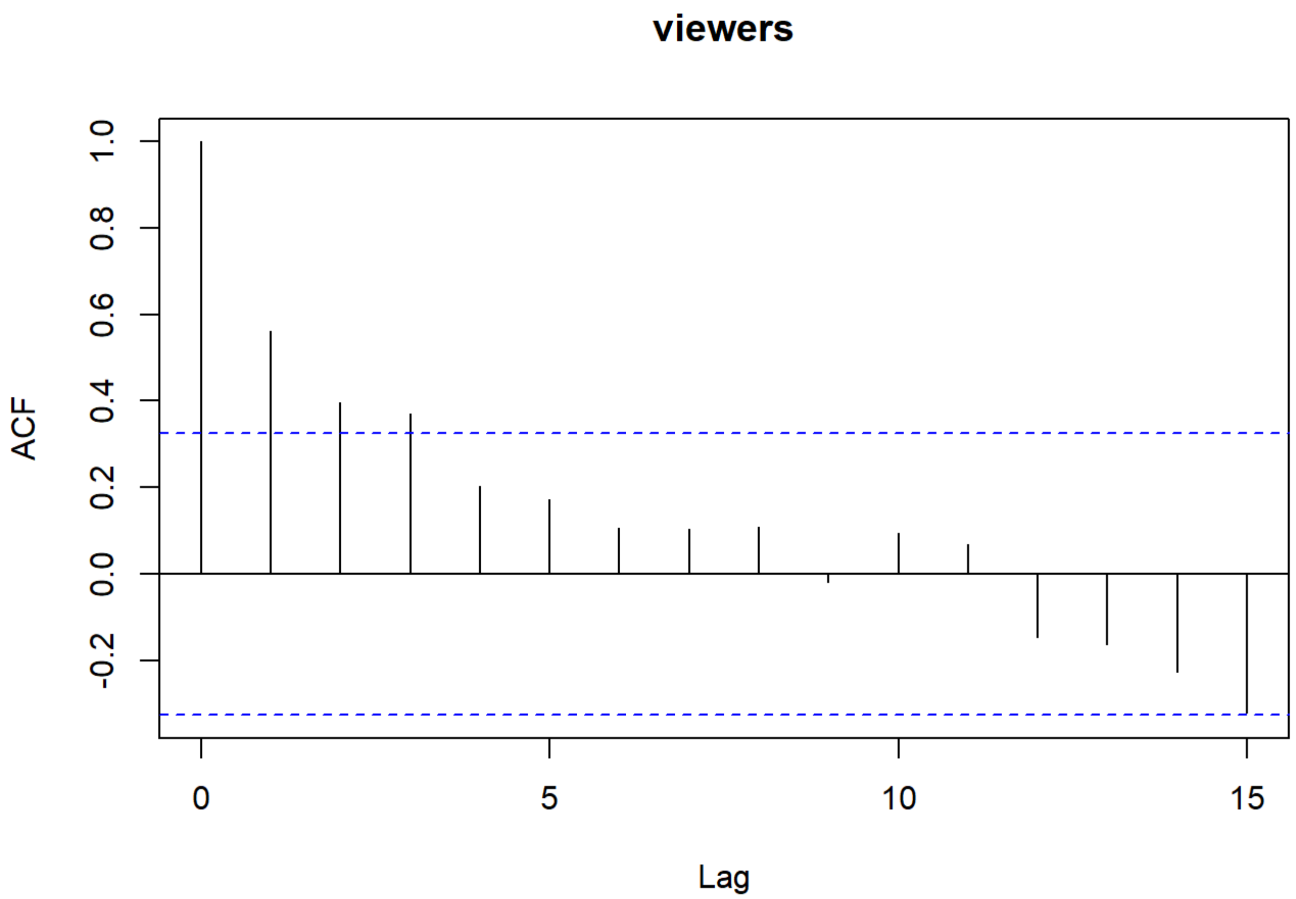
```
d <- levels(factor(df$daypart))

daypart <- list()
train_A <- list()
test_A <- list()
time_train_A <-  list()
train_B <- list()
test_B <- list()
time_train_B <-  list()
train_C <- list()
test_C <- list()
time_train_C <-  list()
train_D <- list()
test_D <- list()
time_train_D <-  list()
train_E <- list()
test_E <- list()
time_train_E <-  list()
mse_A <- list()
mse_B <- list()
mse_C <- list()
mse_D <- list()
mse_E <- list()
```

```
for (i in 1:length(d)){

  daypart <- df %>% filter(daypart == d[i])
################################################## Network A #######################
#####################
  #select "viewer" column from the datasets
  train_A[[i]] <- assign(paste0("train", i),daypart %>% filter(date <201701 & netwo
rk =="A") %>% select(viewers))
  test_A[[i]] <- assign(paste0("test", i),daypart %>% filter(date >201612& network
=="A")  %>% select(viewers))
  time_train_A[[i]] <- assign(paste0("time_train", i), ts(train_A[[i]], frequency =
12, start = 2014))
  decomposedRes <- decompose(time_train_A[[i]], type="additive")
  plot(decomposedRes)
  #stl <- stl(time_train_A[[i]], s.window="period")
  acfRes <- acf(train_A[[i]]) # autocorrelation
  pacfRes <- pacf(train_A[[i]])
  hw <- HoltWinters(time_train_A[[i]])
  plot(hw)
  forecast <- forecast(hw, h = 12)
  plot(forecast)
  mse_A[[i]] <- mean(abs(test_A[[i]]$viewers-forecast$mean))


################################################## Network B #######################
#####################

  train_B[[i]] <- assign(paste0("train_b", i),daypart %>% filter(date <201701 & net
work =="B") %>% select(viewers))
  test_B[[i]] <- assign(paste0("test_b", i),daypart %>% filter(date >201612& networ
k =="B")  %>% select(viewers))
  time_train_B[[i]] <- assign(paste0("time_train_b", i), ts(train_B[[i]], frequency
```

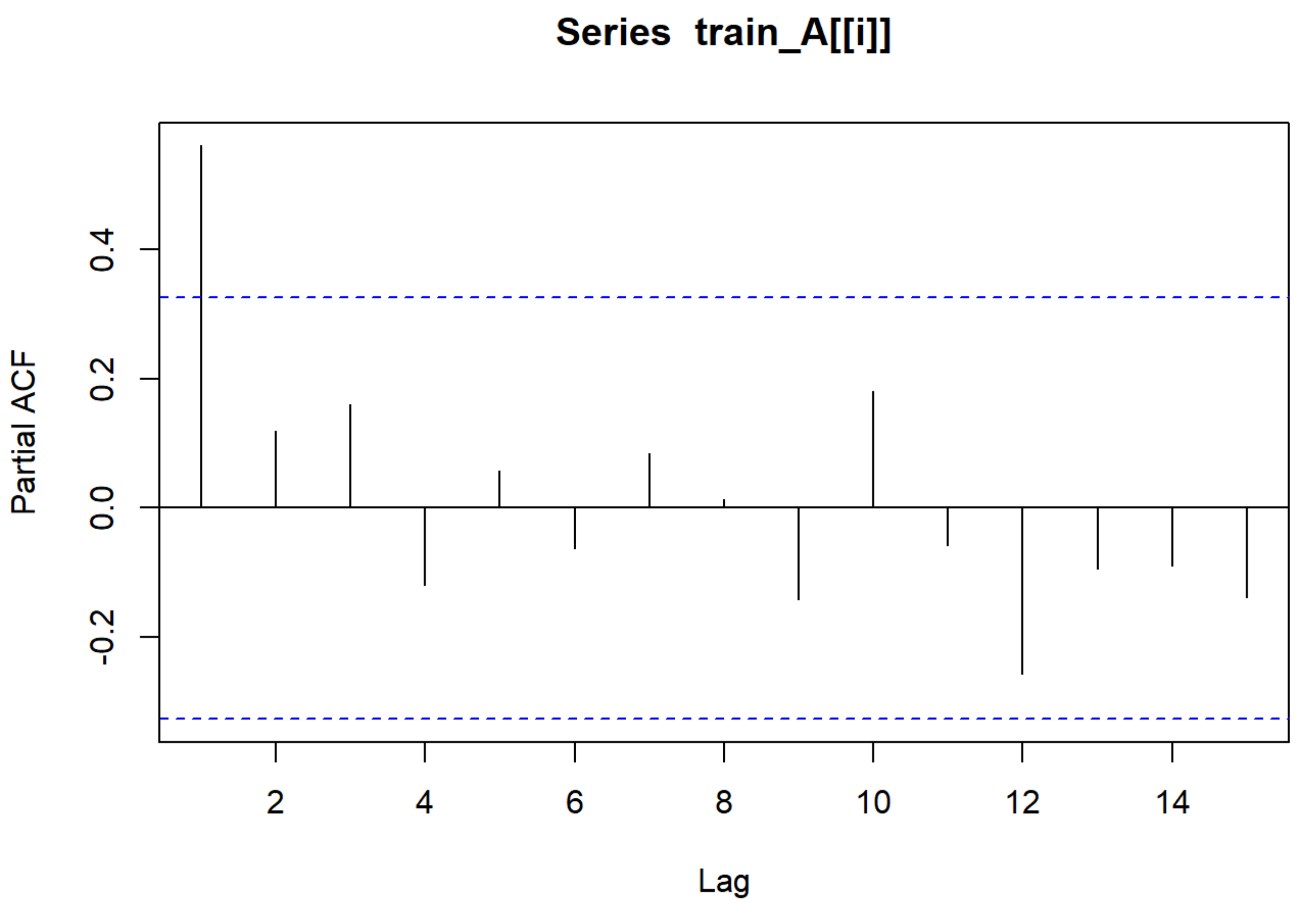
```
  time_train_B[[i]] <- assign(paste0("time_train_B", i), ts(train_B[[i]], frequency
= 12, start = 2014))
  decomposedRes <- decompose(time_train_B[[i]], type="additive")
  plot(decomposedRes)
  #stl <- stl(time_train_B[[i]], s.window="period")
  #acfRes <- acf(train_B[[i]]) # autocorrelation
  #pacfRes <- pacf(train_B[[i]])
  hw <- HoltWinters(time_train_B[[i]])
  plot(hw)
  forecast <- forecast(hw, h = 12)
  # plot(forecast)
  mse_B[[i]] <- mean(abs(test_B[[i]]$viewers-forecast$mean))

################################################ Network C ######################
####################

  train_C[[i]] <- assign(paste0("train_C", i),daypart %>% filter(date <201701 & net
work =="C") %>% select(viewers))
  test_C[[i]] <- assign(paste0("test_C", i),daypart %>% filter(date >201612& networ
k =="C")  %>% select(viewers))
  time_train_C[[i]] <- assign(paste0("time_train_C", i), ts(train_C[[i]], frequency
= 12, start = 2014))
  decomposedRes <- decompose(time_train_C[[i]], type="additive")
  plot(decomposedRes)
  #stl <- stl(time_train_C[[i]], s.window="period")
  acfRes <- acf(train_C[[i]]) # autocorrelation
  pacfRes <- pacf(train_C[[i]])
  hw <- HoltWinters(time_train_C[[i]])
  plot(hw)
  forecast <- forecast(hw, h = 12)
  mse_C[i] <- mean(abs(test_C[[i]]$viewers-forecast$mean))


################################################ Network D ######################
####################

  train_D[[i]] <- assign(paste0("train_D", i),daypart %>% filter(date <201701 & net
work =="D") %>% select(viewers))
  test_D[[i]] <- assign(paste0("test_D", i),daypart %>% filter(date >201612& networ
k =="D")  %>% select(viewers))
  time_train_D[[i]] <- assign(paste0("time_train_D", i), ts(train_D[[i]], frequency
= 12, start = 2014))
  decomposedRes <- decompose(time_train_D[[i]], type="additive")
  plot(decomposedRes)
  #stl <- stl(time_train_D[[i]], s.window="period")
  acfRes <- acf(train_D[[i]]) # autocorrelation
  pacfRes <- pacf(train_D[[i]])
  hw <- HoltWinters(time_train_D[[i]])
  plot(hw)
  forecast <- forecast(hw, h = 12)
  mse_D[i] <- mean(abs(test_D[[i]]$viewers-forecast$mean))


################################################ Network E ######################
#####################

  train_E[[i]] <- assign(paste0("train_E", i),daypart %>% filter(date <201701 & net
work =="E") %>% select(viewers))
```

```
work =="E") %>% select(viewers))
  test_E[[i]] <- assign(paste0("test_E", i),daypart %>% filter(date >201612& networ
k =="E")  %>% select(viewers))
  time_train_E[[i]] <- assign(paste0("time_train_E", i), ts(train_E[[i]], frequency
= 12, start = 2014))
  decomposedRes <- decompose(time_train_E[[i]], type="additive")
  plot(decomposedRes)
  #stl <- stl(time_train_E[[i]], s.window="period")
  #acfRes <- acf(train_E[[i]]) # autocorrelation
  #pacfRes <- pacf(train_E[[i]])
  hw <- HoltWinters(time_train_E[[i]])
  plot(hw)
  forecast <- forecast(hw, h = 12)
  mse_E[[i]] <- mean(abs(test_E[[i]]$viewers-forecast$mean))


}
```

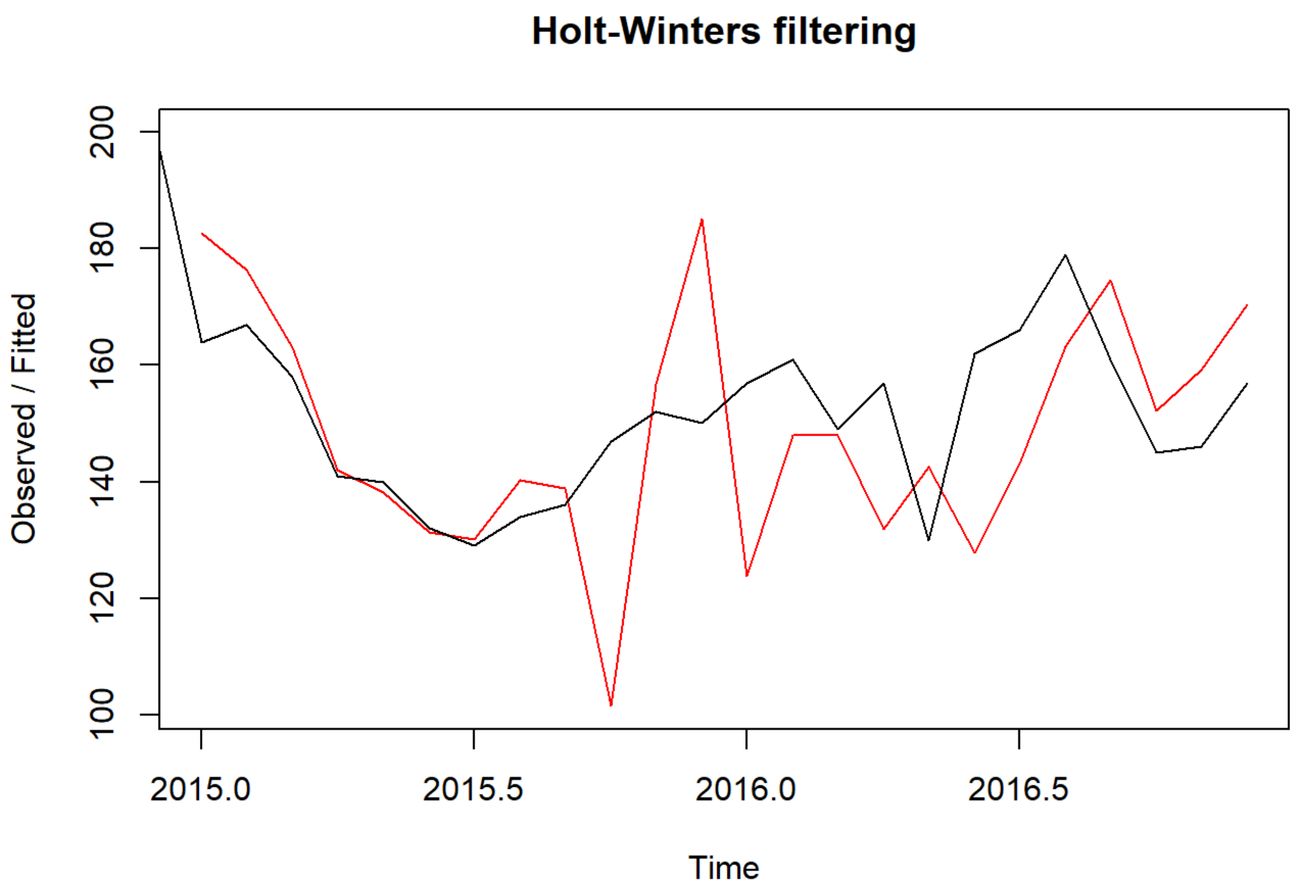




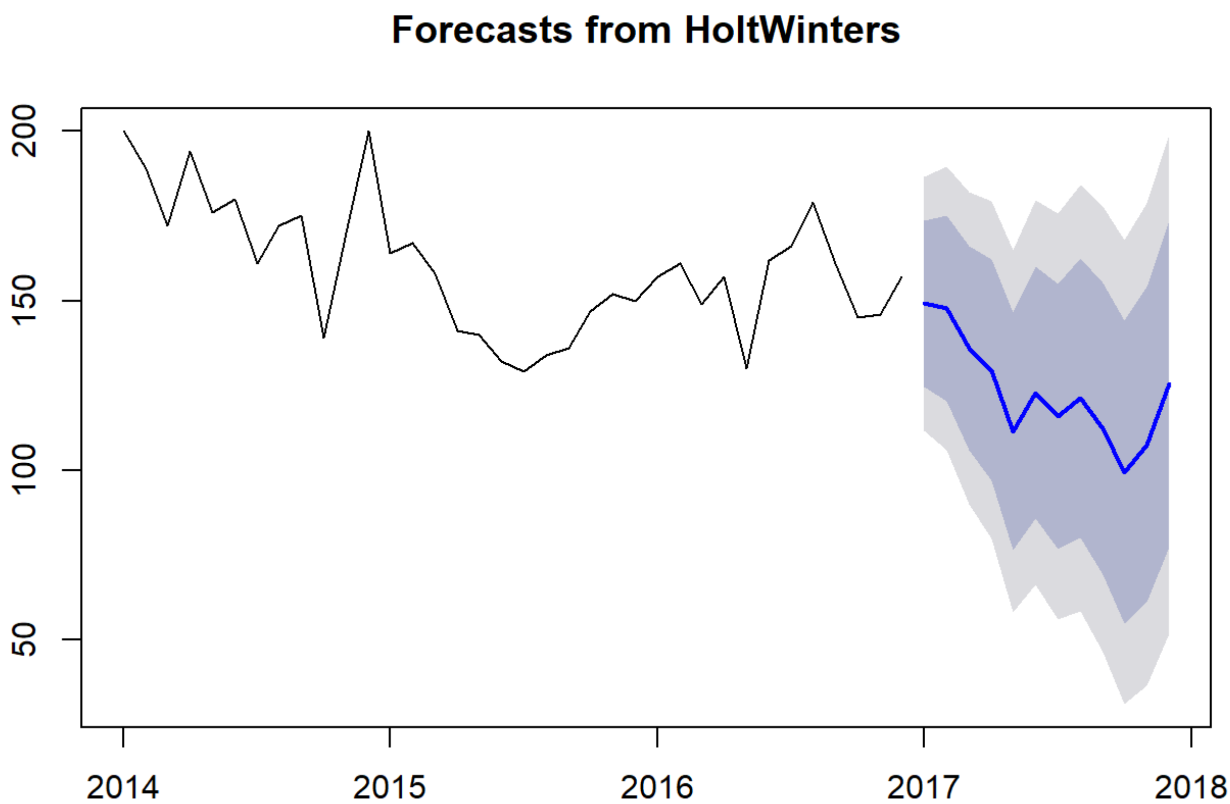
viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

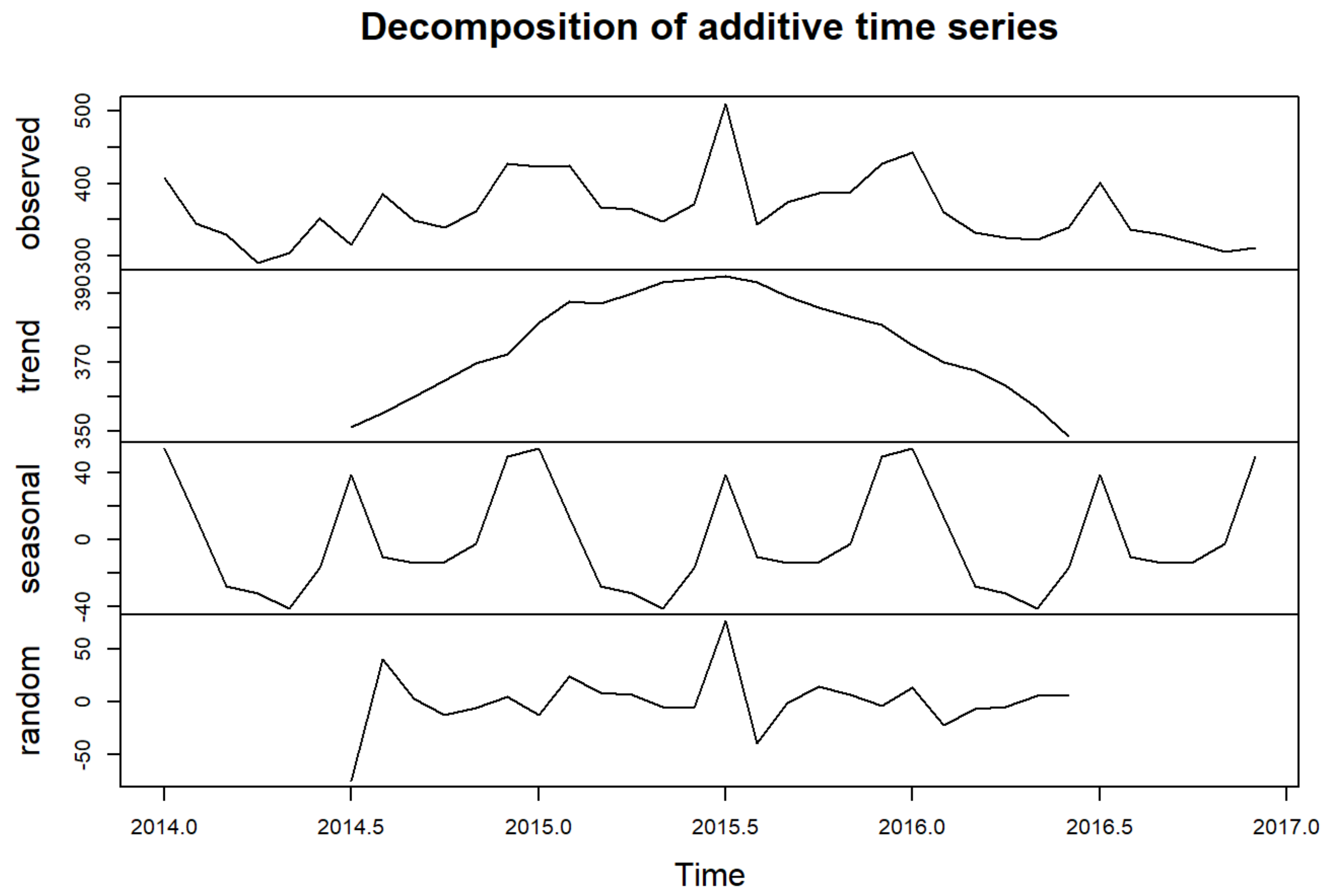
Series train_A[[i]]
Partial ACF
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag

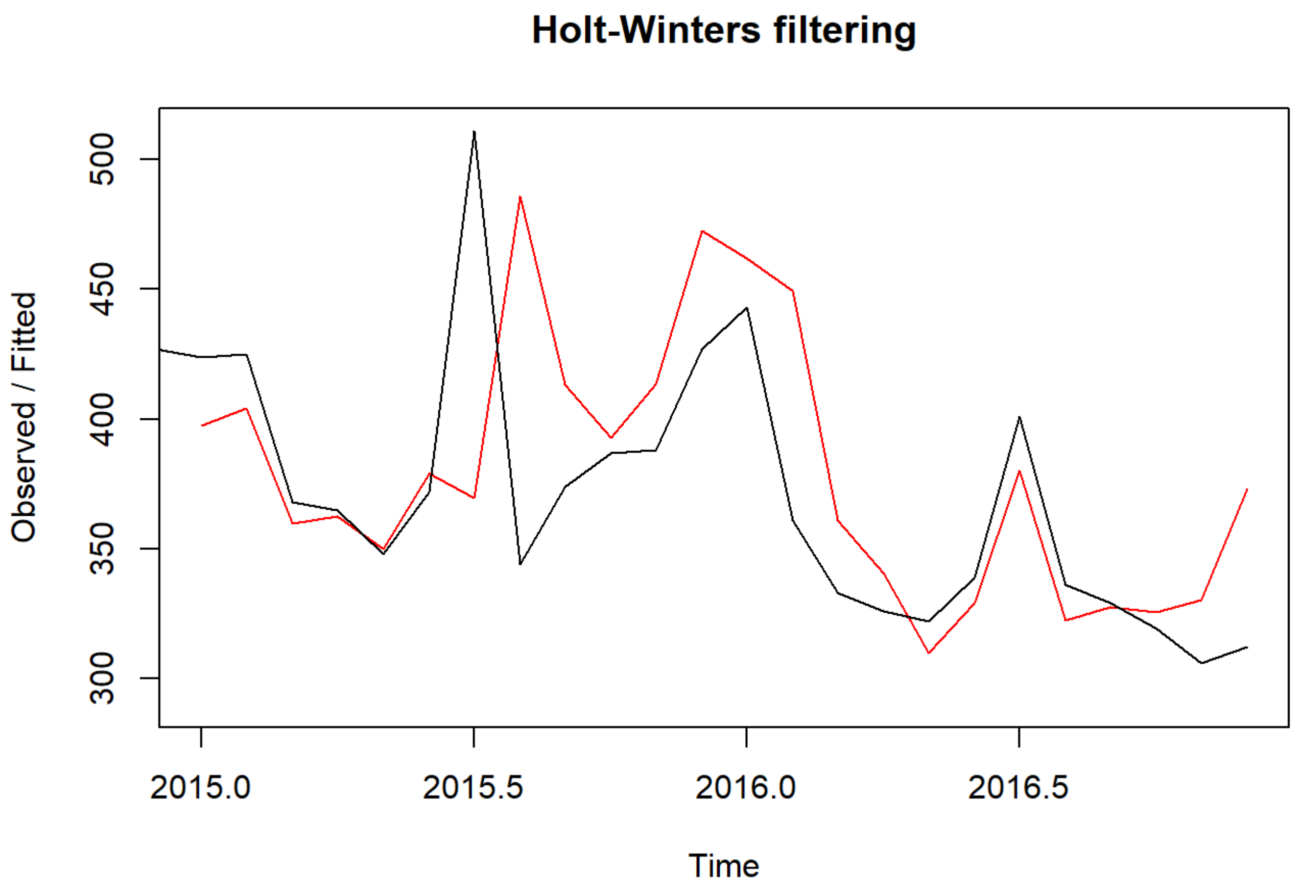


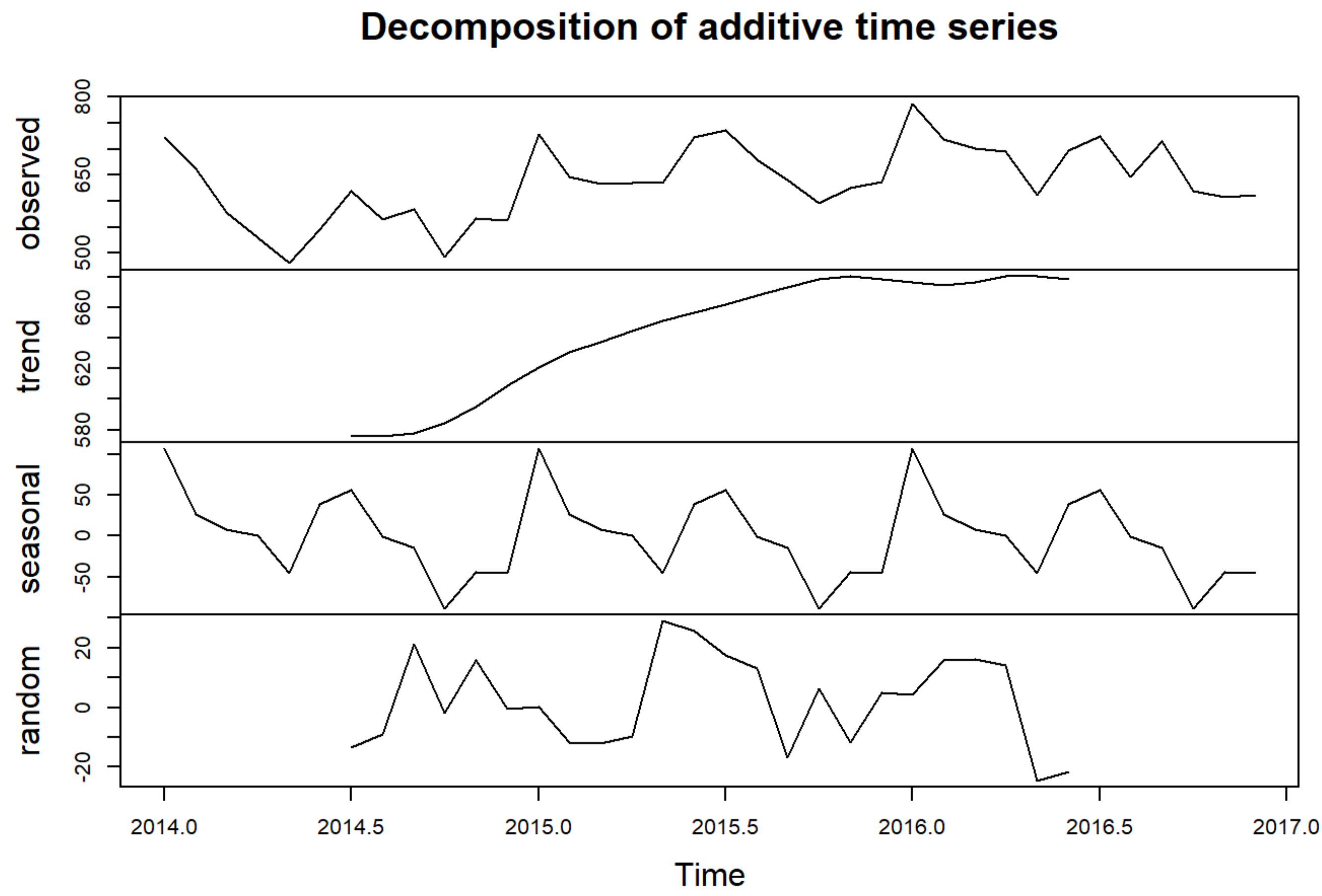
Holt-Winters filtering
Observed / Fitted
200
180
160
140
120
100
2015.0
2015.5
2016.0
2016.5
Time

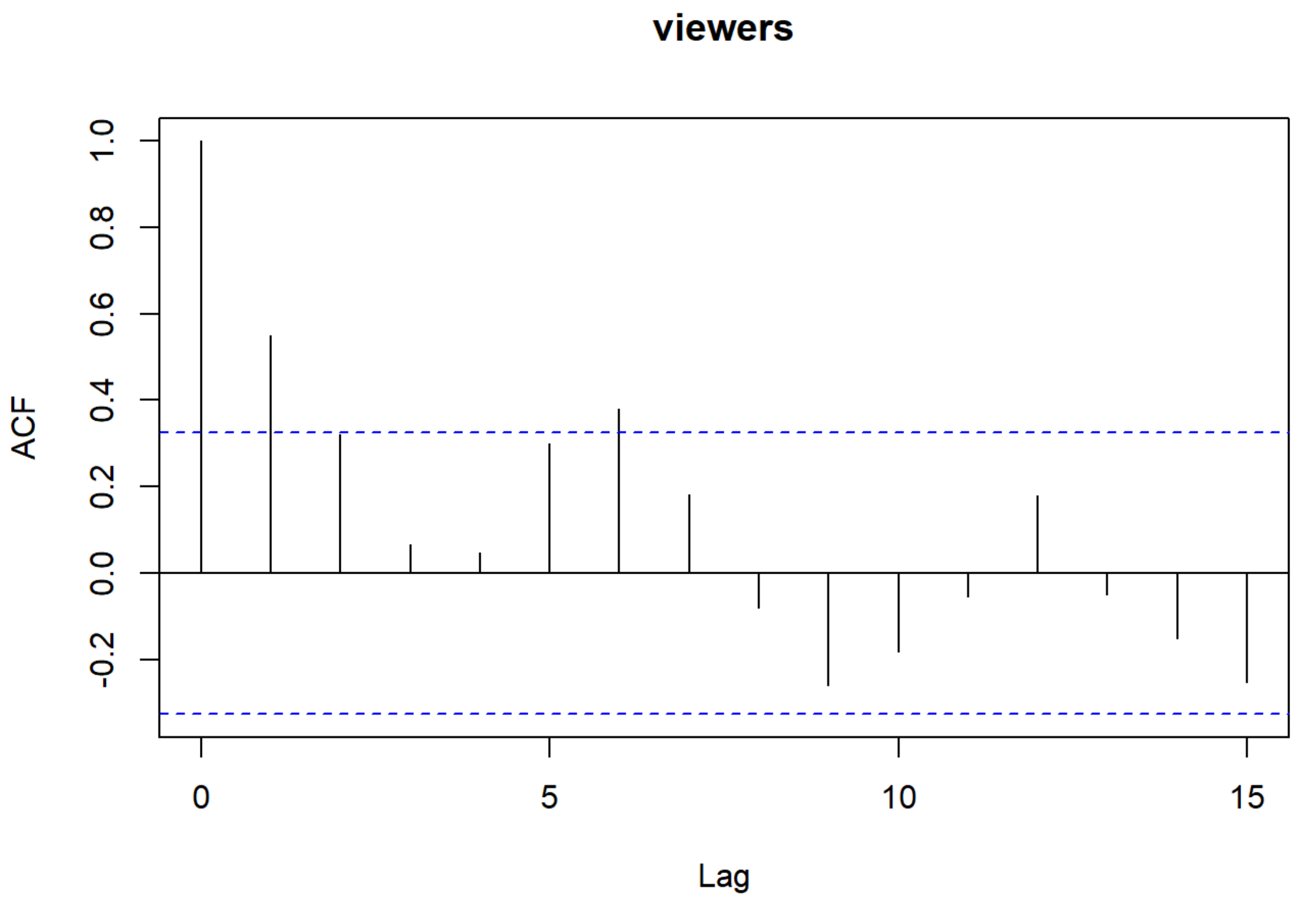



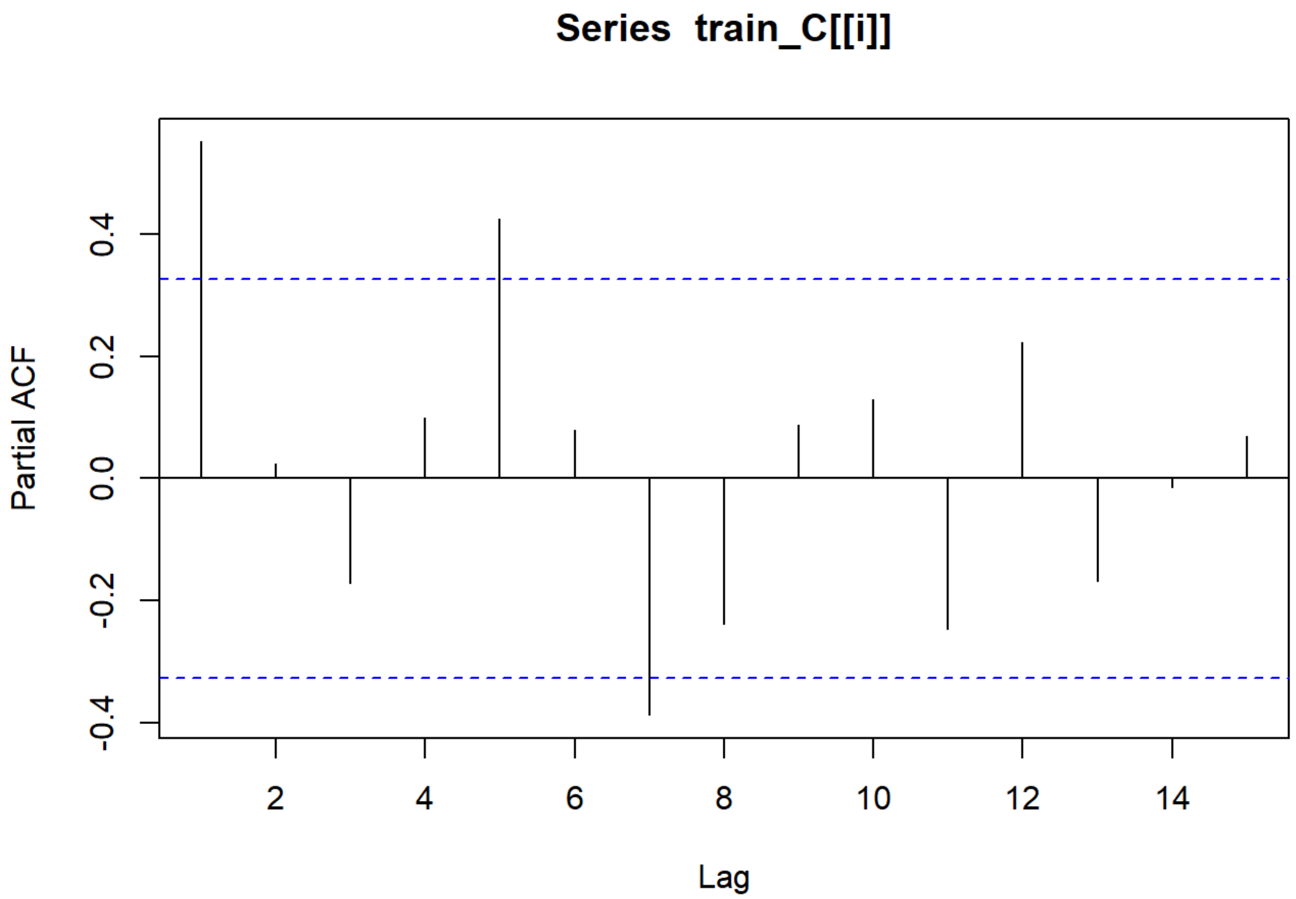
Forecasts from HoltWinters
200
150
100
50
2014
2015
2016
2017
2018

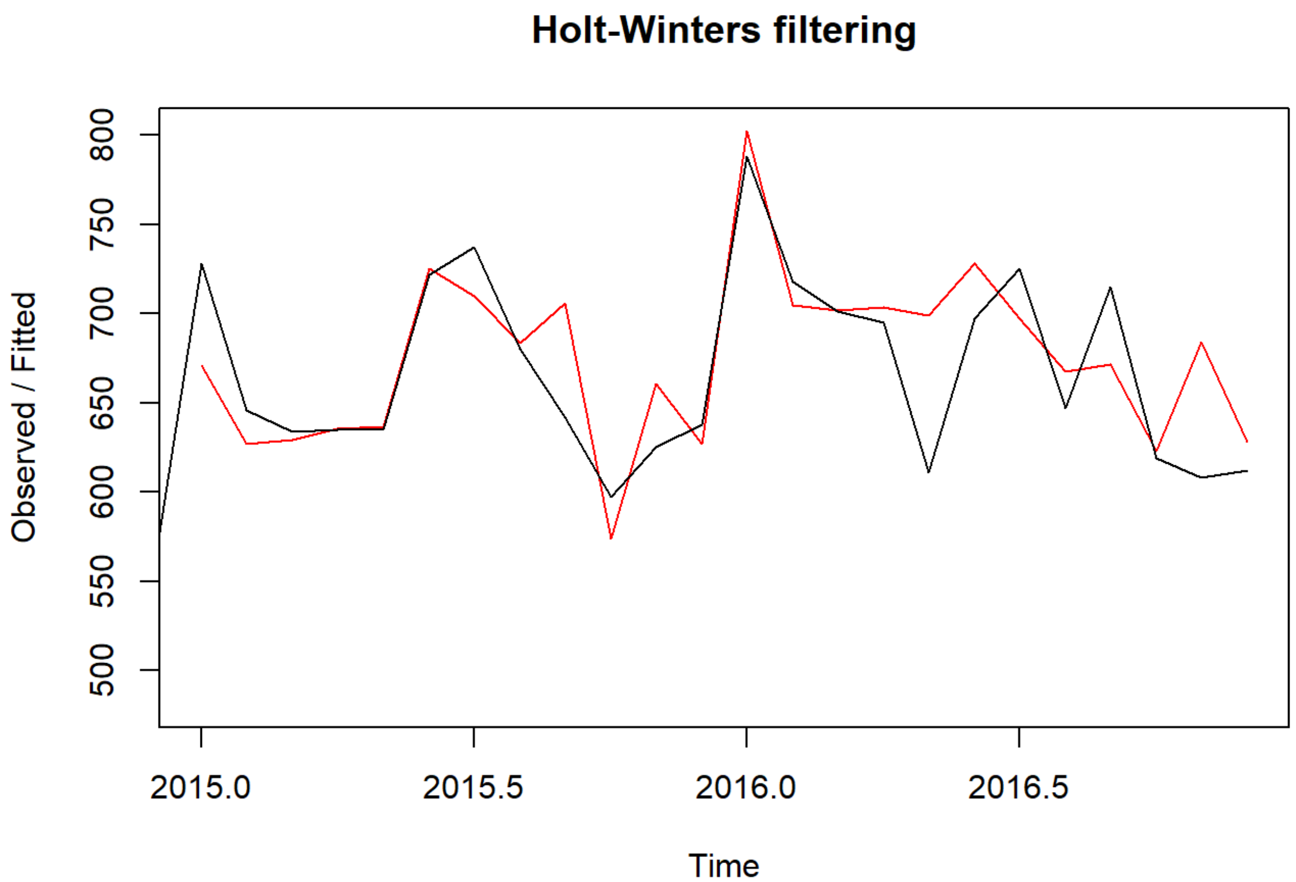

Decomposition of additive time series
observed
trend
seasonal
random
Time
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0

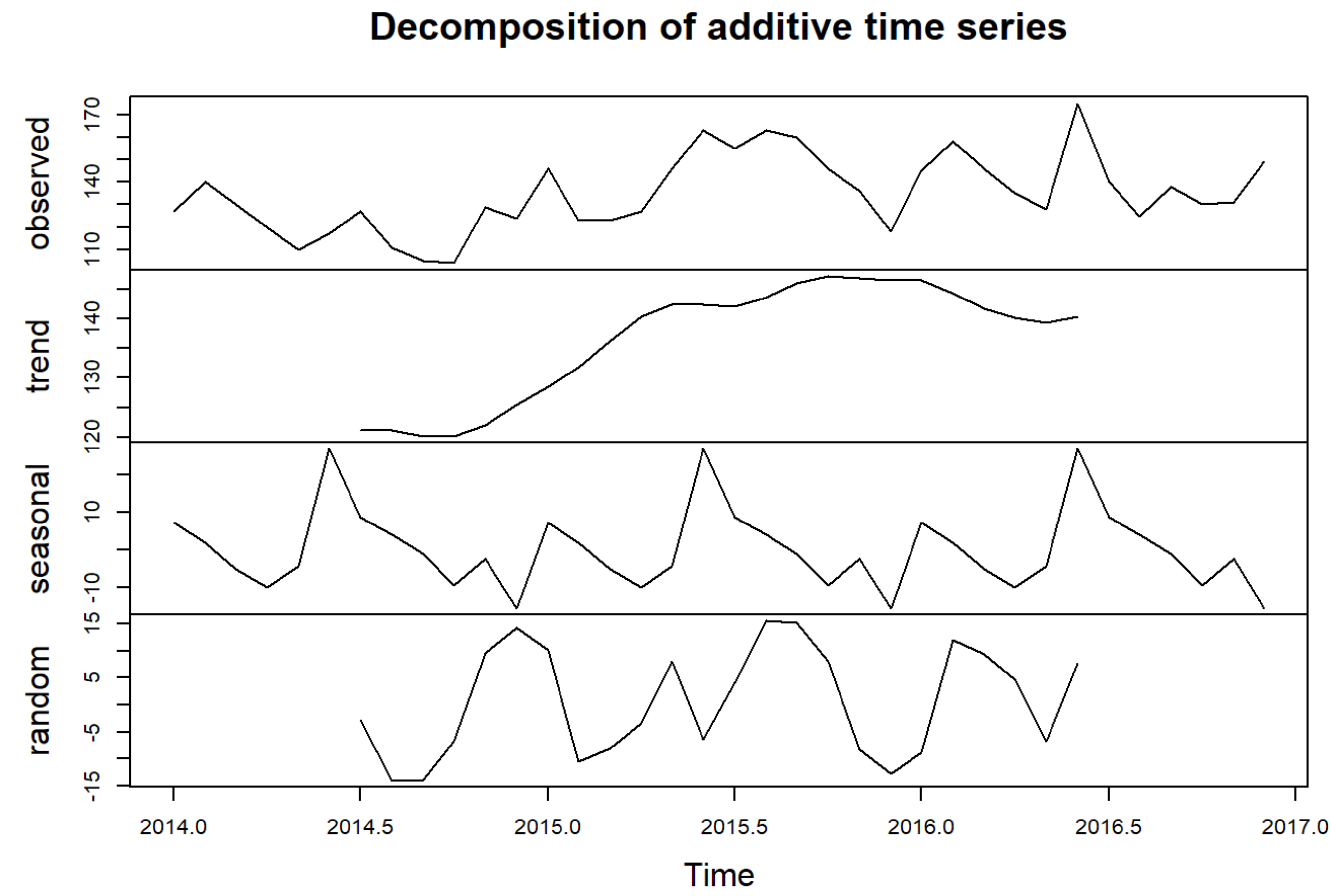

Holt-Winters filtering
Observed / Fitted
Time
2015.0
2015.5
2016.0
2016.5


Decomposition of additive time series
observed
trend
seasonal
random
Time
800
650
500
660
620
580
50
0
-50
20
0
-20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0

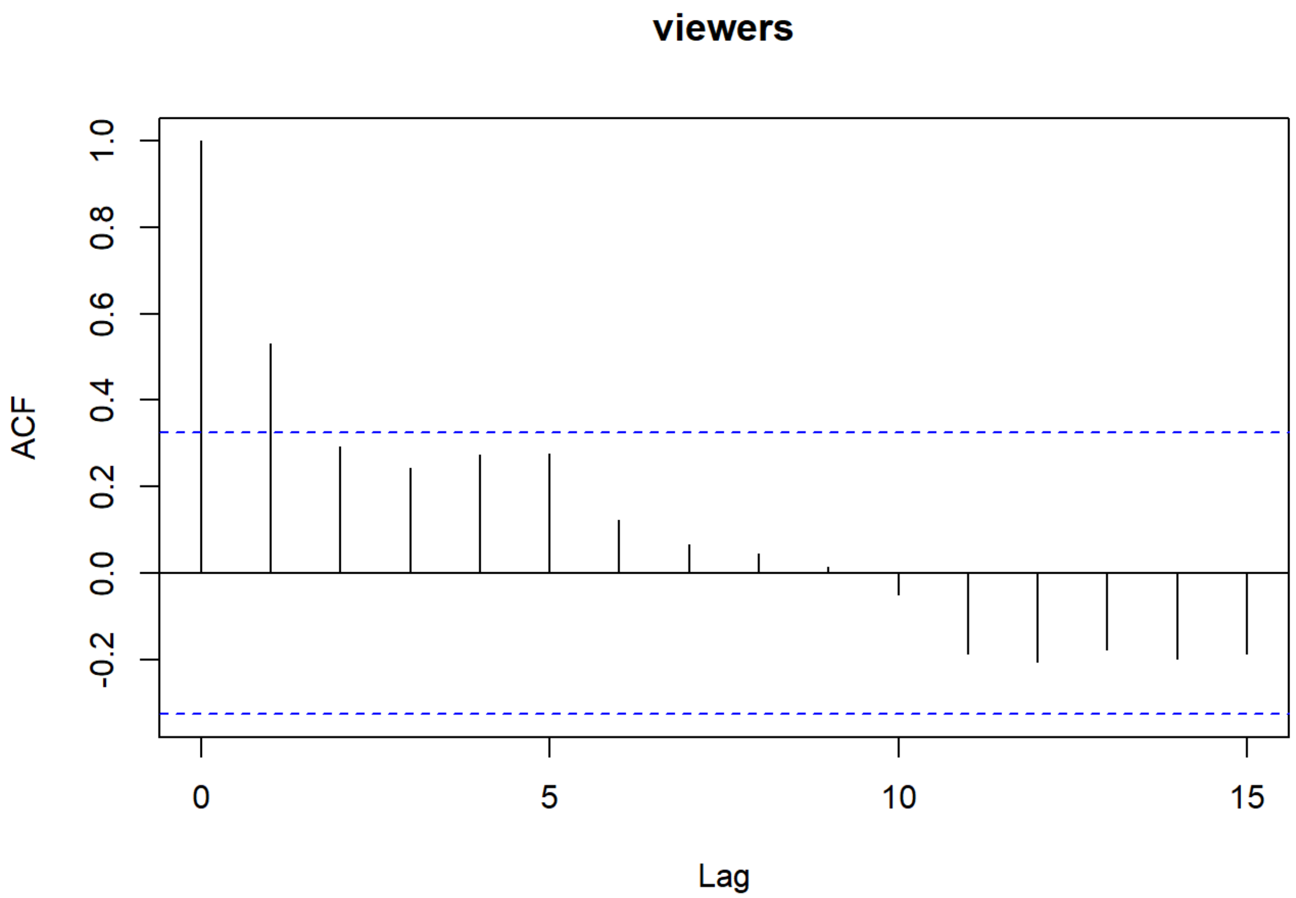

viewers
ACF
Lag
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15


Series train_C[[i]]
Partial ACF
-0.4
-0.2
0.0
0.2
0.4
2
4
6
8
10
12
14
Lag

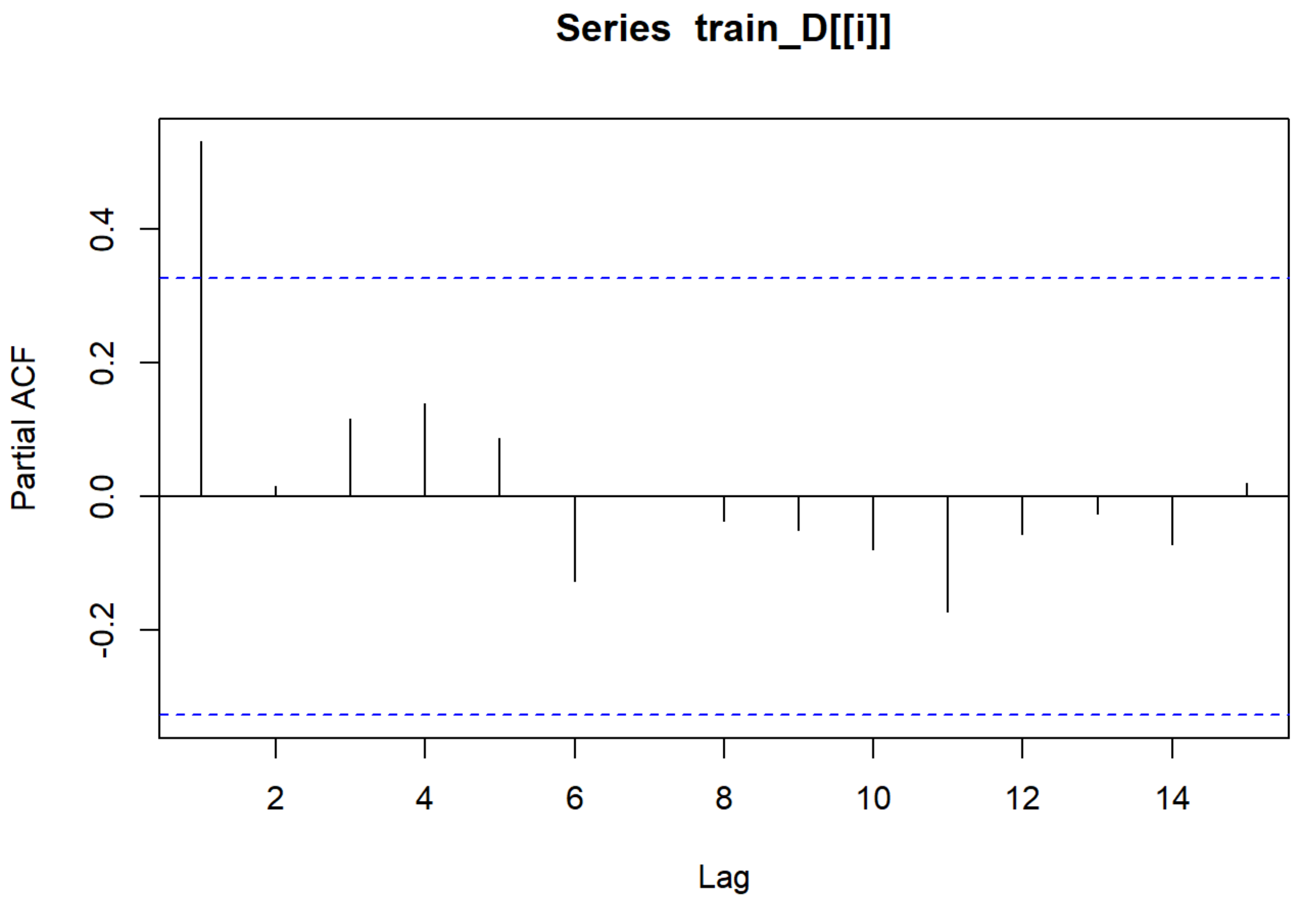

Holt-Winters filtering
Observed / Fitted
500
550
600
650
700
750
800
2015.0
2015.5
2016.0
2016.5
Time

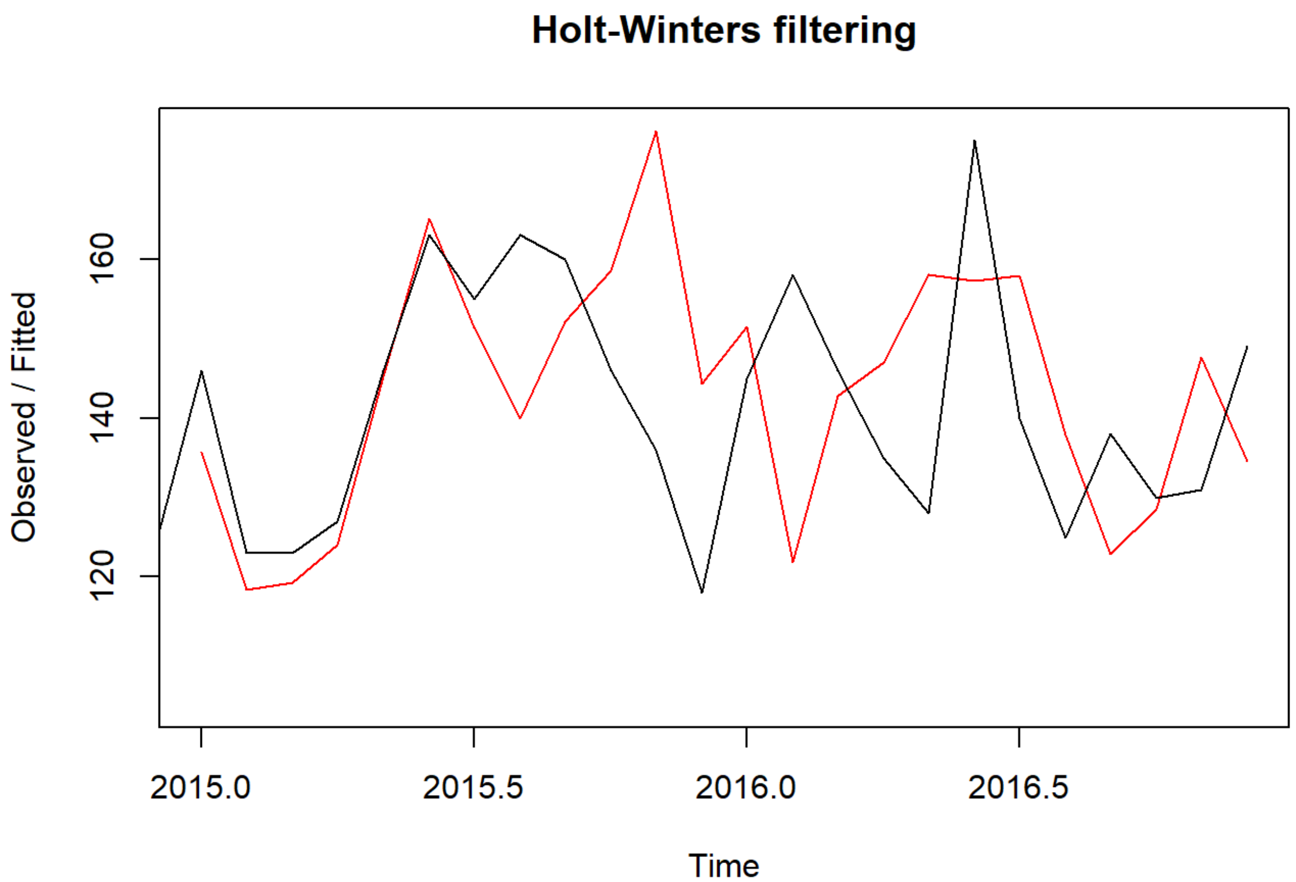


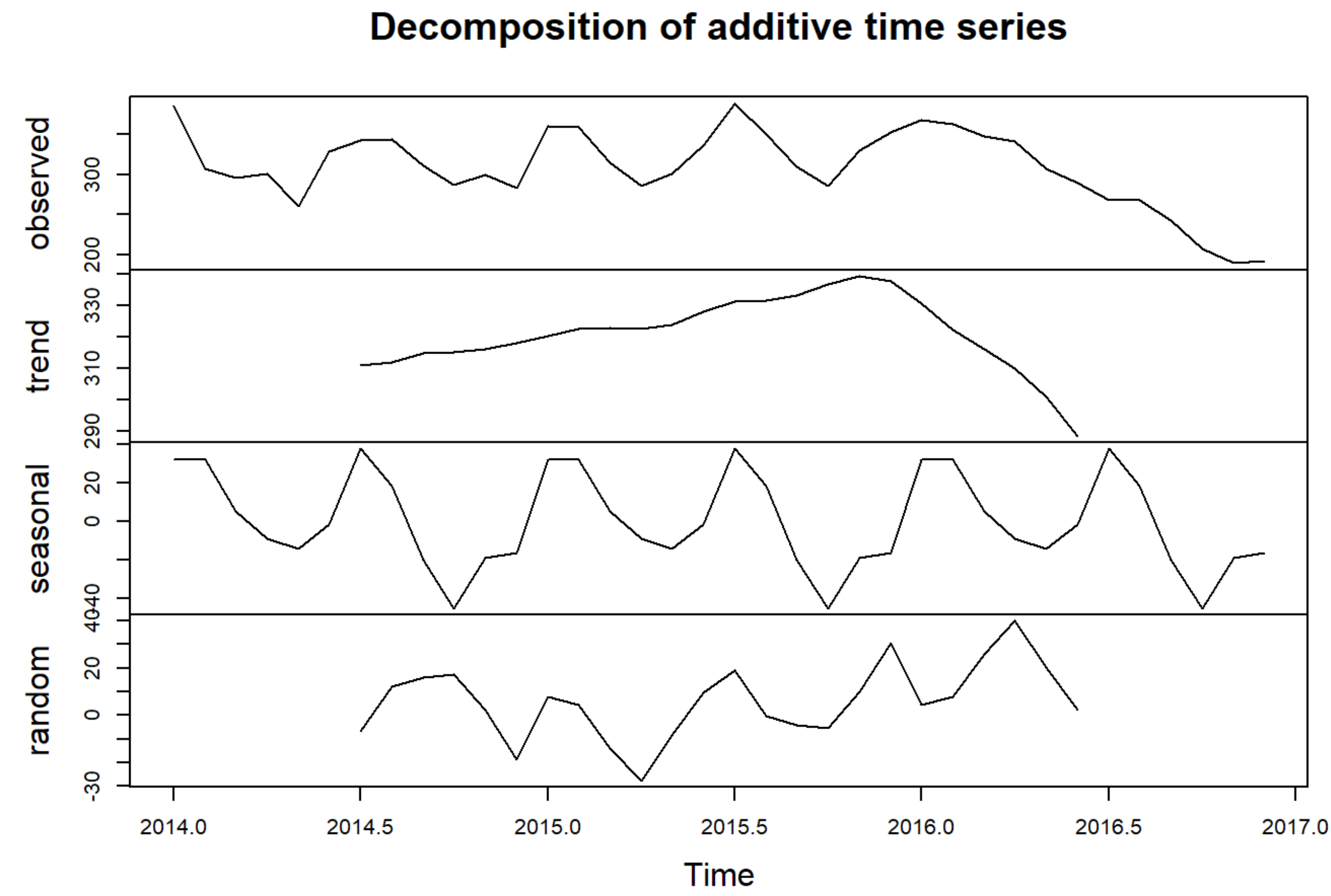
Decomposition of additive time series
observed
trend
seasonal
random
Time

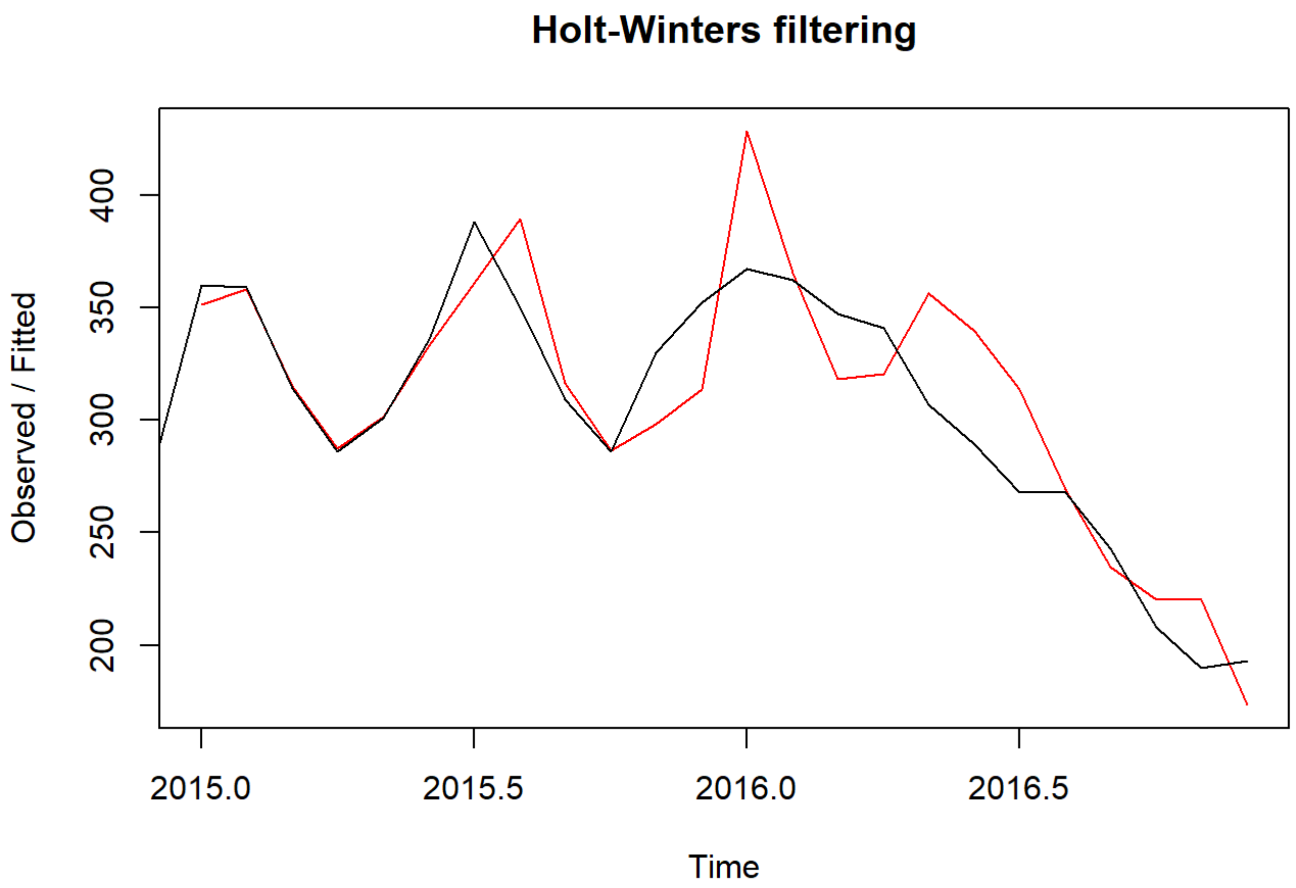



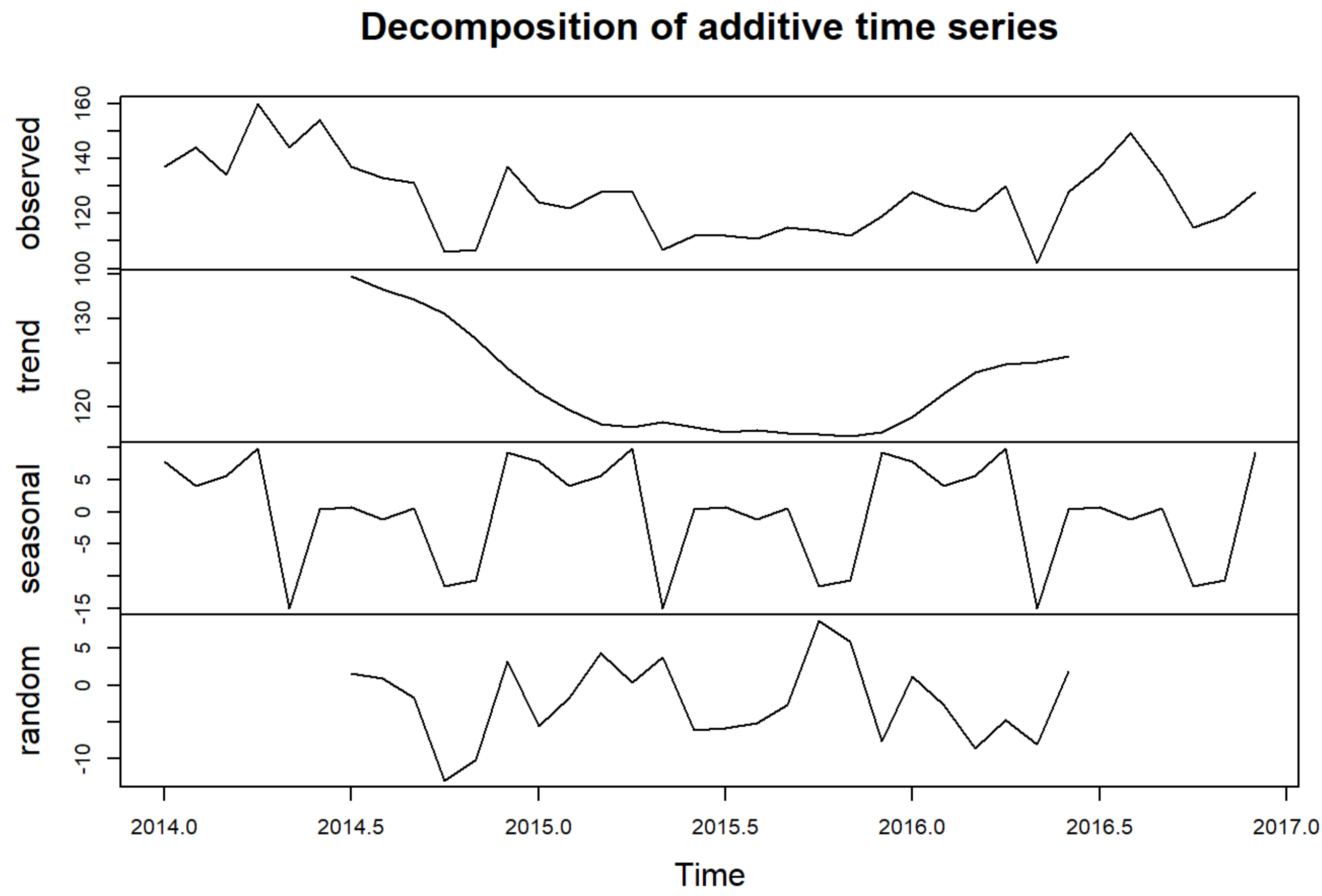
viewers
ACF
Lag


Series train_D[[i]]
Partial ACF
-0.2
0.0
0.2
0.4
2
4
6
8
10
12
14
Lag

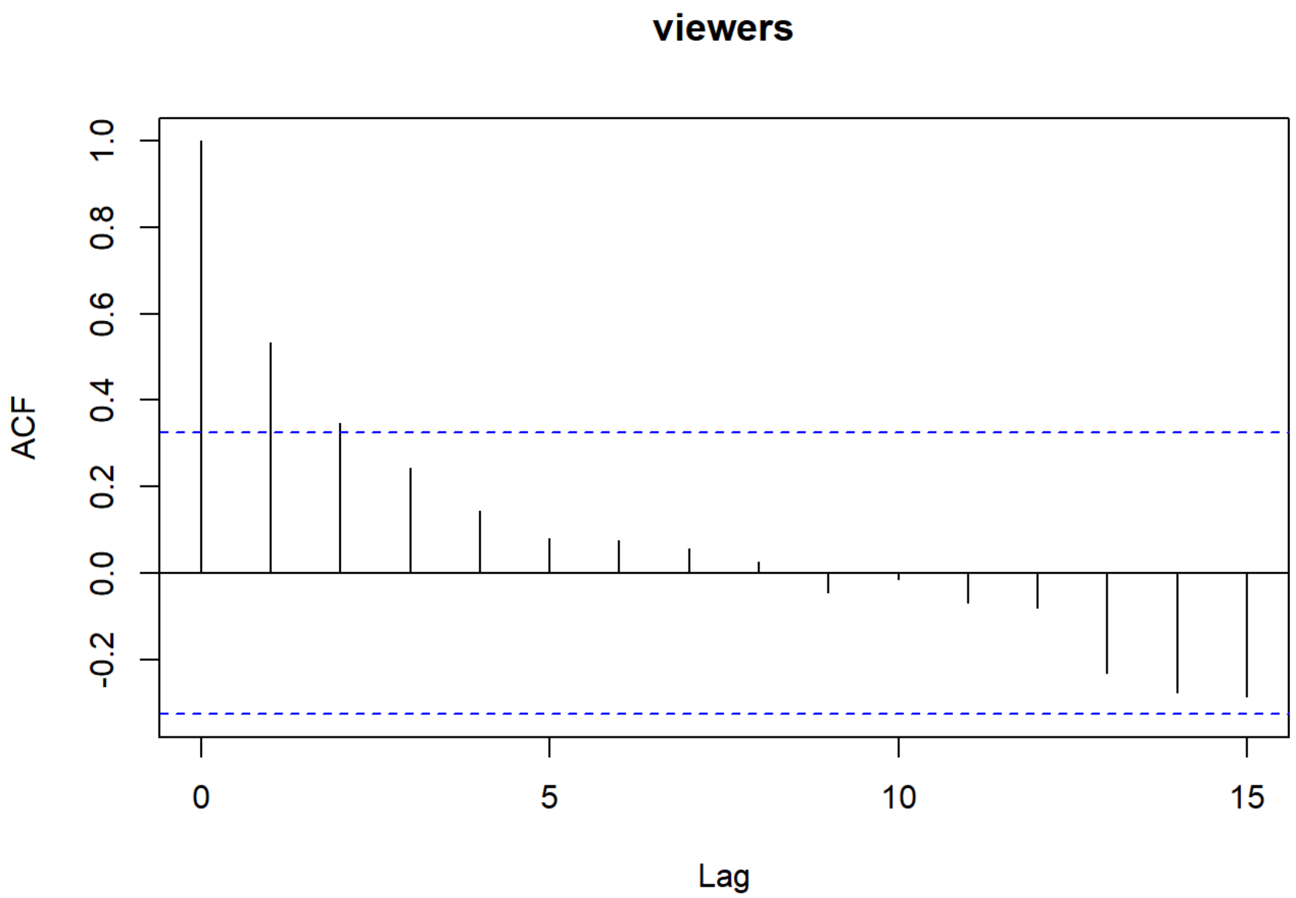

Holt-Winters filtering
Observed / Fitted
120
140
160
2015.0
2015.5
2016.0
2016.5
Time


Decomposition of additive time series
observed
300
200
trend
330
310
290
seasonal
20
0
-40
random
40
20
0
-30
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

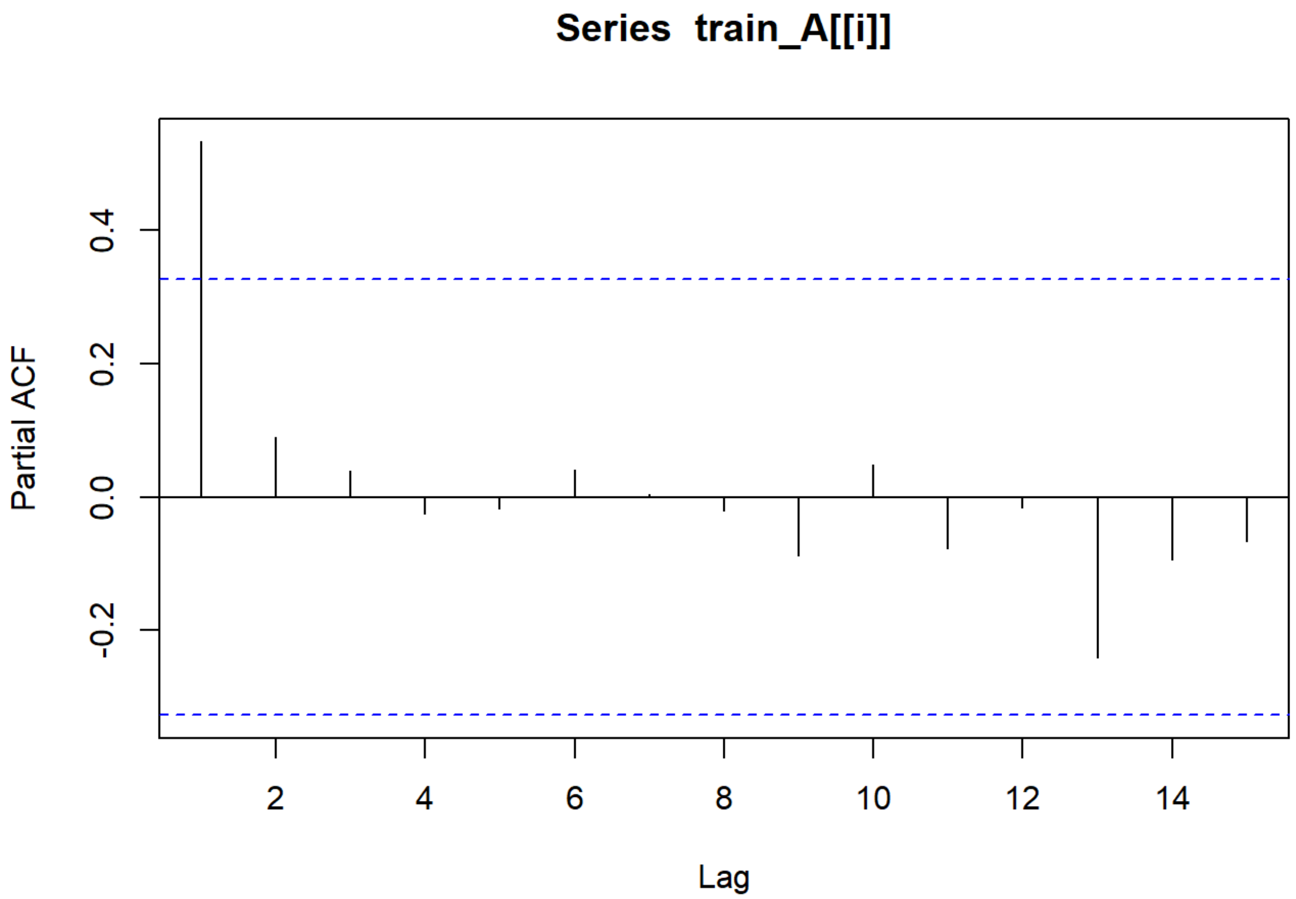

Holt-Winters filtering
Observed / Fitted
400
350
300
250
200
2015.0
2015.5
2016.0
2016.5
Time

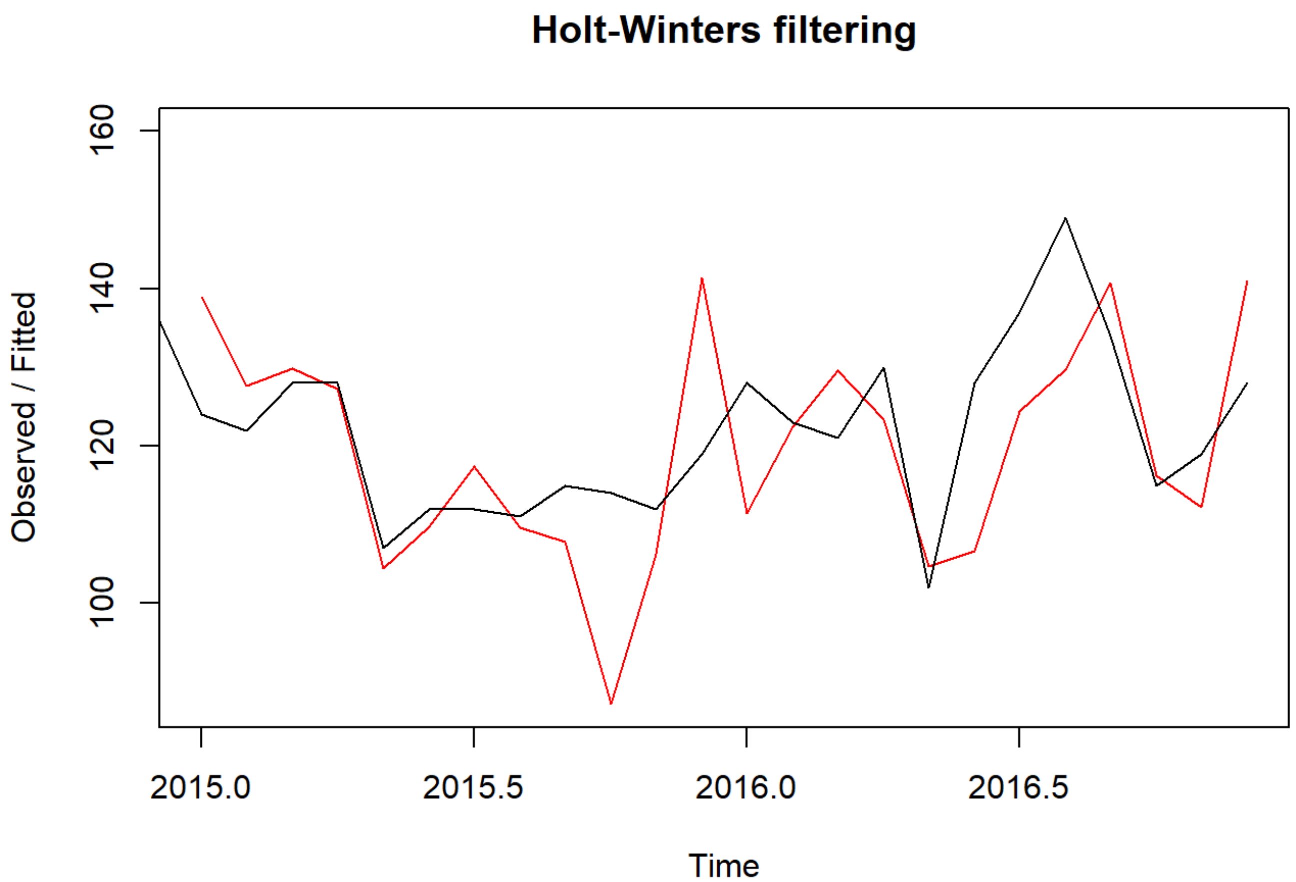


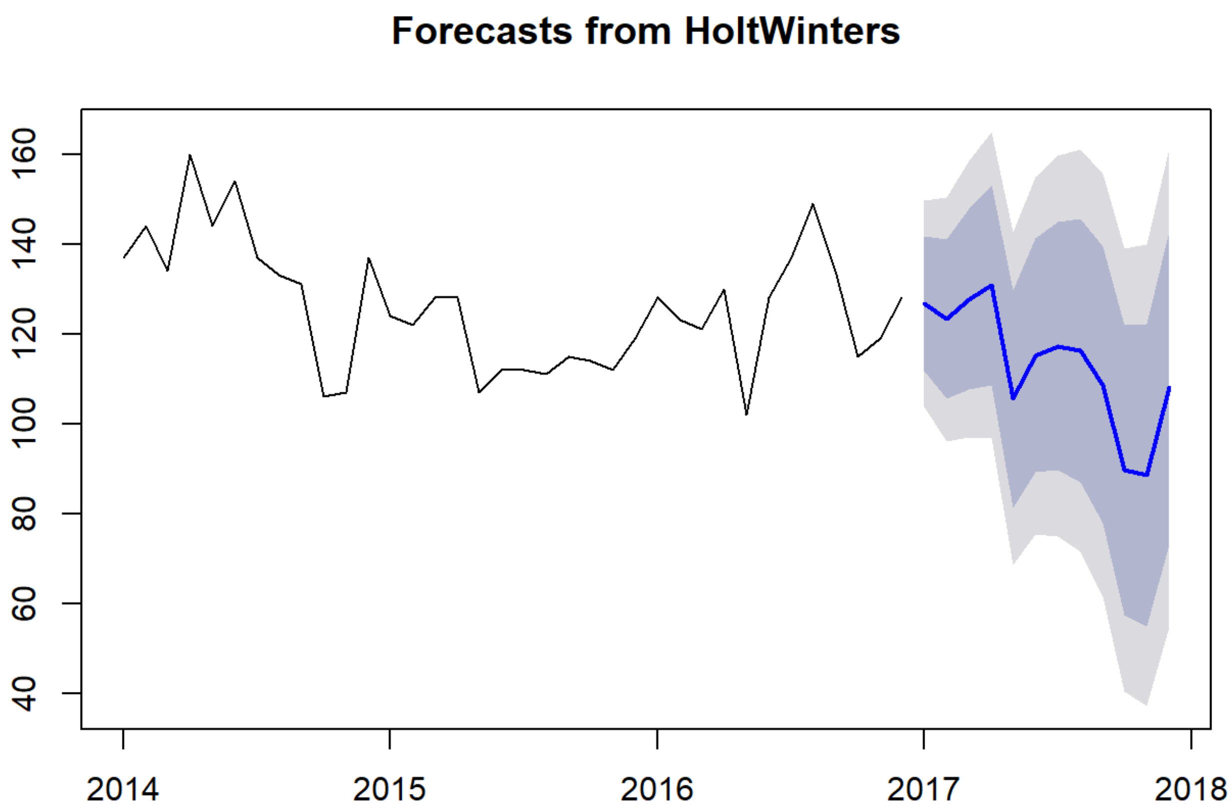
Decomposition of additive time series
observed
trend
seasonal
random
Time
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0

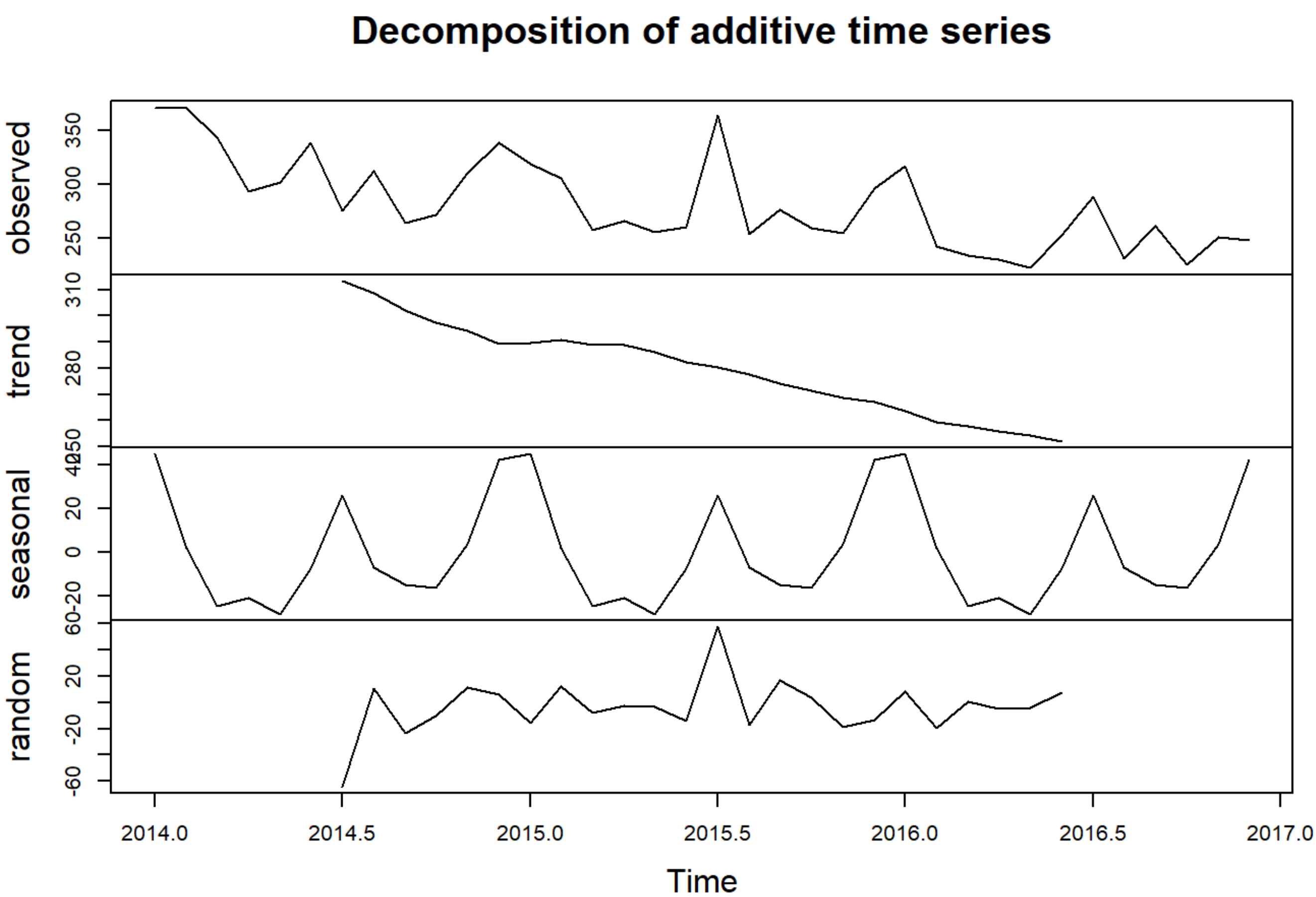
viewers
ACF
Lag


Series train_A[[i]]
Partial ACF
-0.2
0.0
0.2
0.4
2
4
6
8
10
12
14
Lag

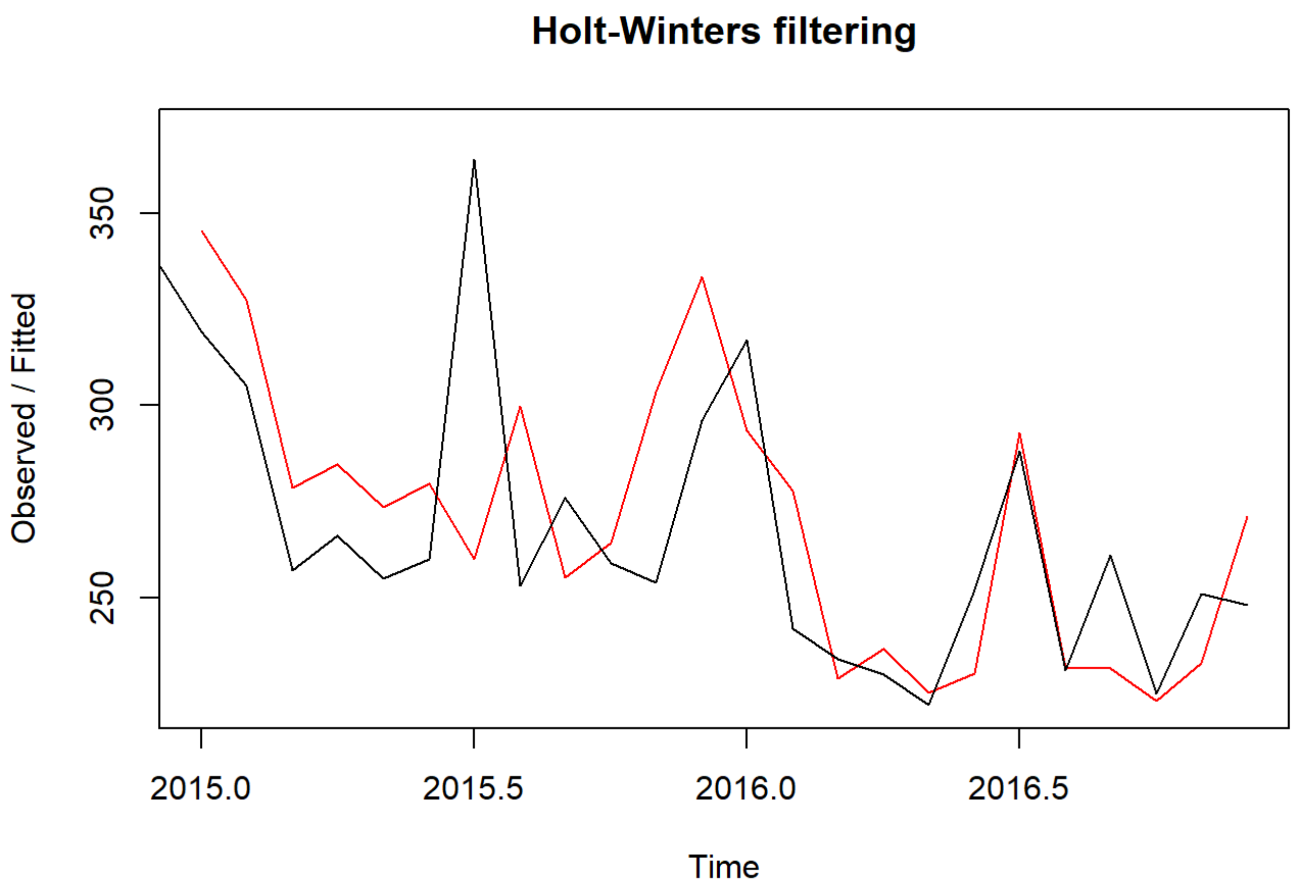

Holt-Winters filtering
Observed / Fitted
100
120
140
160
2015.0
2015.5
2016.0
2016.5
Time



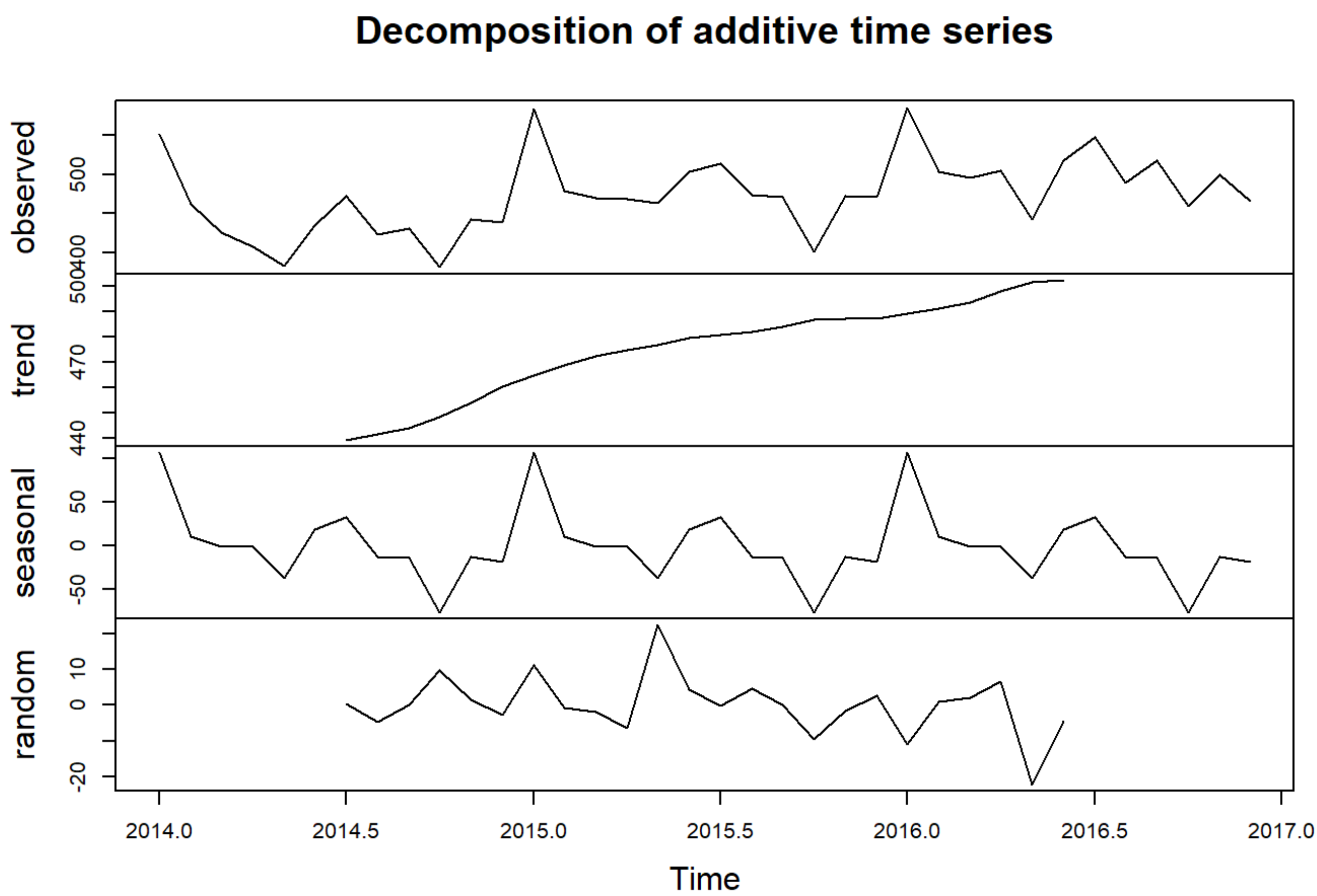
Forecasts from HoltWinters
40
60
80
100
120
140
160
2014
2015
2016
2017
2018

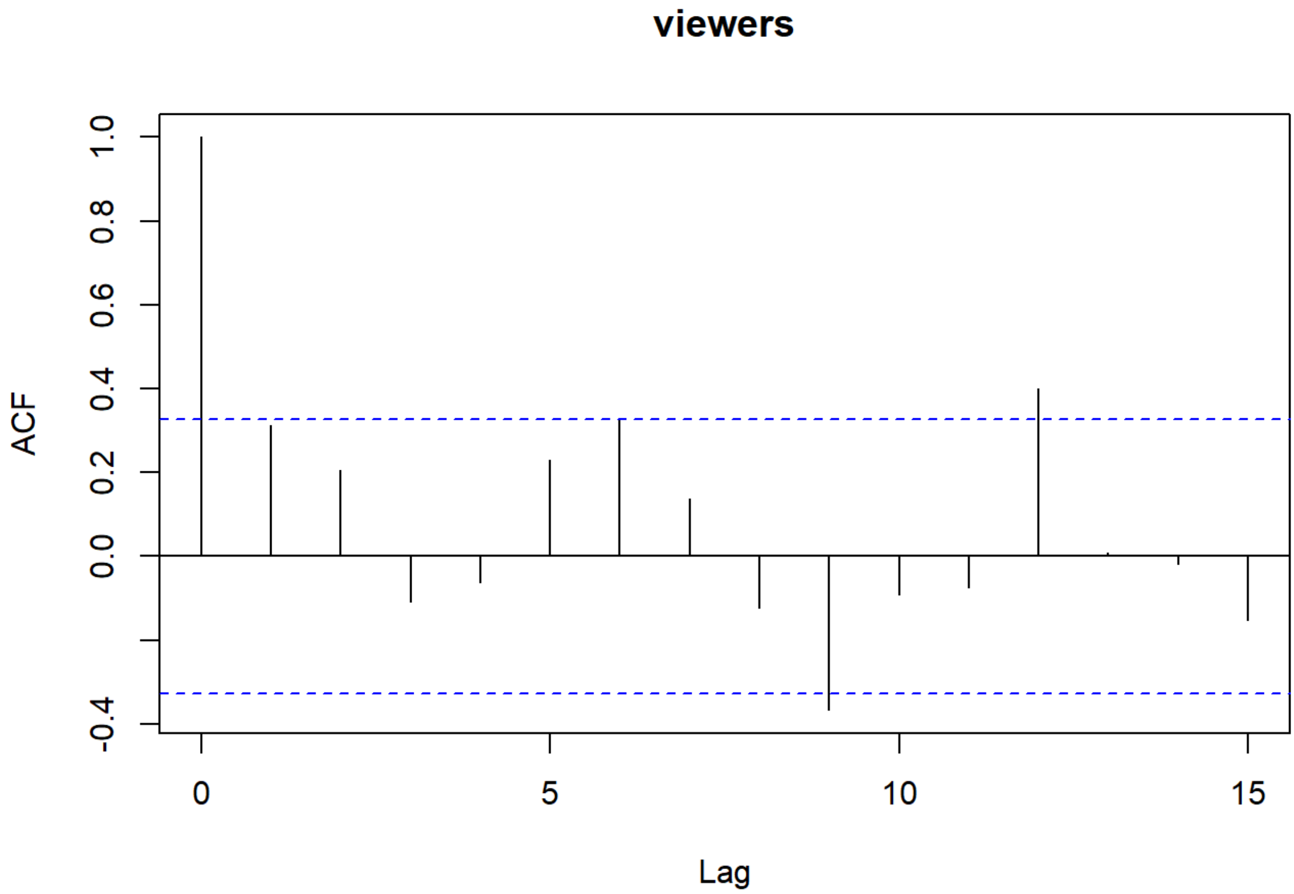
Decomposition of additive time series
observed
trend
seasonal
random
250
300
350
250
280
310
-20
0
20
40
-60
-20
20
60
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

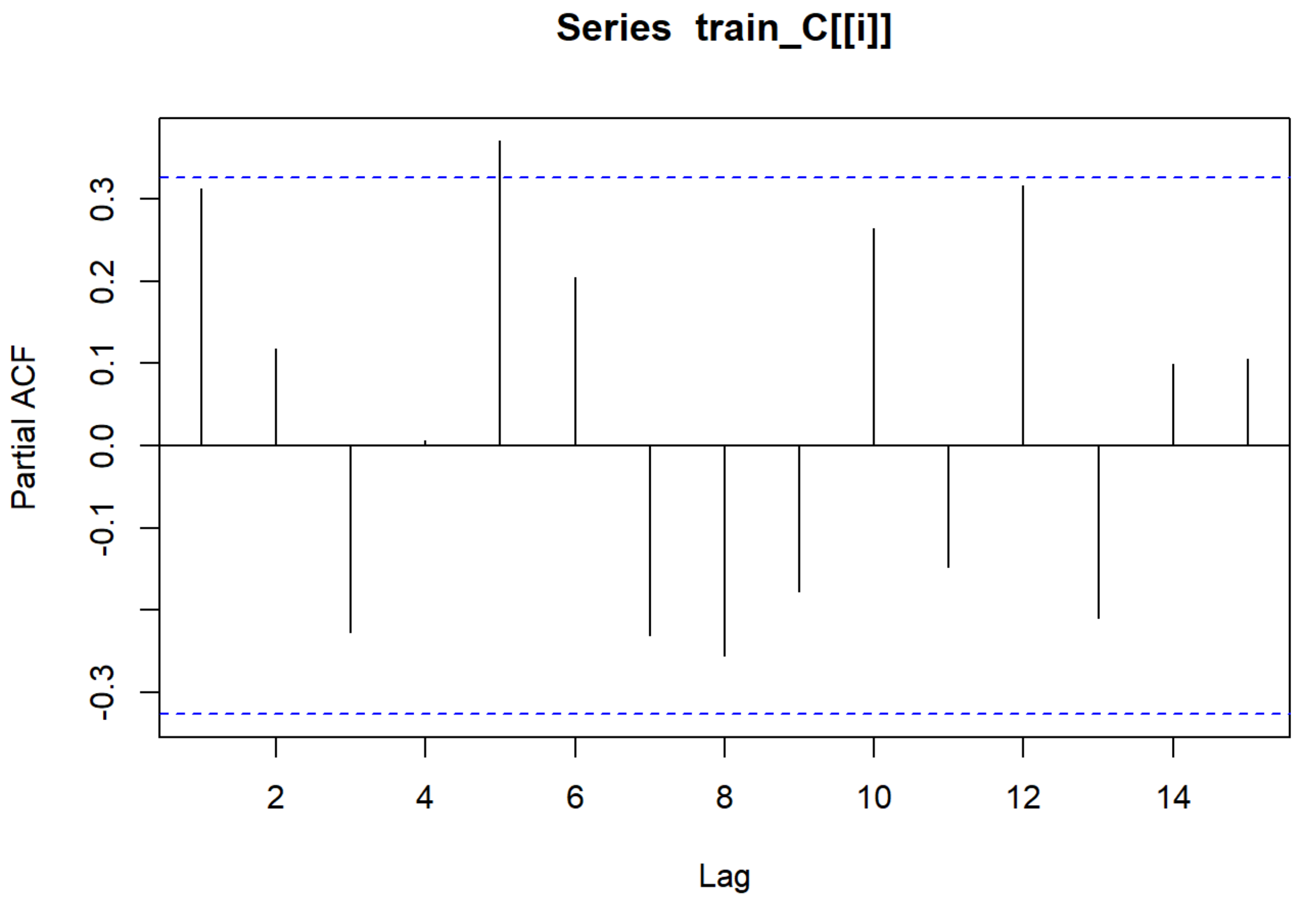


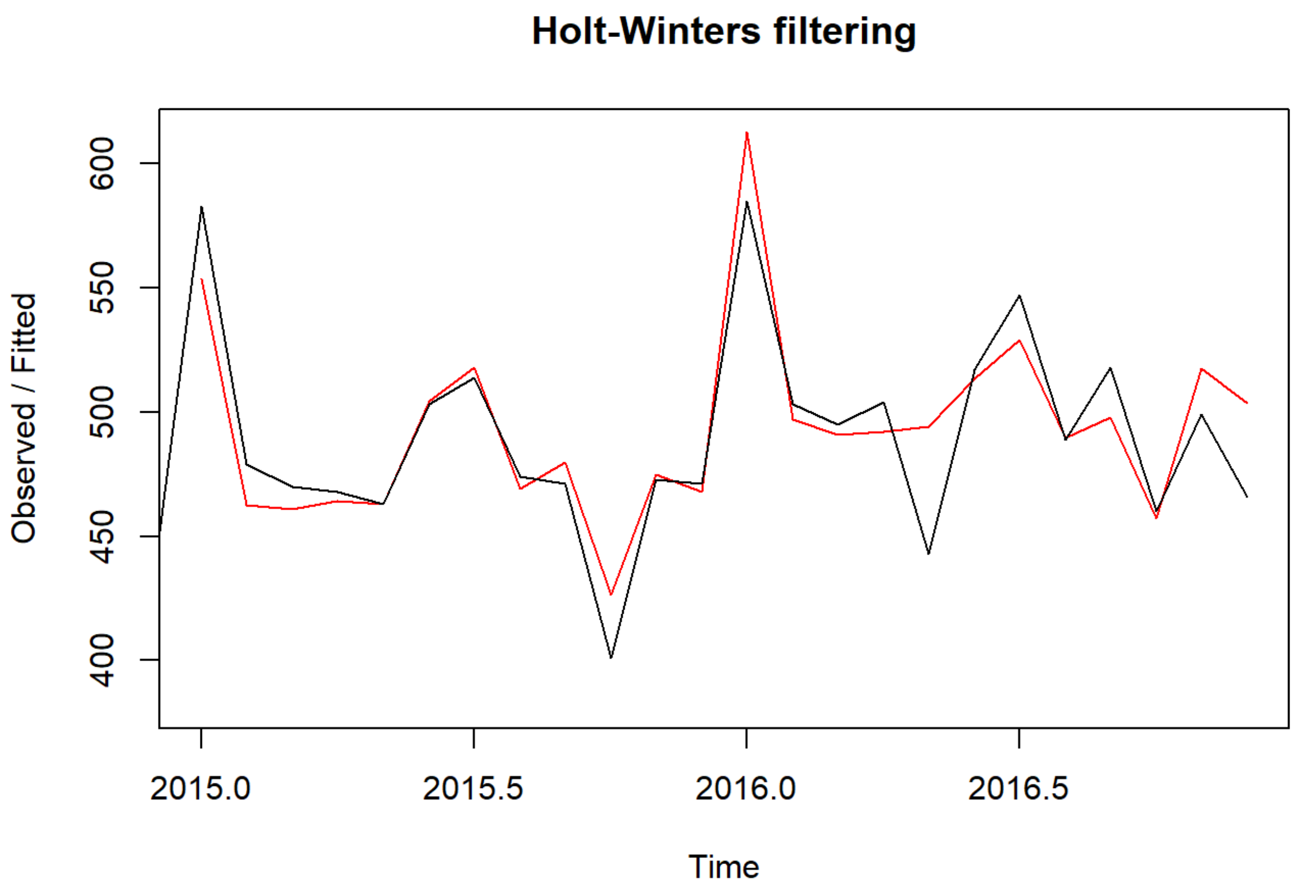
Holt-Winters filtering
Observed / Fitted
350
300
250
2015.0
2015.5
2016.0
2016.5
Time

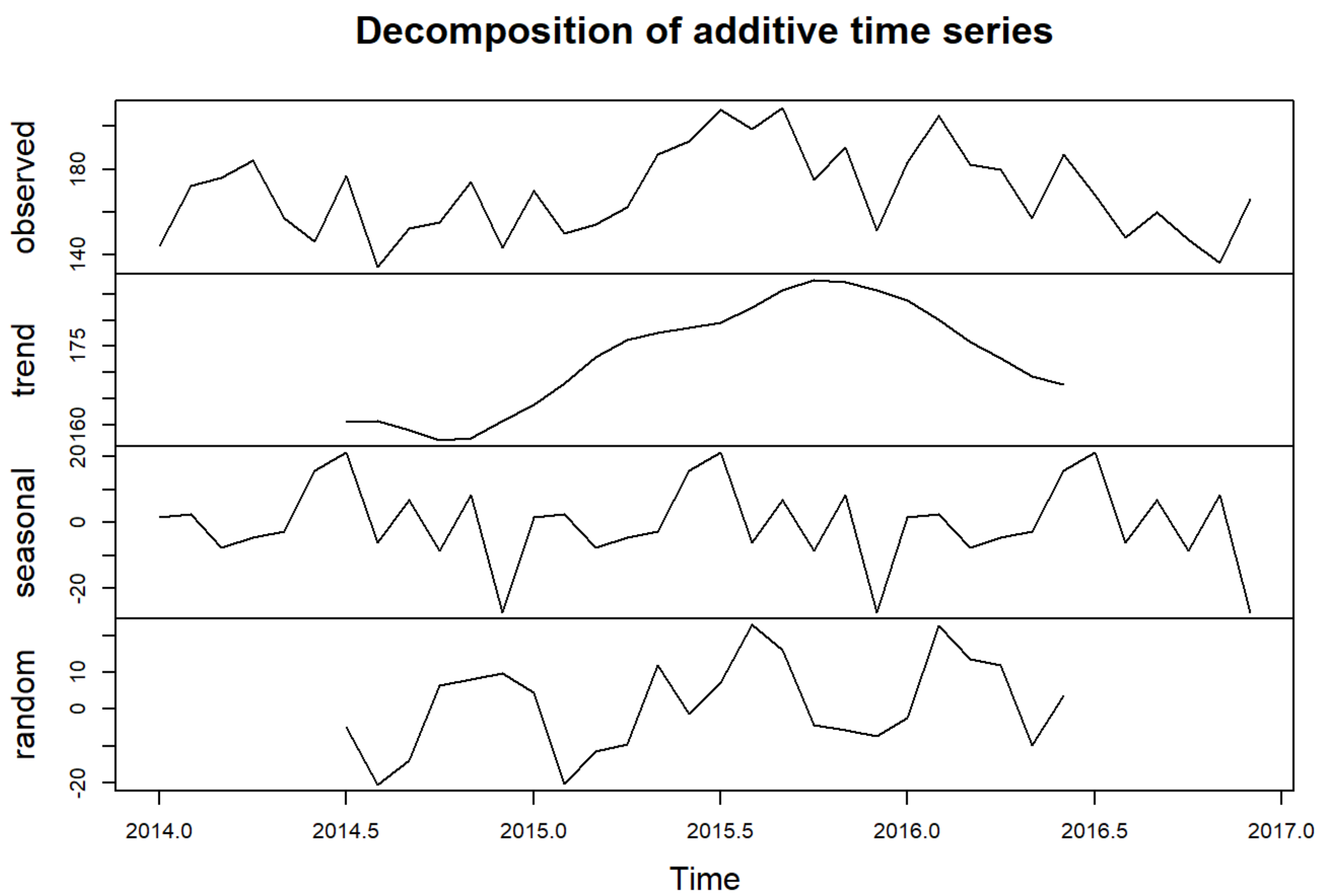



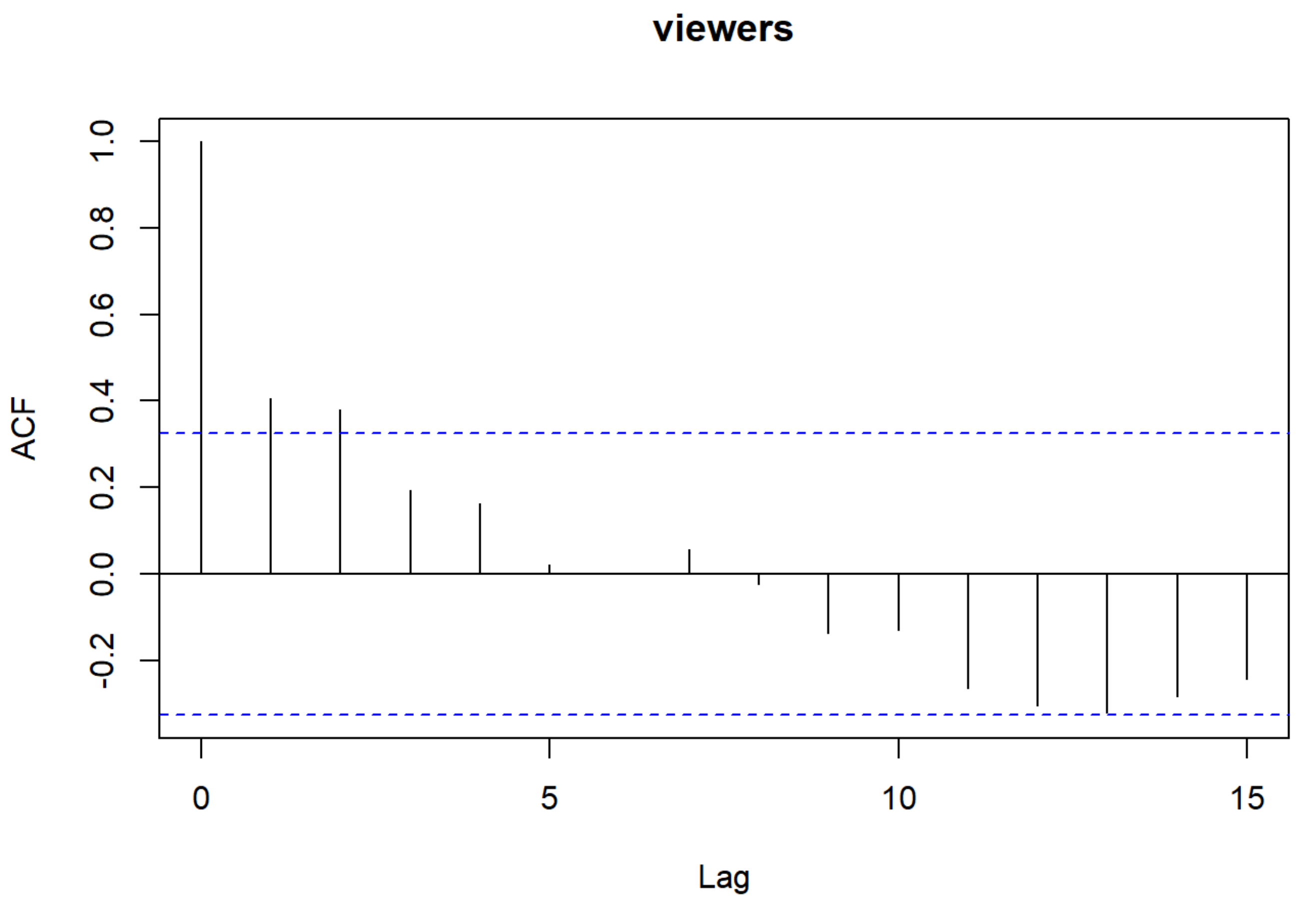
Decomposition of additive time series
observed
500
400
trend
500
470
440
seasonal
50
0
-50
random
10
0
-20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

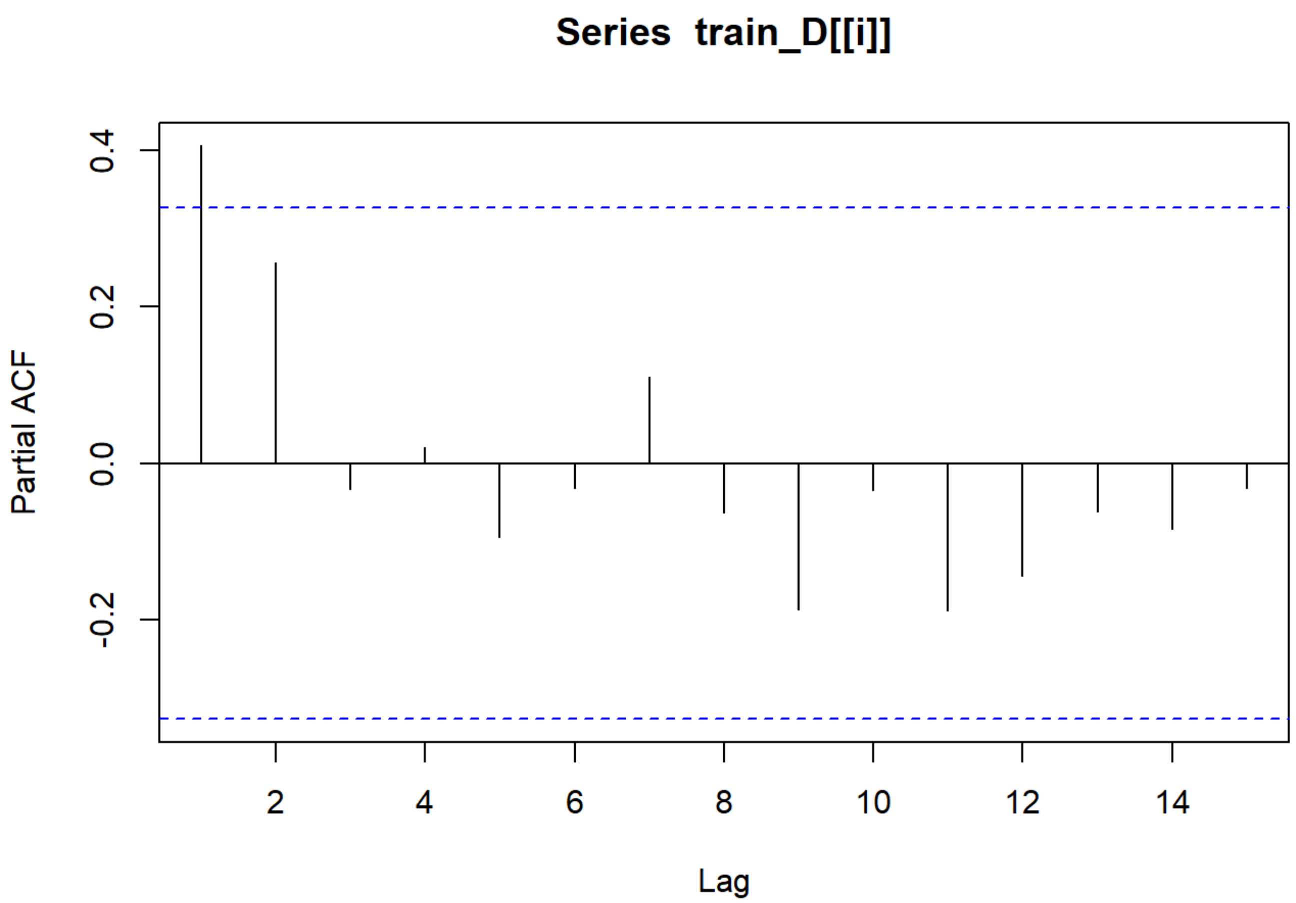

viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.4
0
5
10
15
Lag

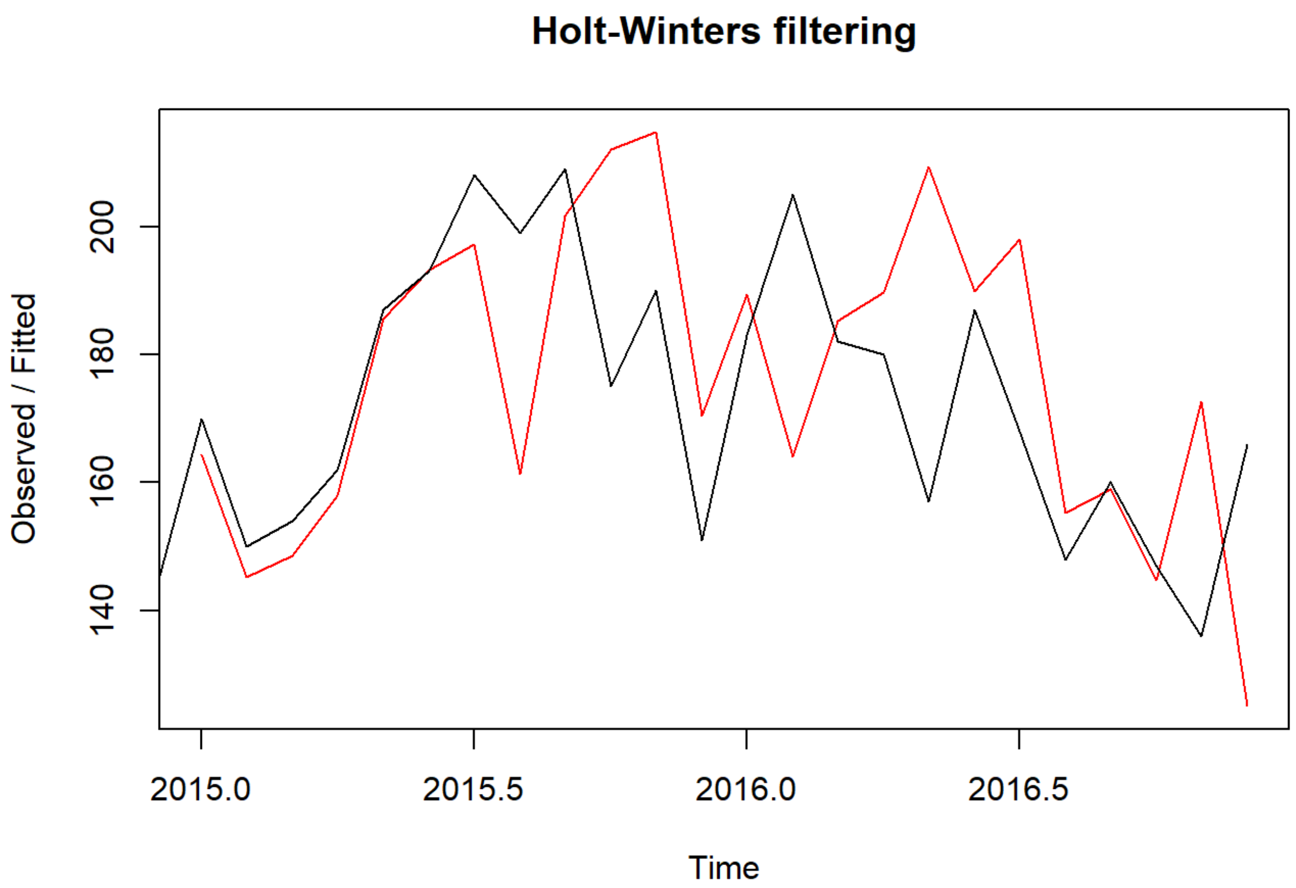

Series train_C[[i]]
Partial ACF
0.3
0.2
0.1
0.0
-0.1
-0.3
2
4
6
8
10
12
14
Lag

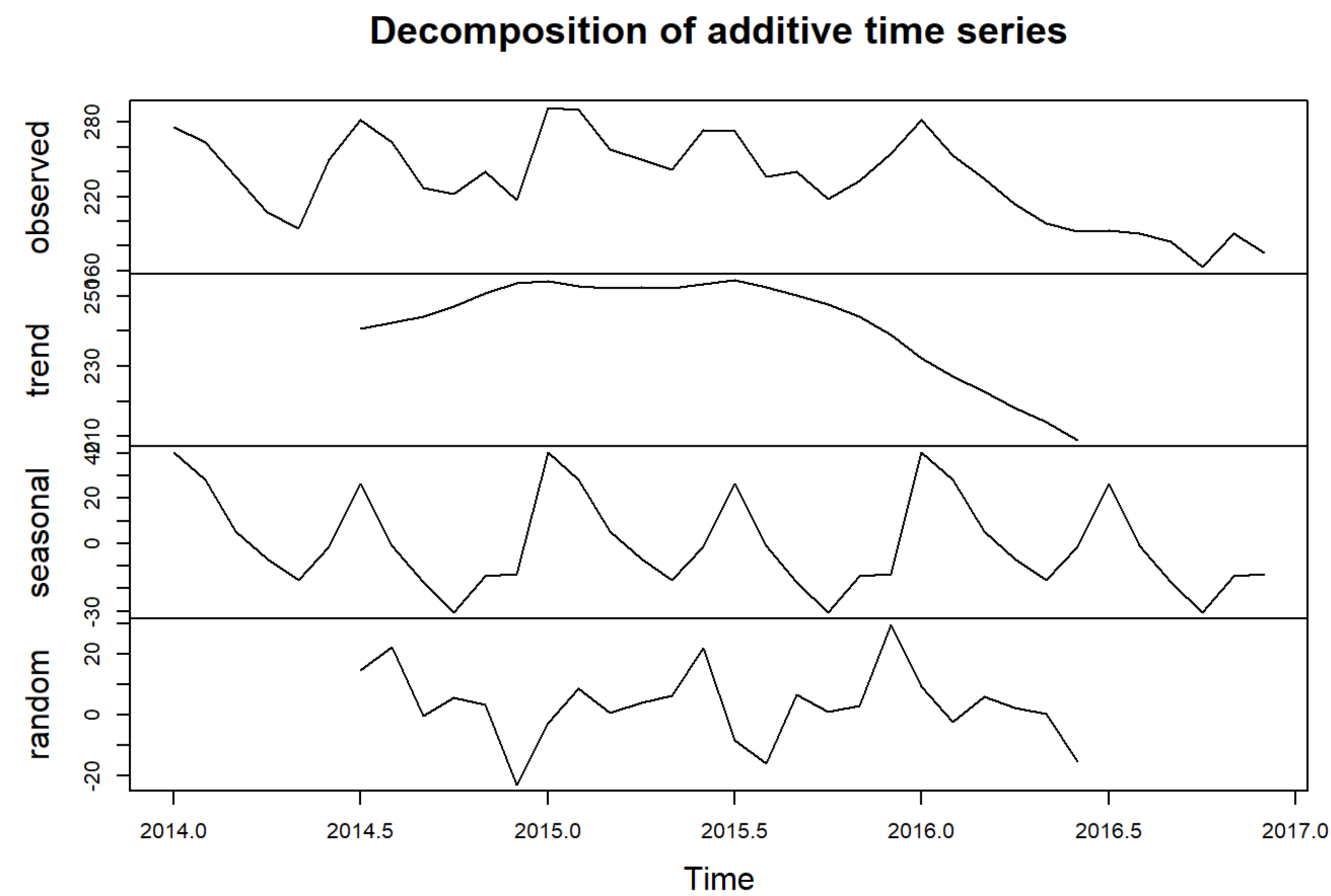

Holt-Winters filtering
Observed / Fitted
400
450
500
550
600
2015.0
2015.5
2016.0
2016.5
Time

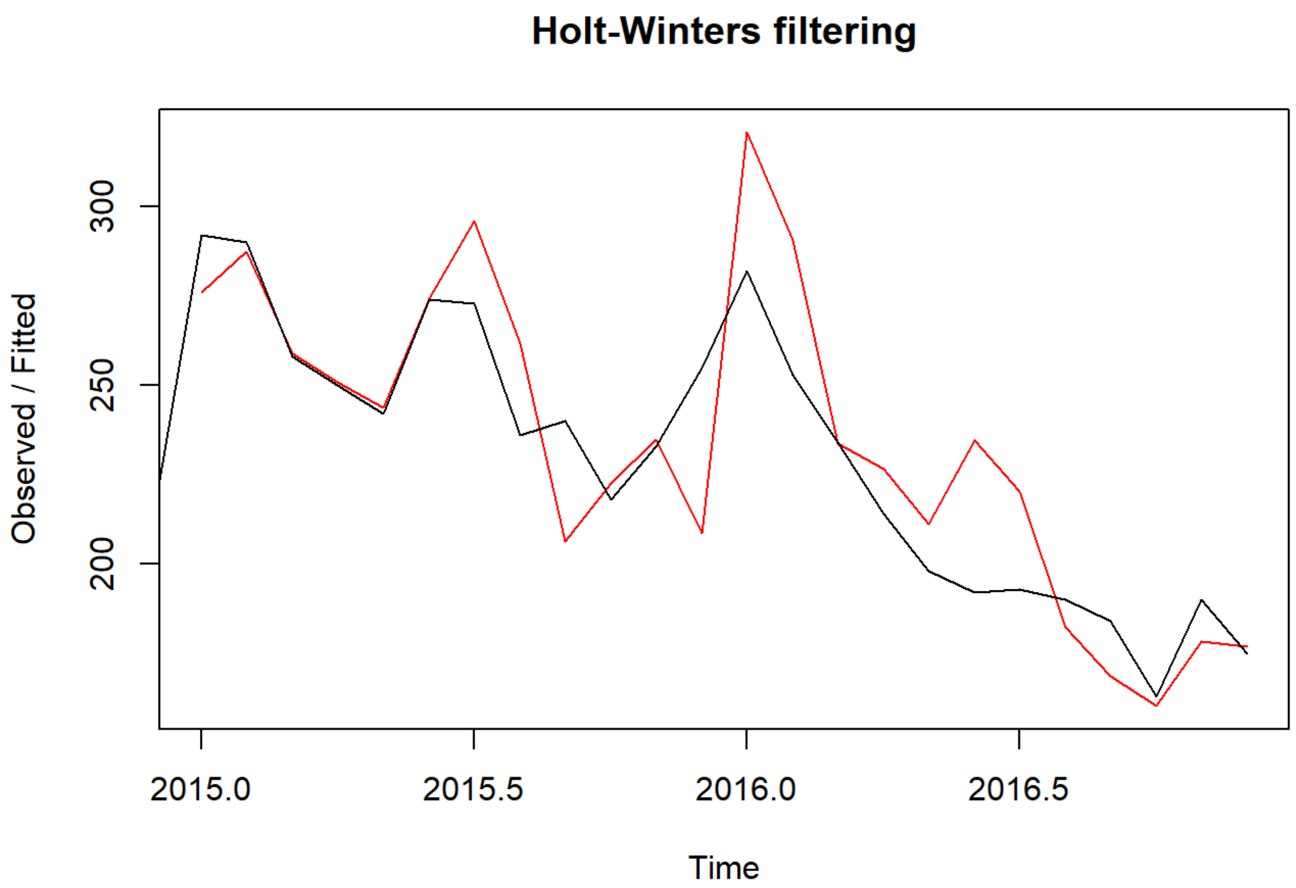

Decomposition of additive time series
observed
140
180
trend
160
175
seasonal
-20
0
20
random
-20
0
10
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time


viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

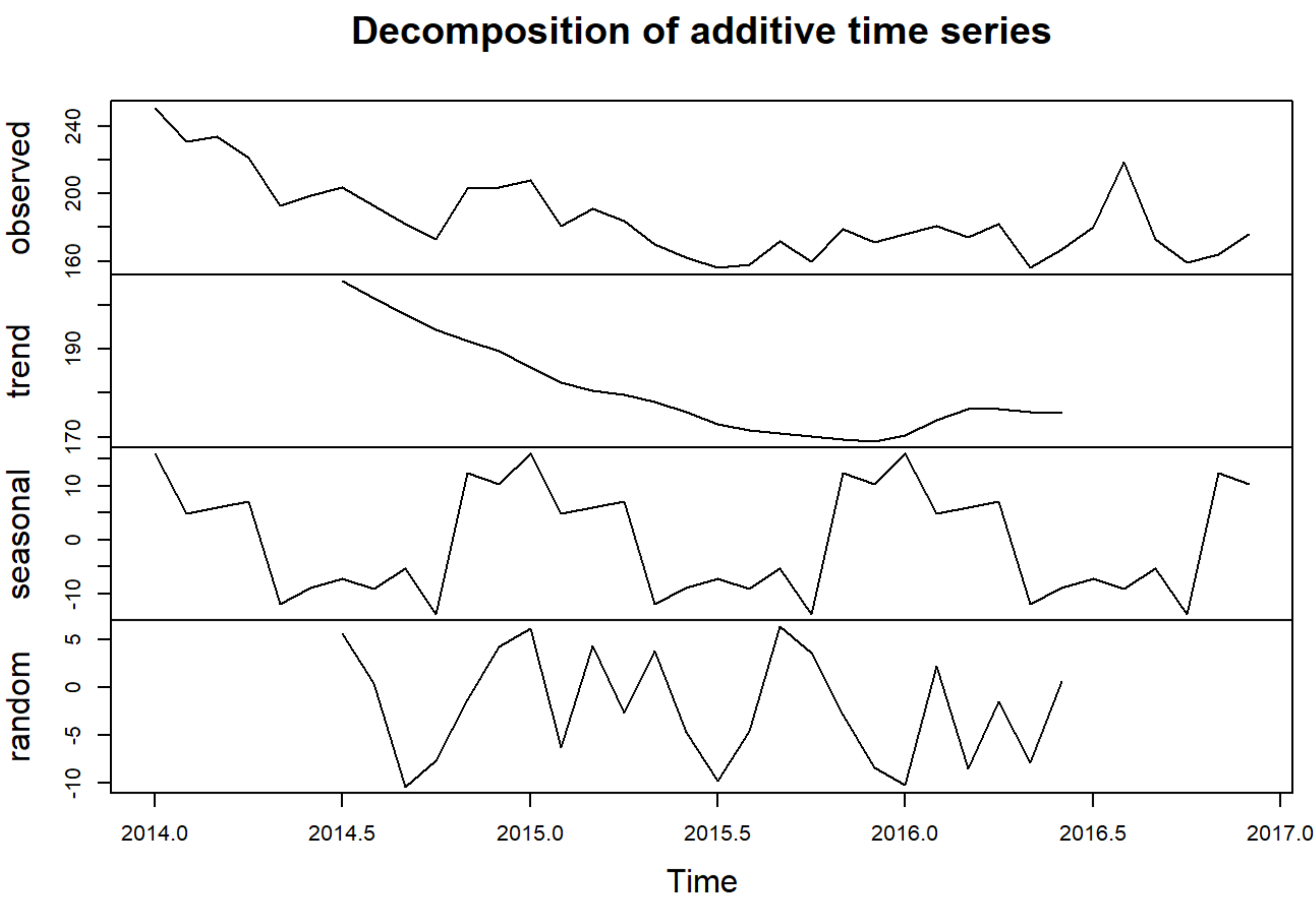

Series train_D[[i]]
Partial ACF
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag


Holt-Winters filtering
Observed / Fitted
140
160
180
200
2015.0
2015.5
2016.0
2016.5
Time

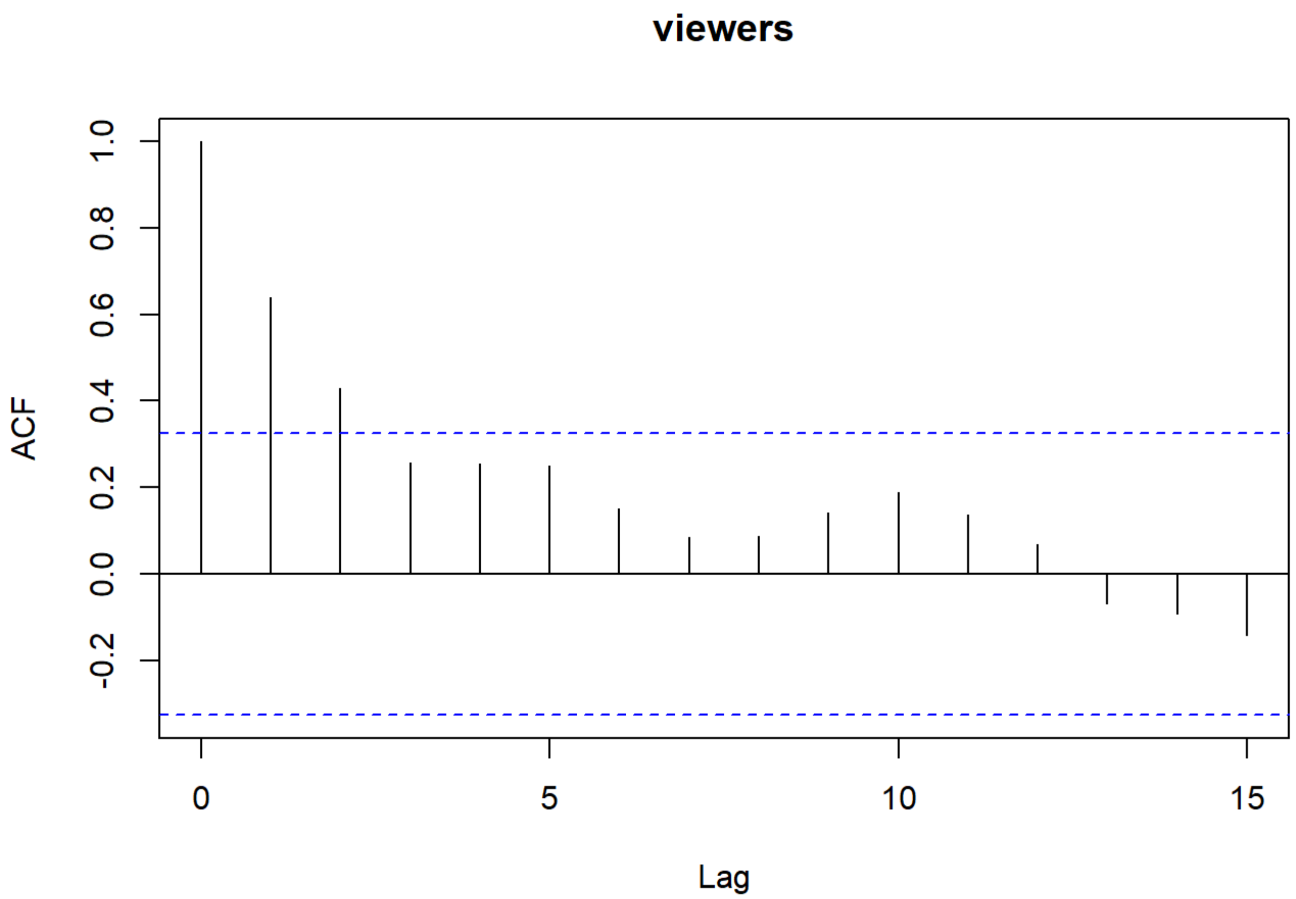

Decomposition of additive time series
observed
trend
seasonal
random
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

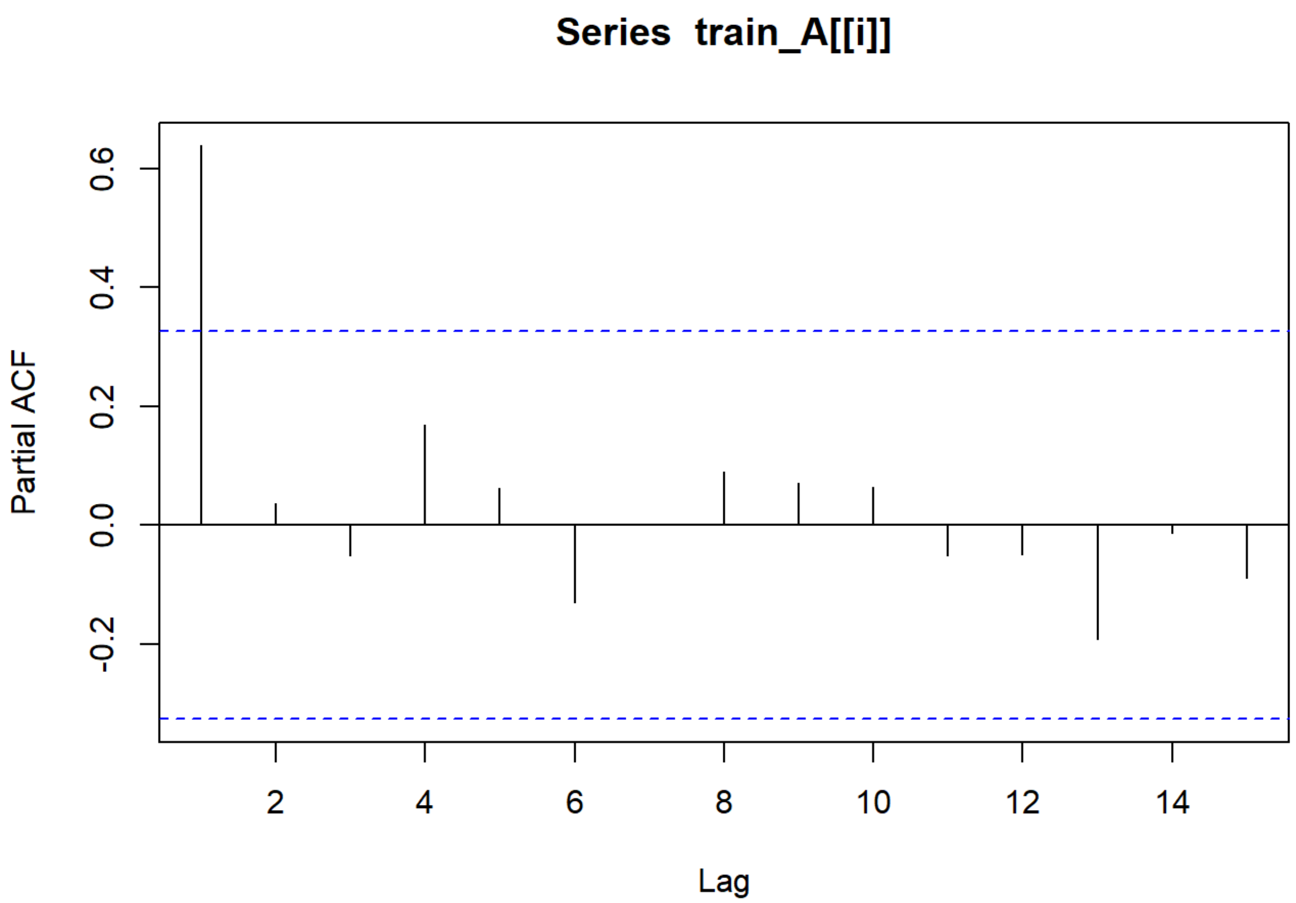


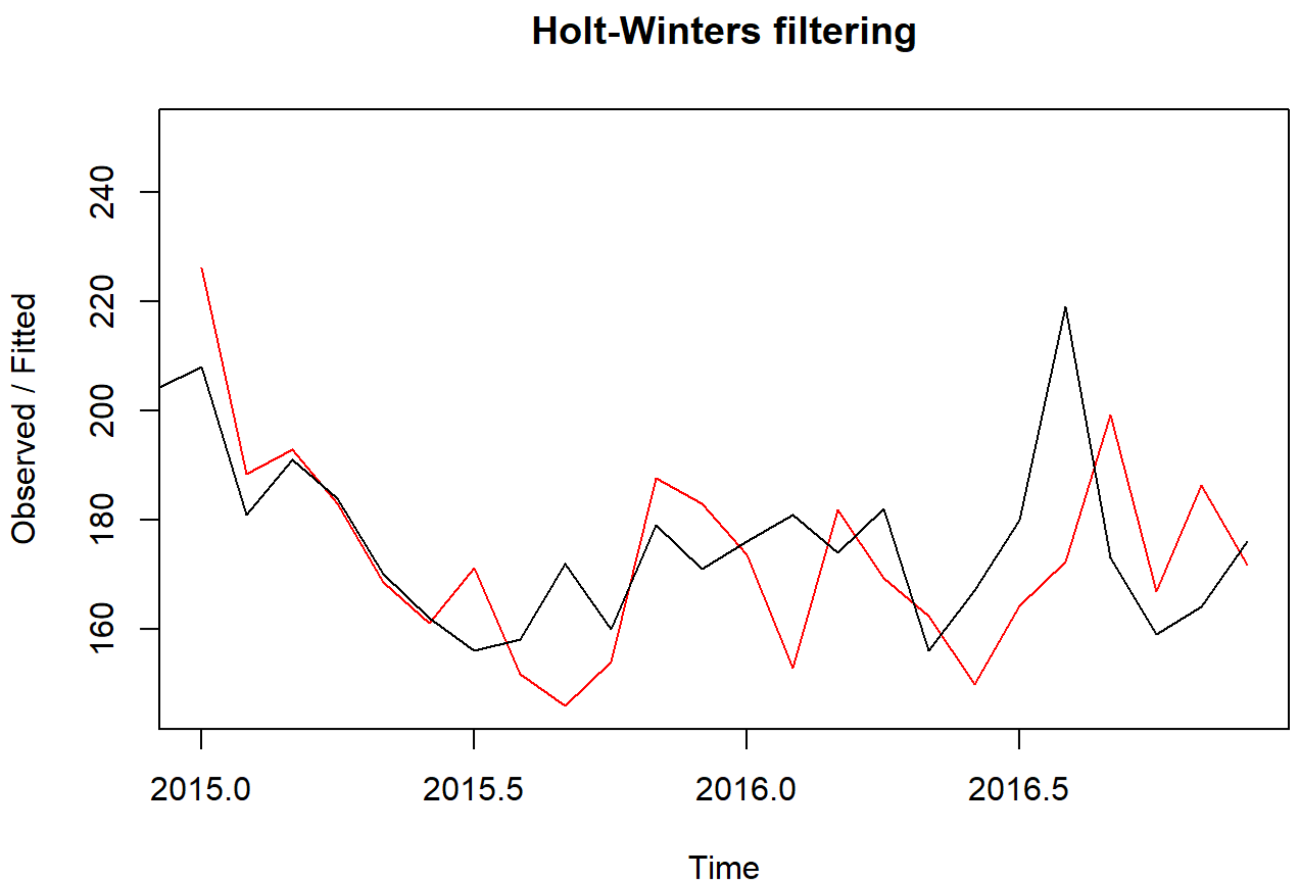
Holt-Winters filtering
Observed / Fitted
300
250
200
2015.0
2015.5
2016.0
2016.5
Time

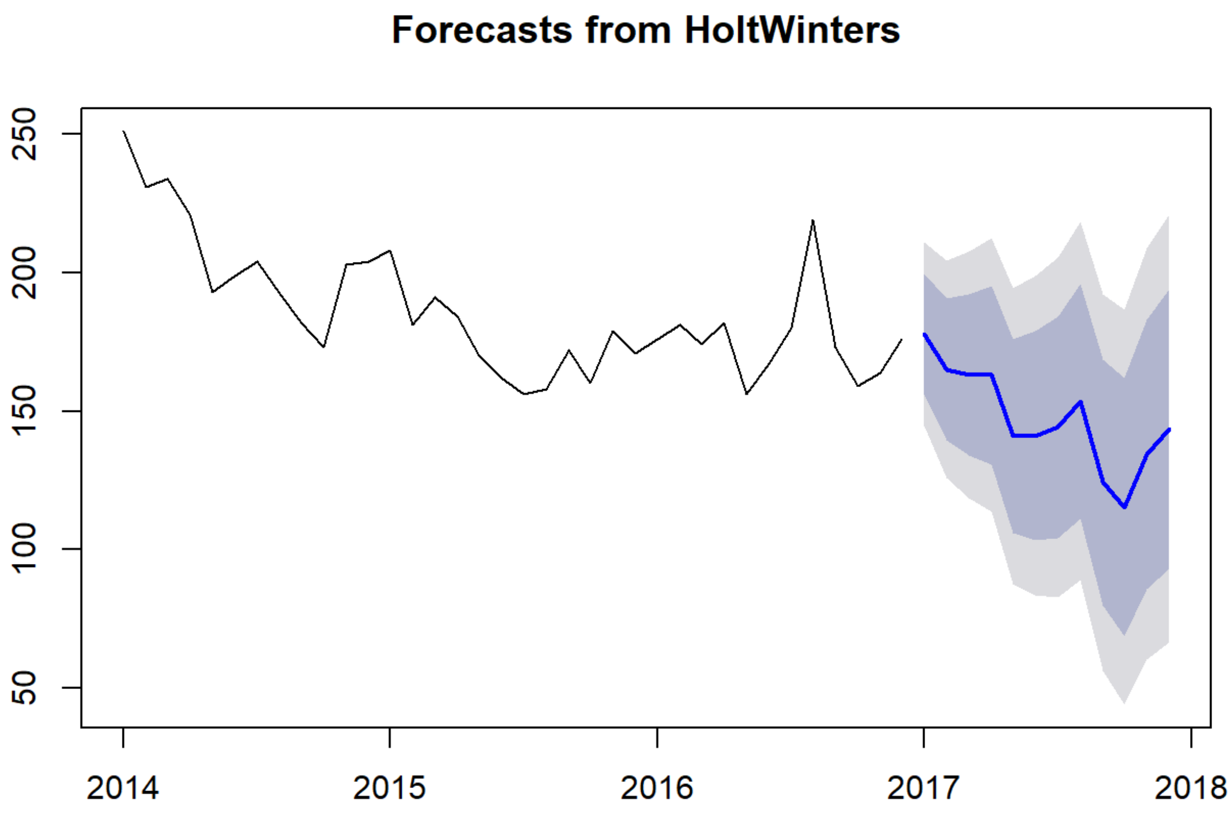



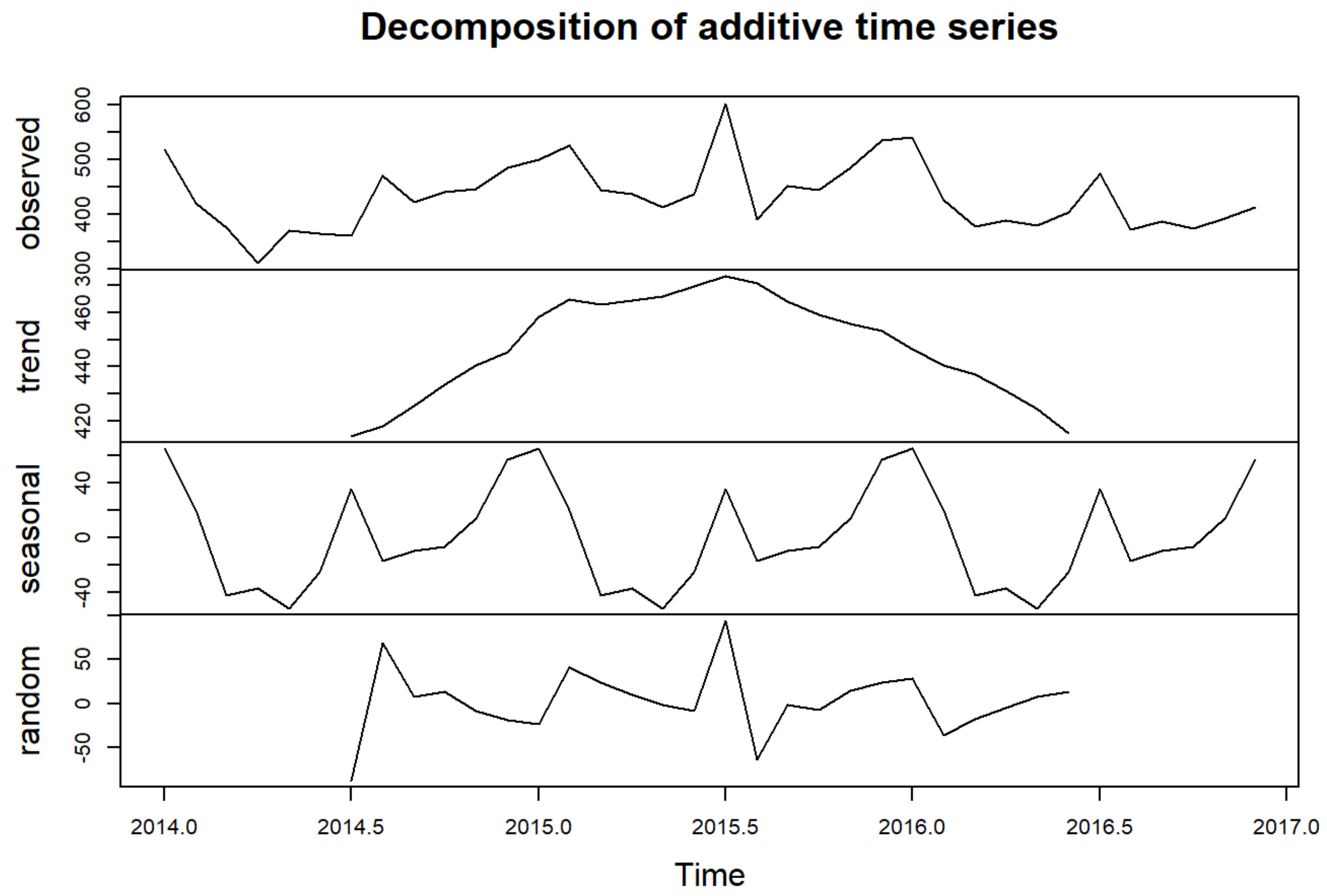
Decomposition of additive time series
observed
240
200
160
trend
190
170
seasonal
10
0
-10
random
5
0
-5
-10
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time


viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

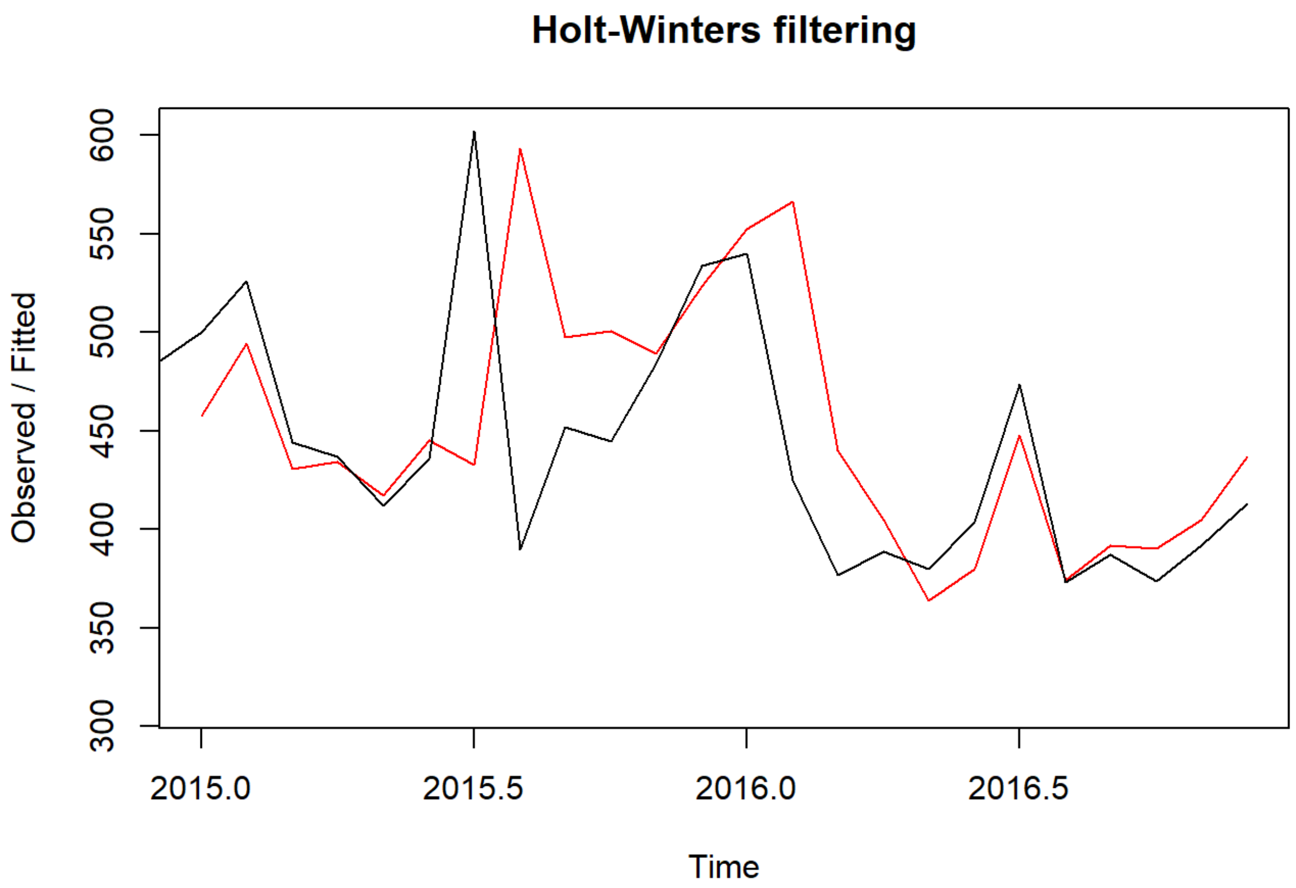

Series train_A[[i]]
Partial ACF
0.6
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag


Holt-Winters filtering
Observed / Fitted
160
180
200
220
240
2015.0
2015.5
2016.0
2016.5
Time

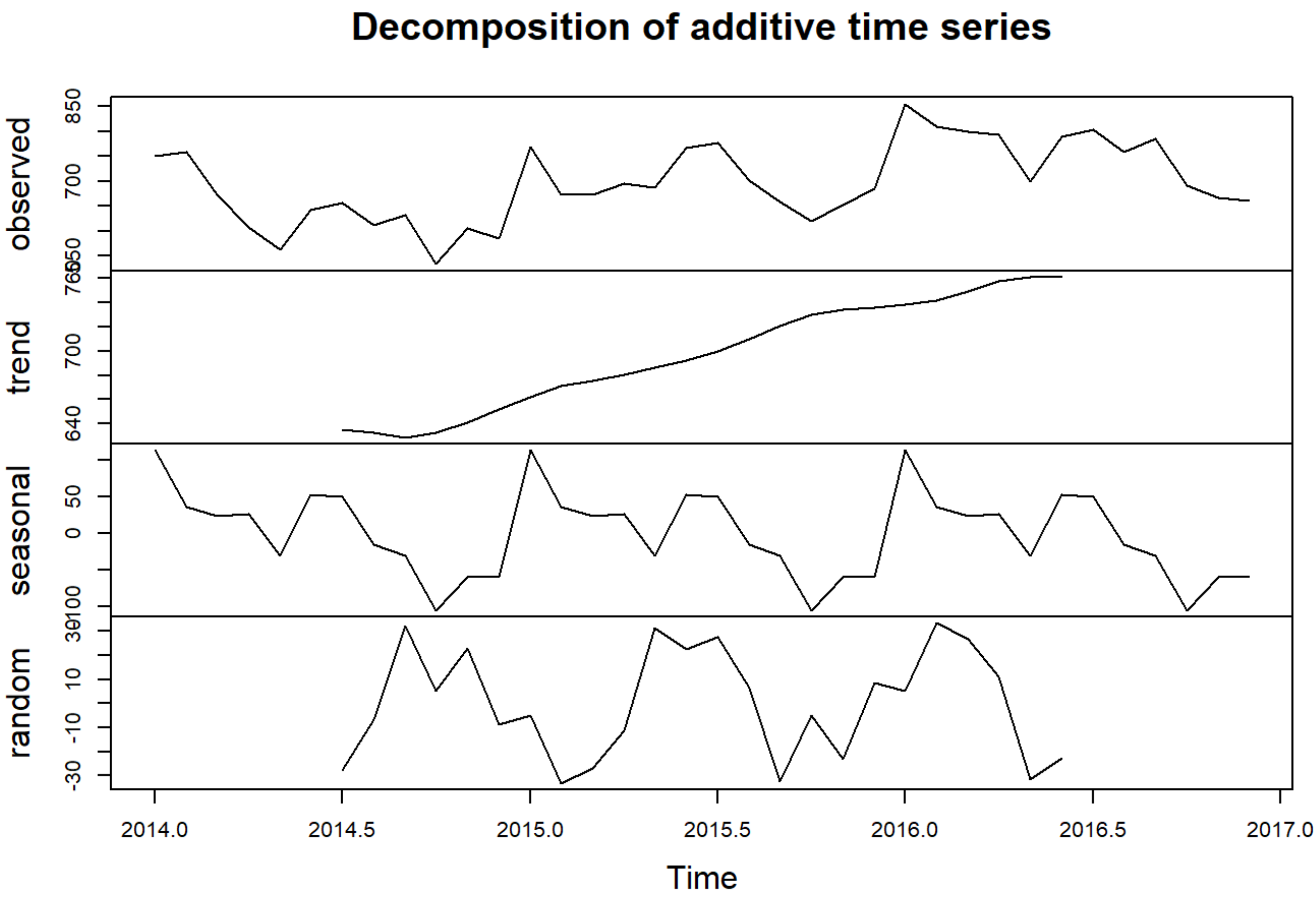

Forecasts from HoltWinters
50
100
150
200
250
2014
2015
2016
2017
2018



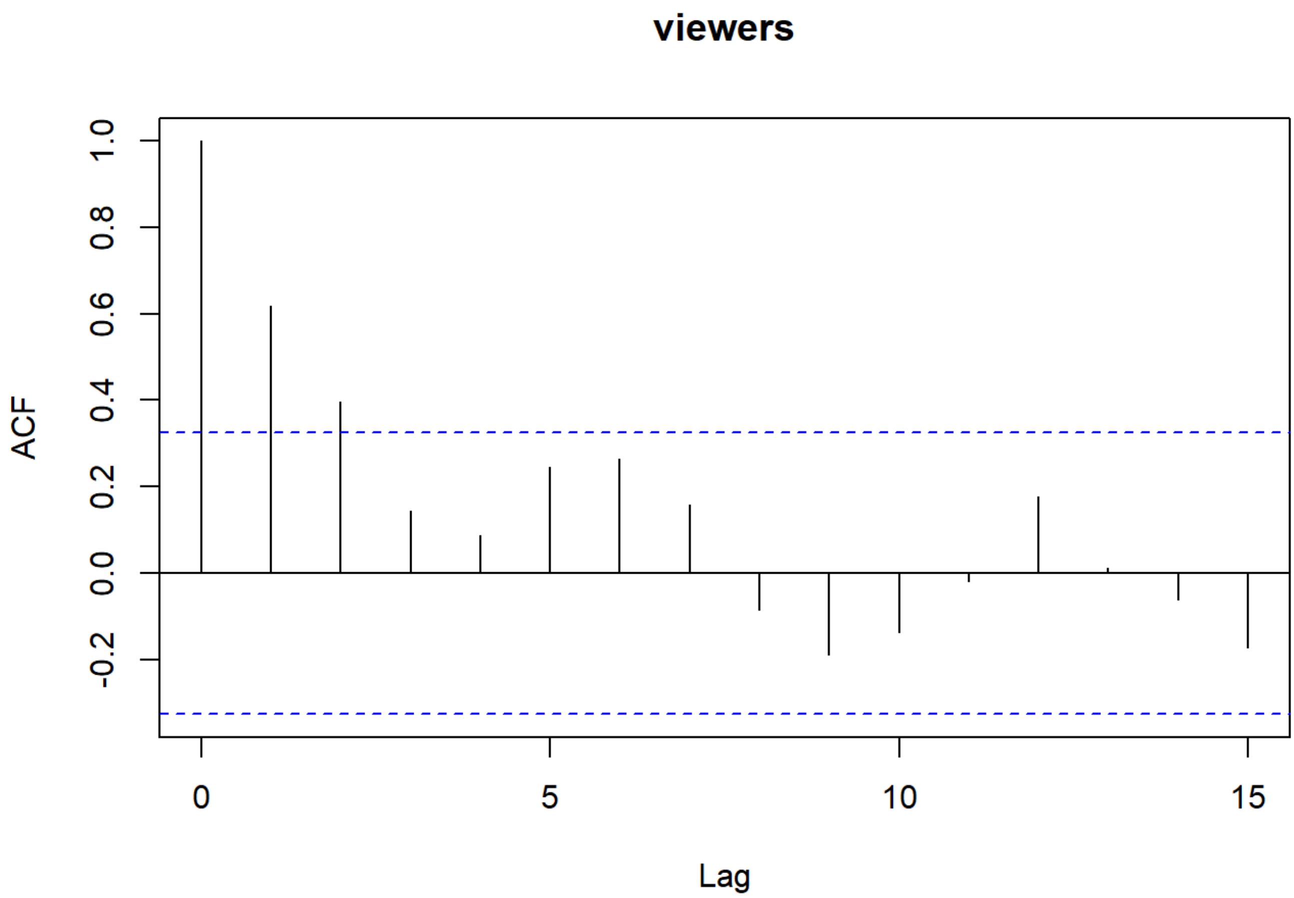
Decomposition of additive time series
observed
trend
seasonal
random
Time

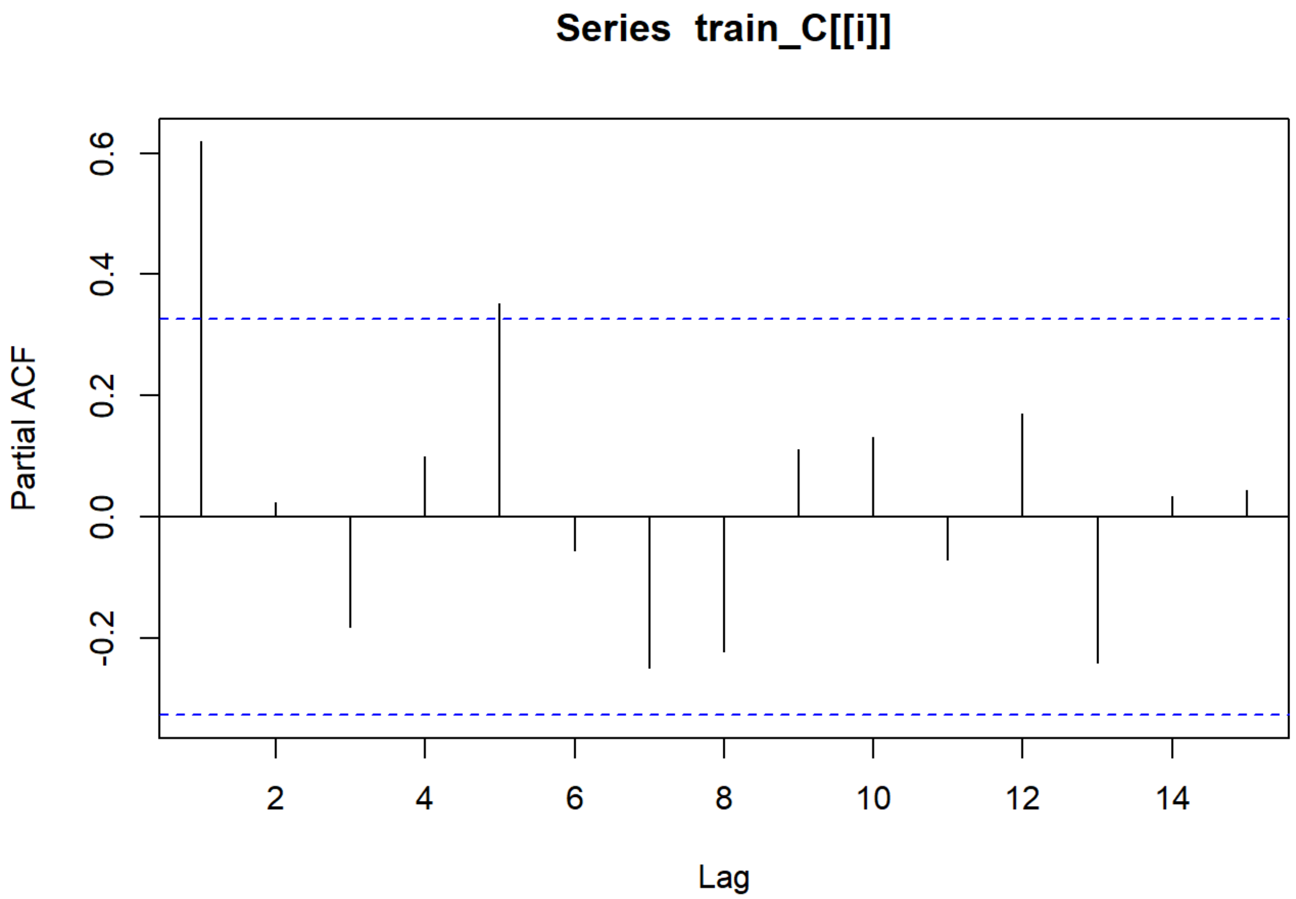
Holt-Winters filtering
Observed / Fitted
Time

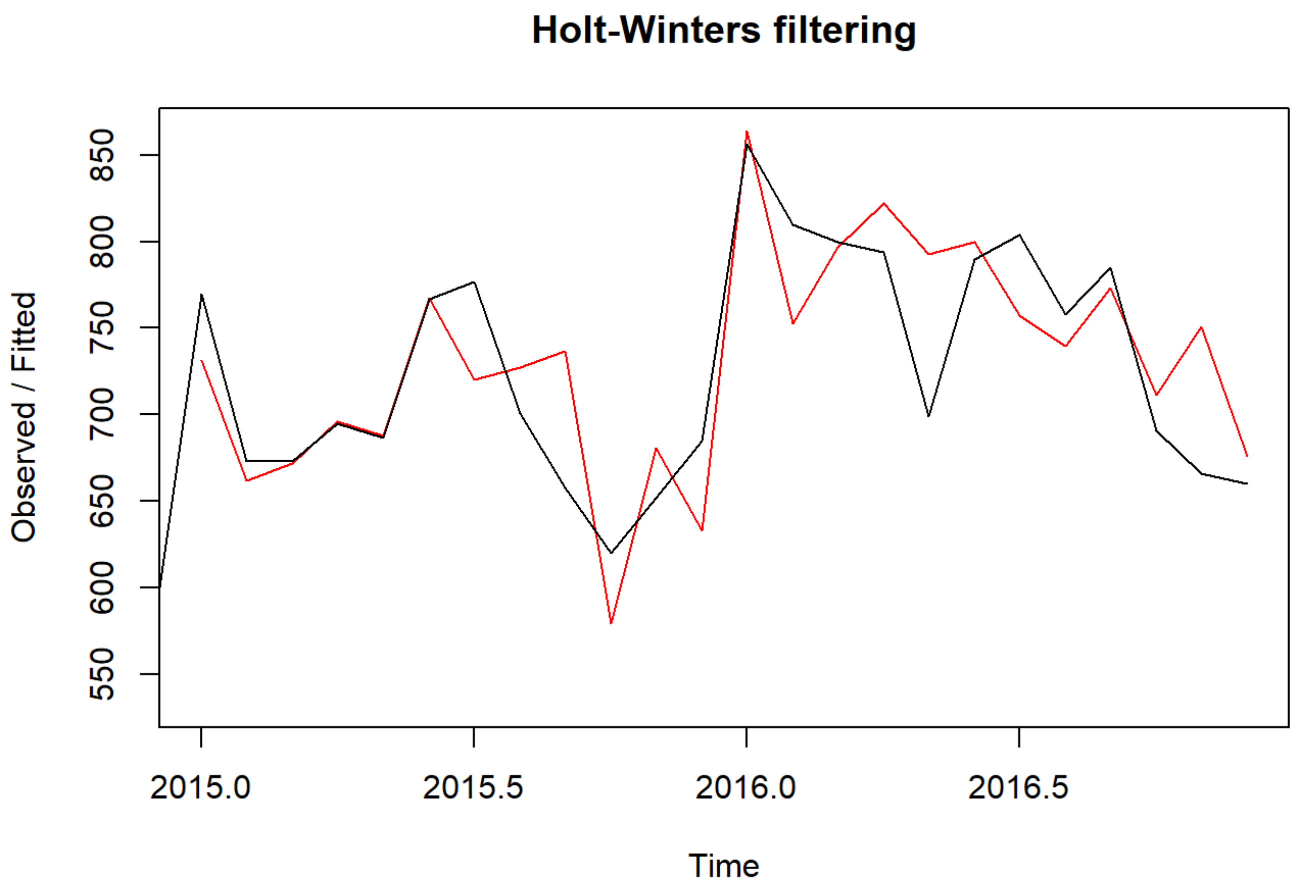


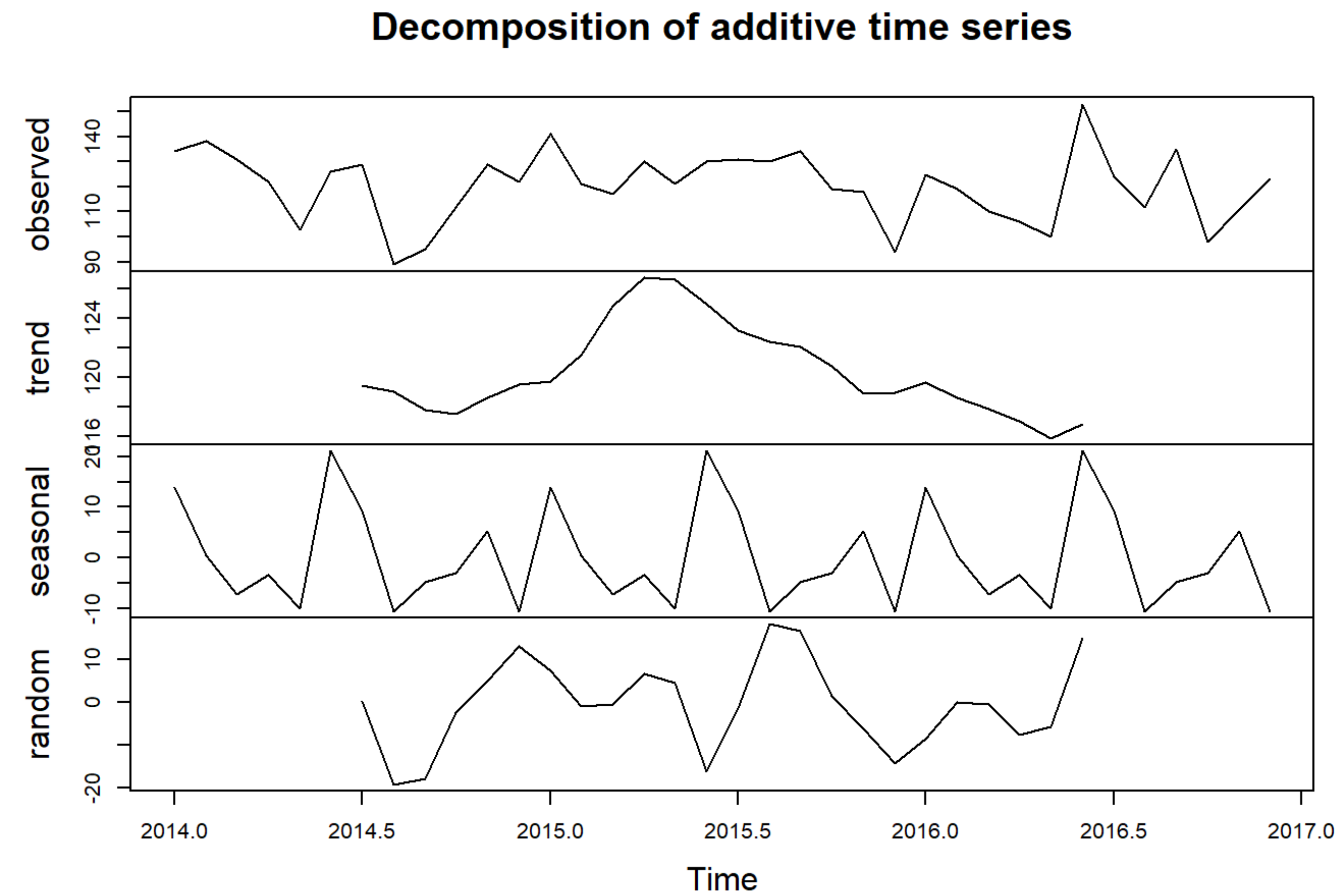
Decomposition of additive time series
observed
trend
seasonal
random
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

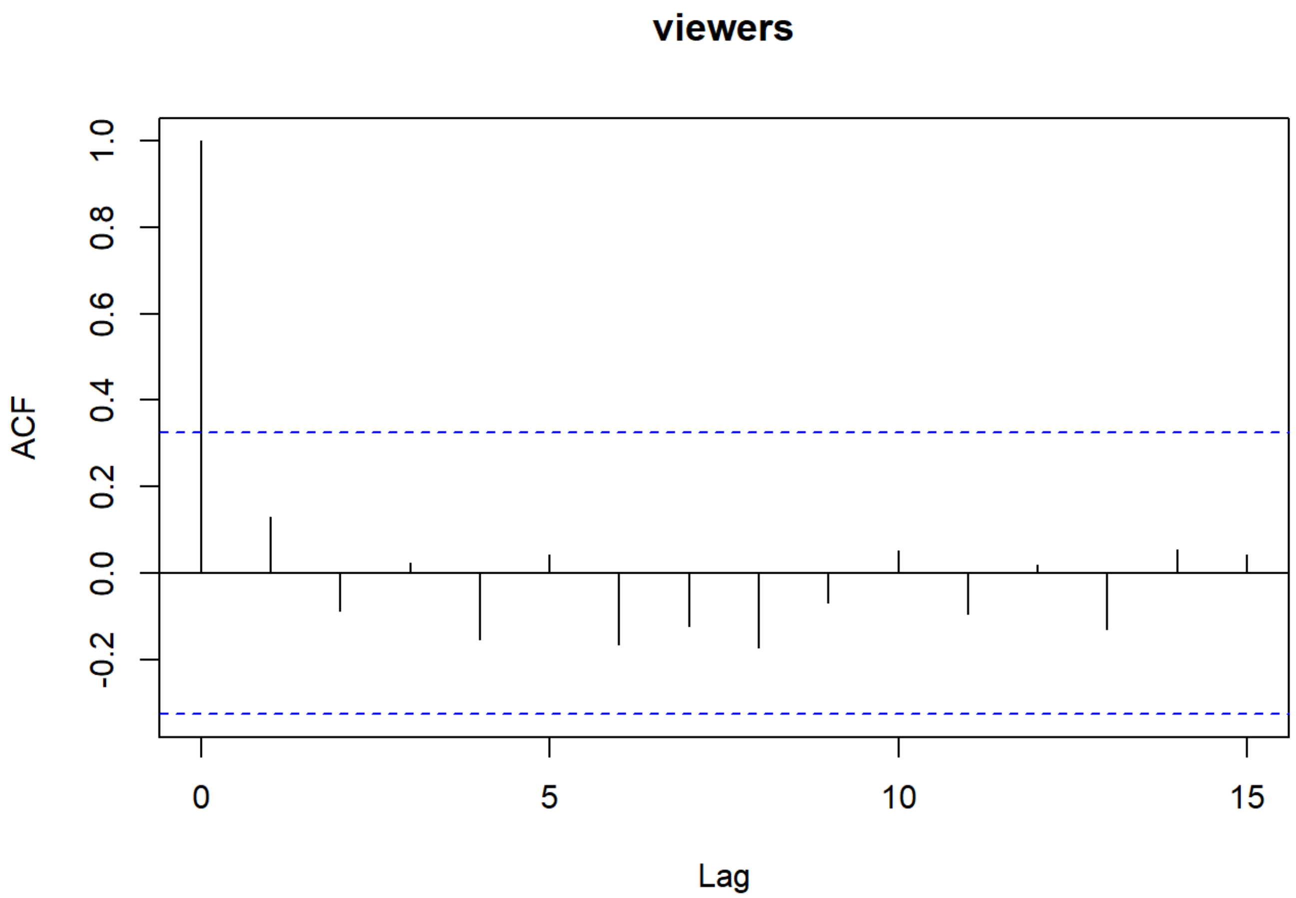



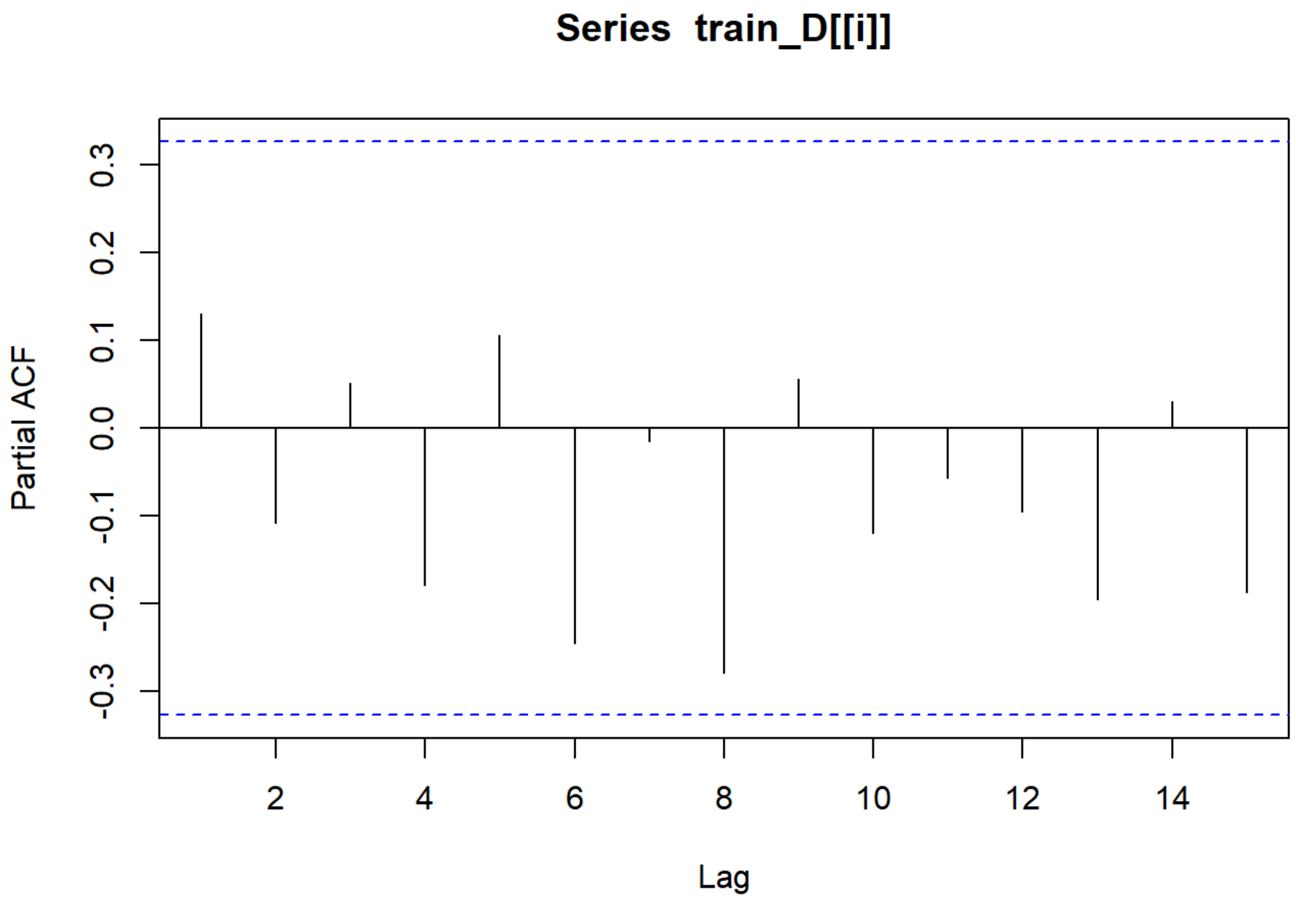
viewers
ACF
Lag


Series train_C[[i]]
Partial ACF
Lag
-0.2
0.0
0.2
0.4
0.6
2
4
6
8
10
12
14

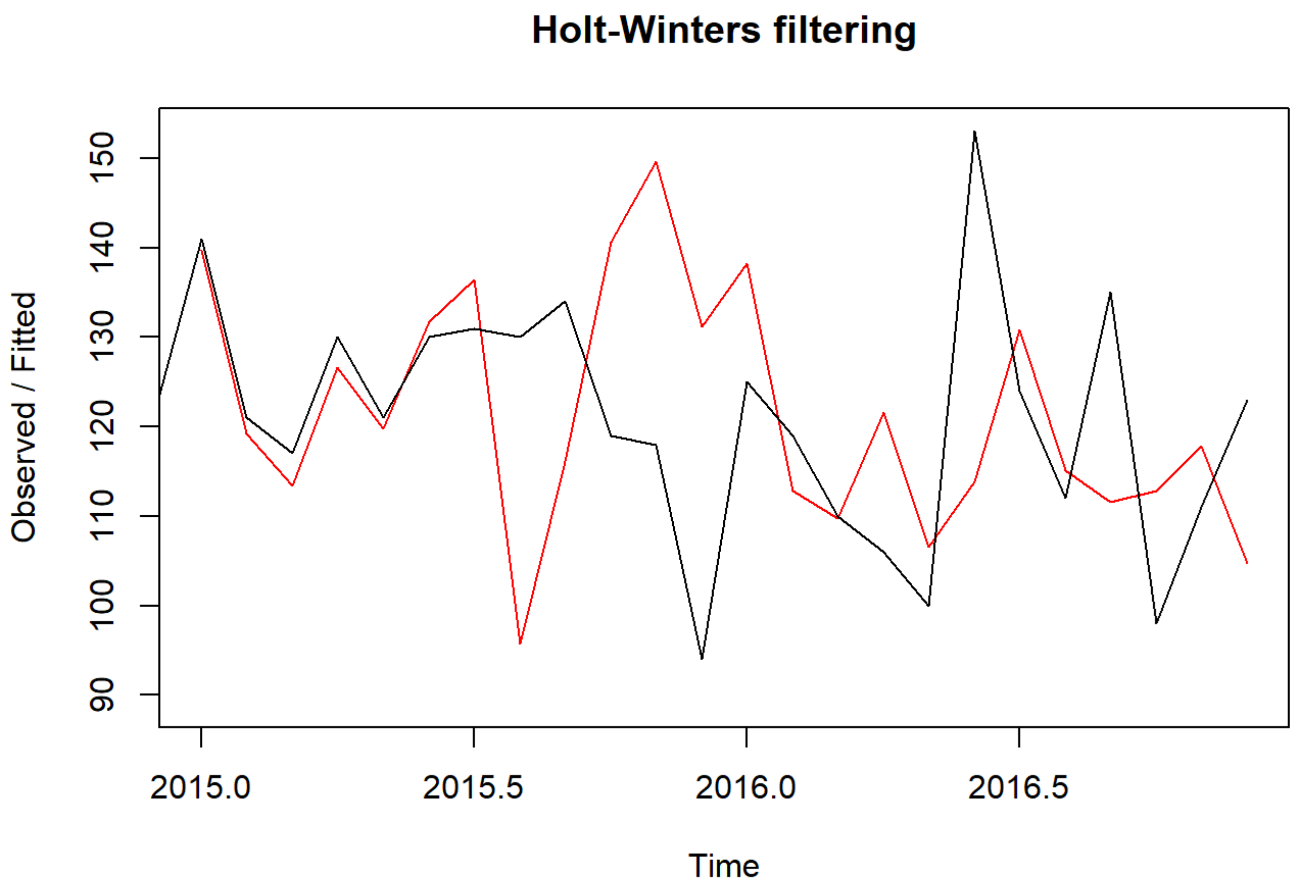

Holt-Winters filtering
Observed / Fitted
Time
550
600
650
700
750
800
850
2015.0
2015.5
2016.0
2016.5


Decomposition of additive time series
observed
90
110
140
trend
116
120
124
seasonal
-10
0
10
20
random
-20
0
10
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

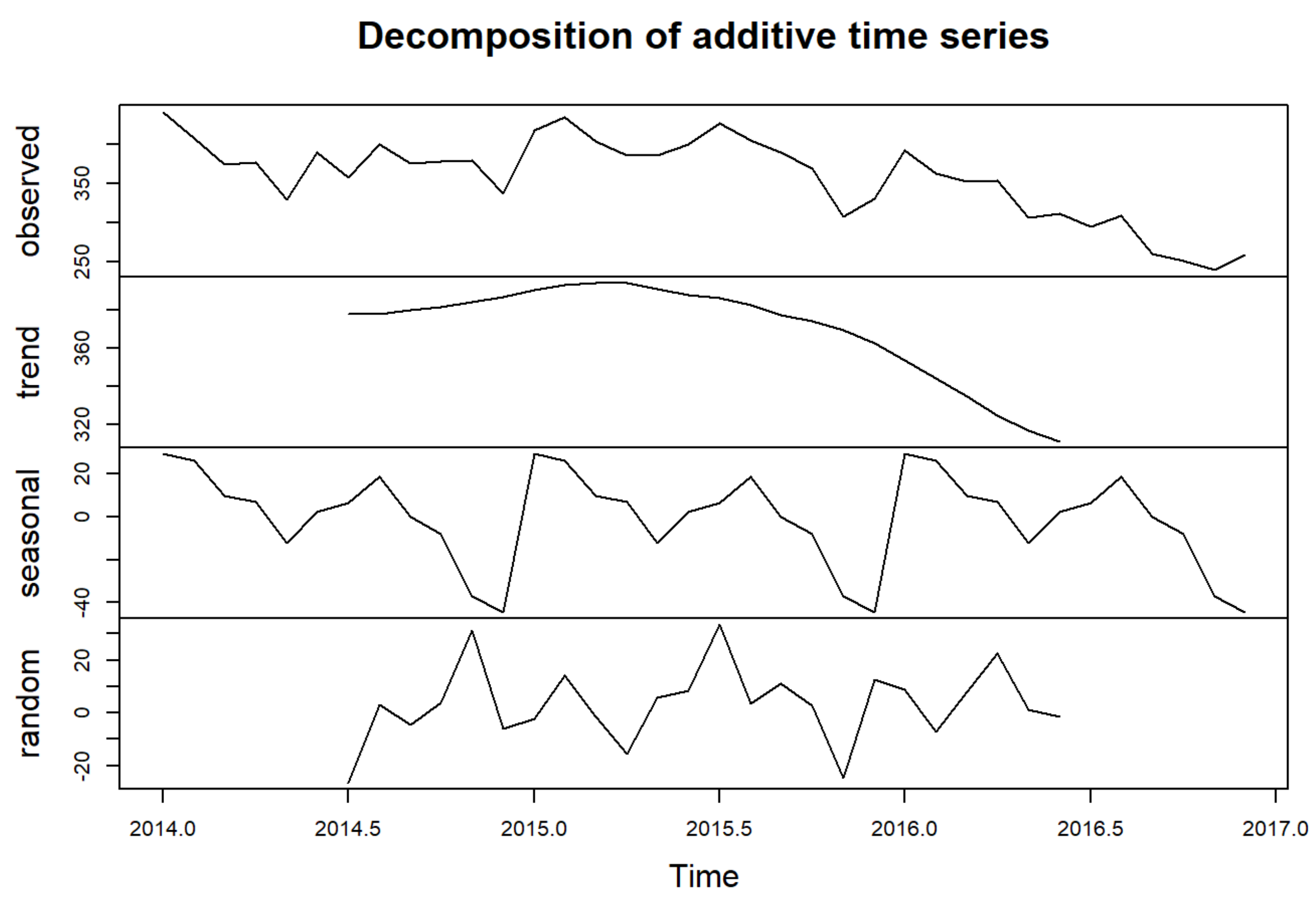

viewers
ACF
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
Lag

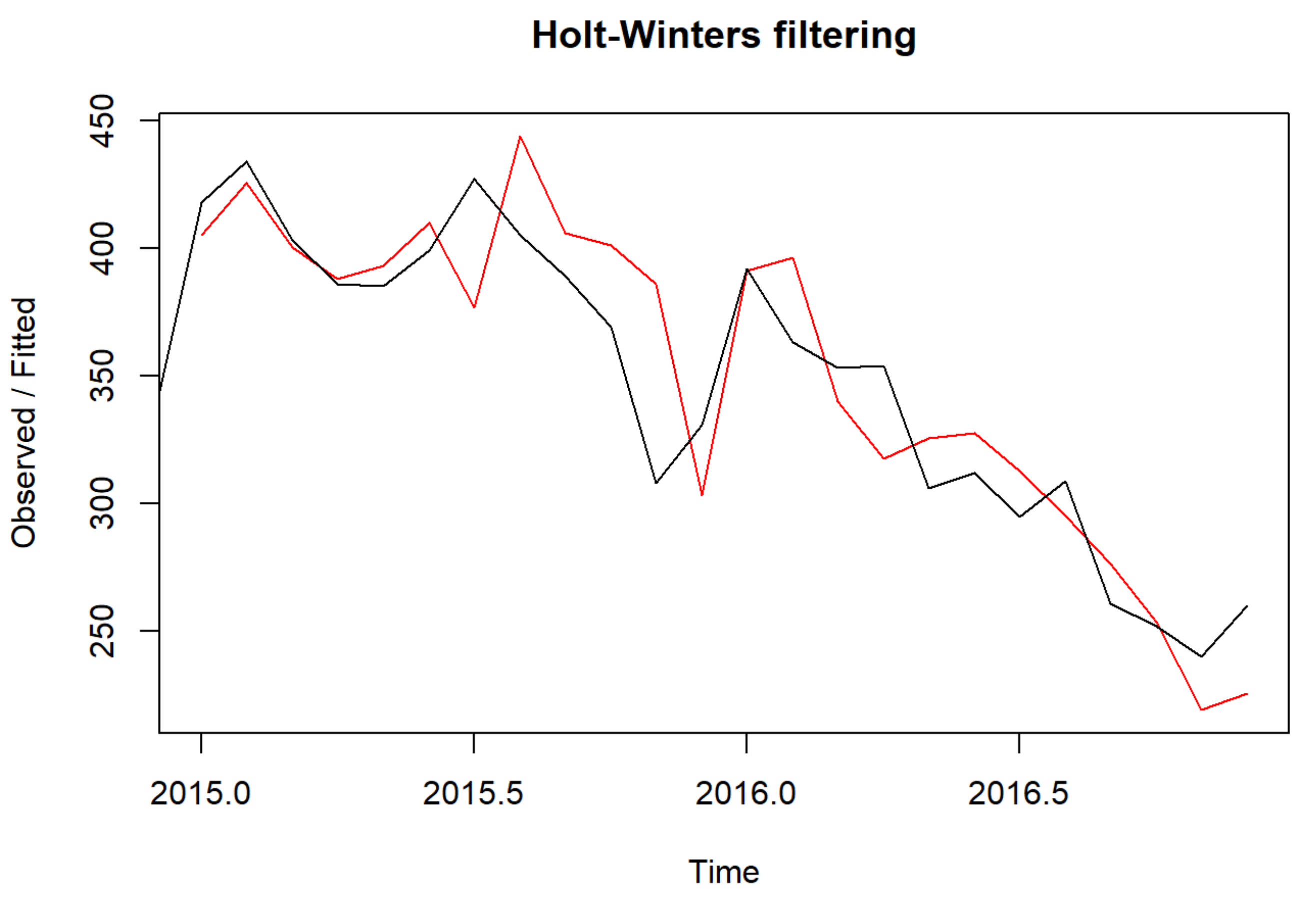


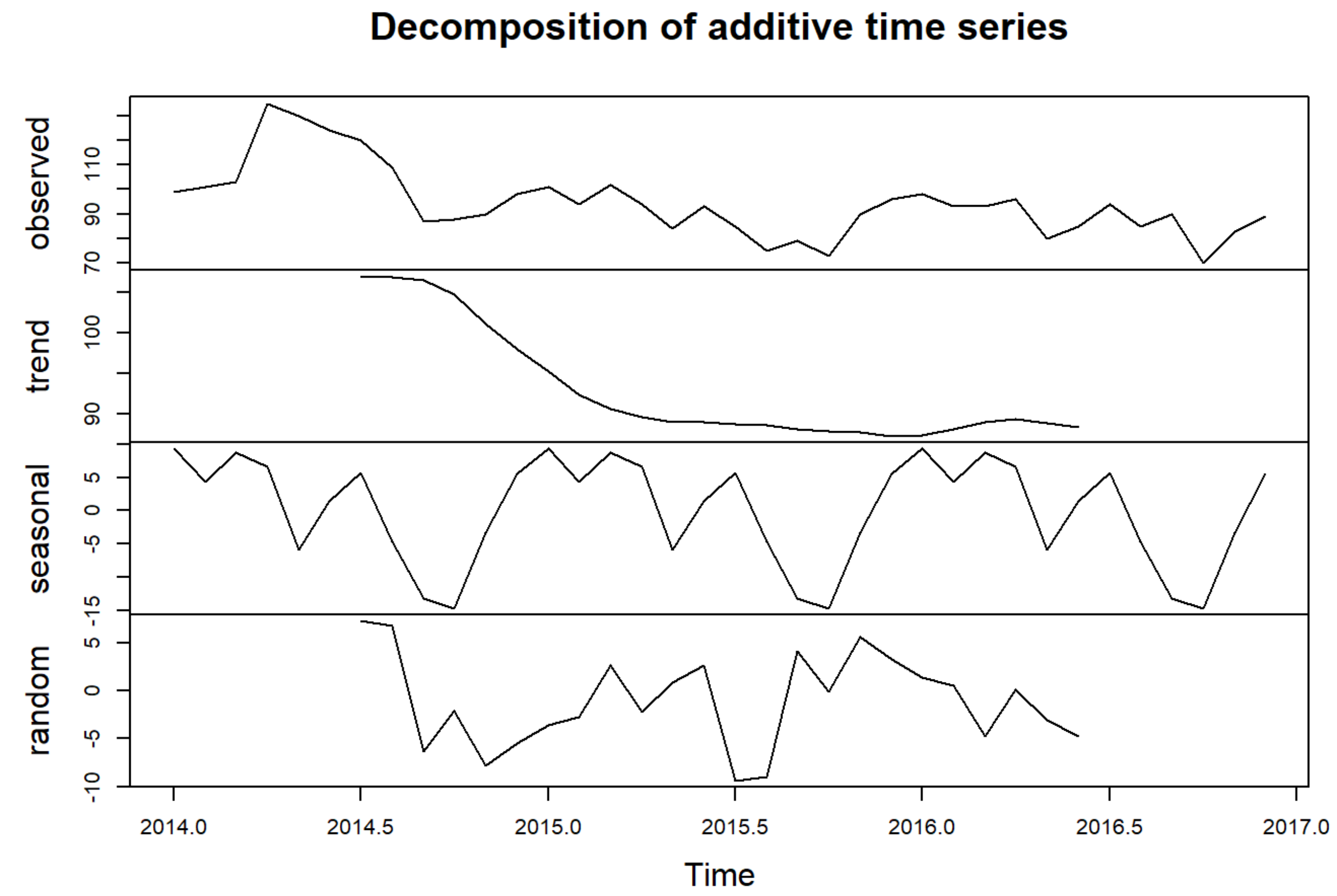
Series train_D[[i]]
Partial ACF
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
2
4
6
8
10
12
14
Lag

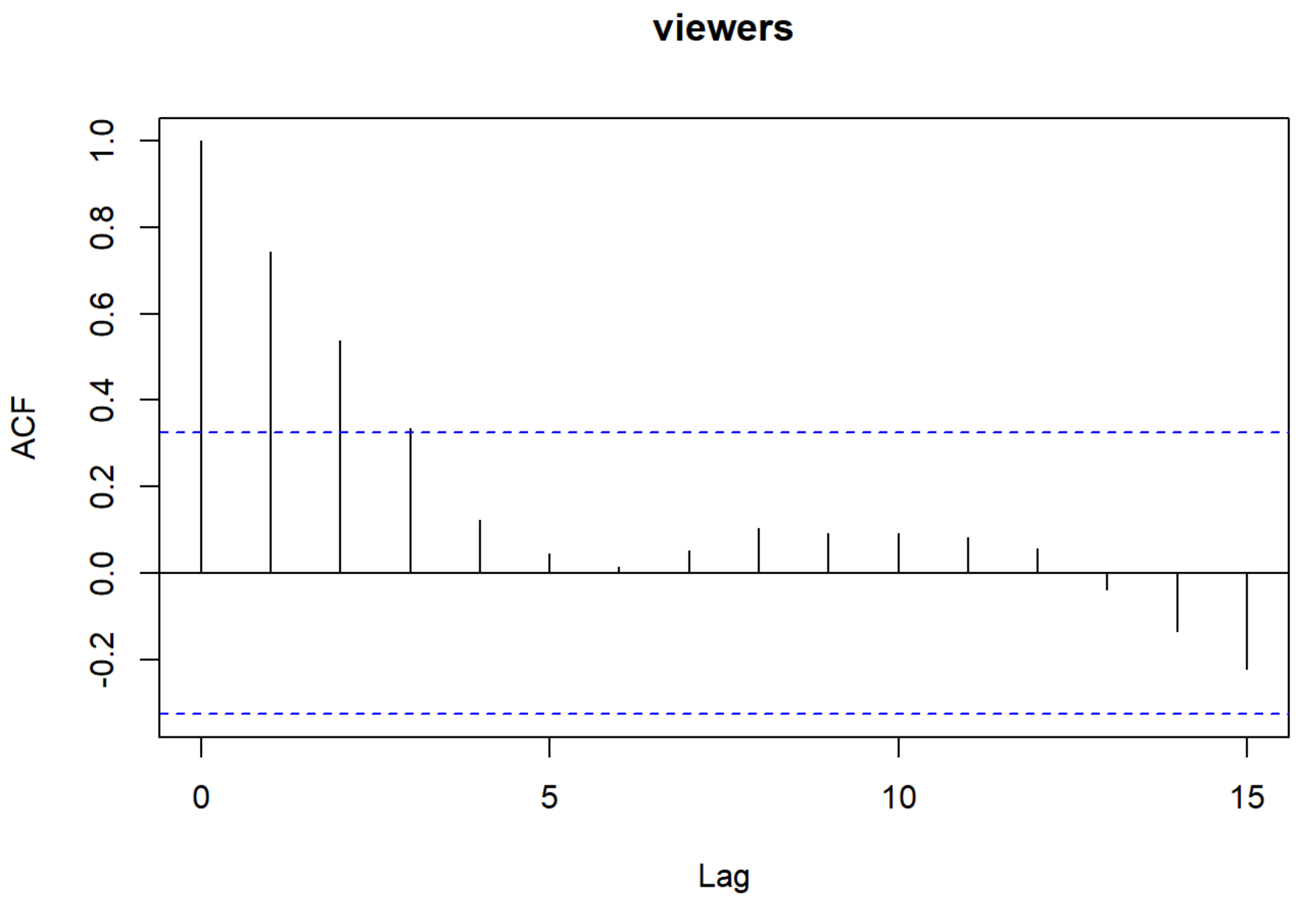
Holt-Winters filtering
Observed / Fitted
150
140
130
120
110
100
90
2015.0
2015.5
2016.0
2016.5
Time


Decomposition of additive time series
observed
trend
seasonal
random
350
250
360
320
20
0
-40
20
0
-20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

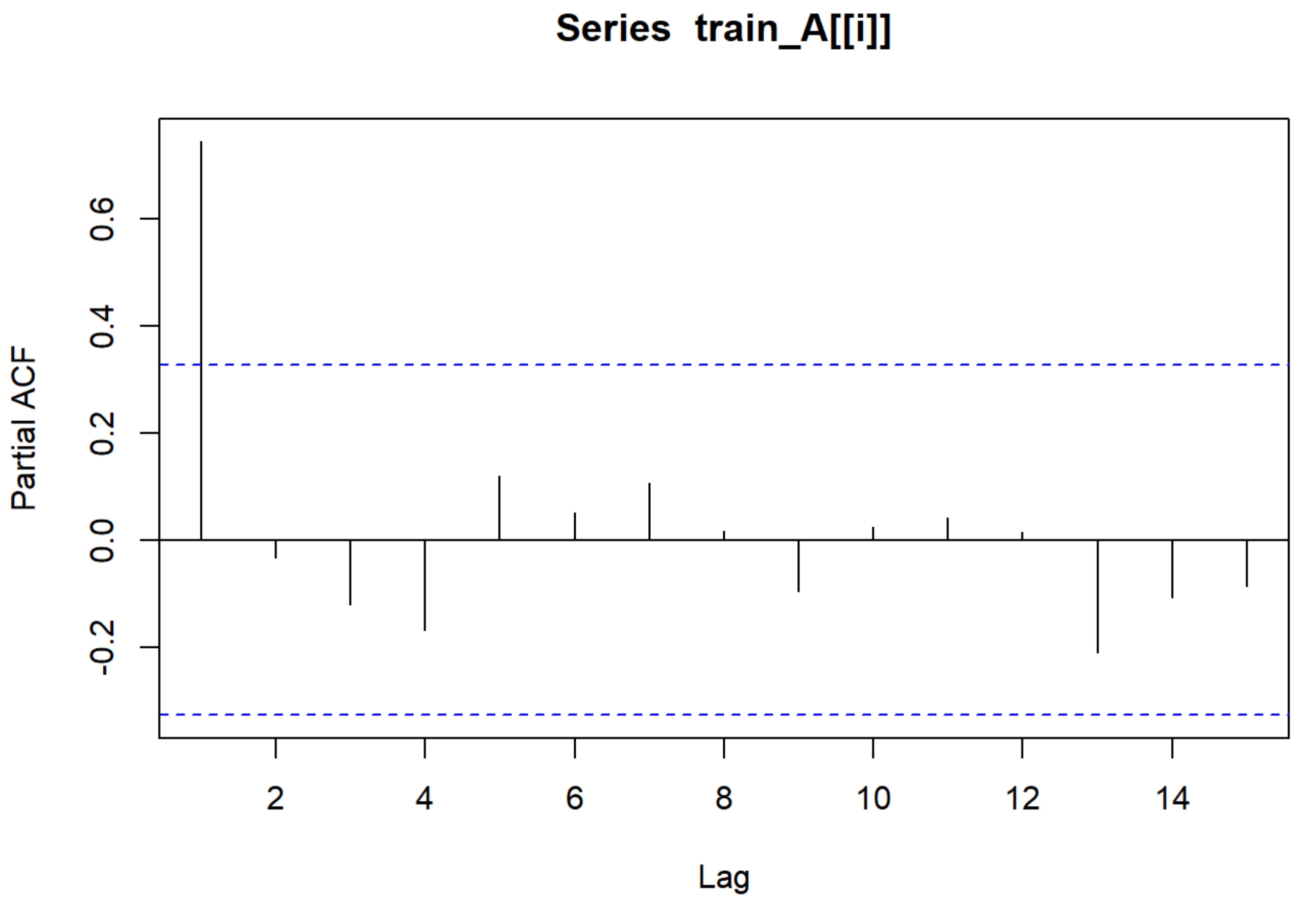

Holt-Winters filtering
Observed / Fitted
450
400
350
300
250
2015.0
2015.5
2016.0
2016.5
Time

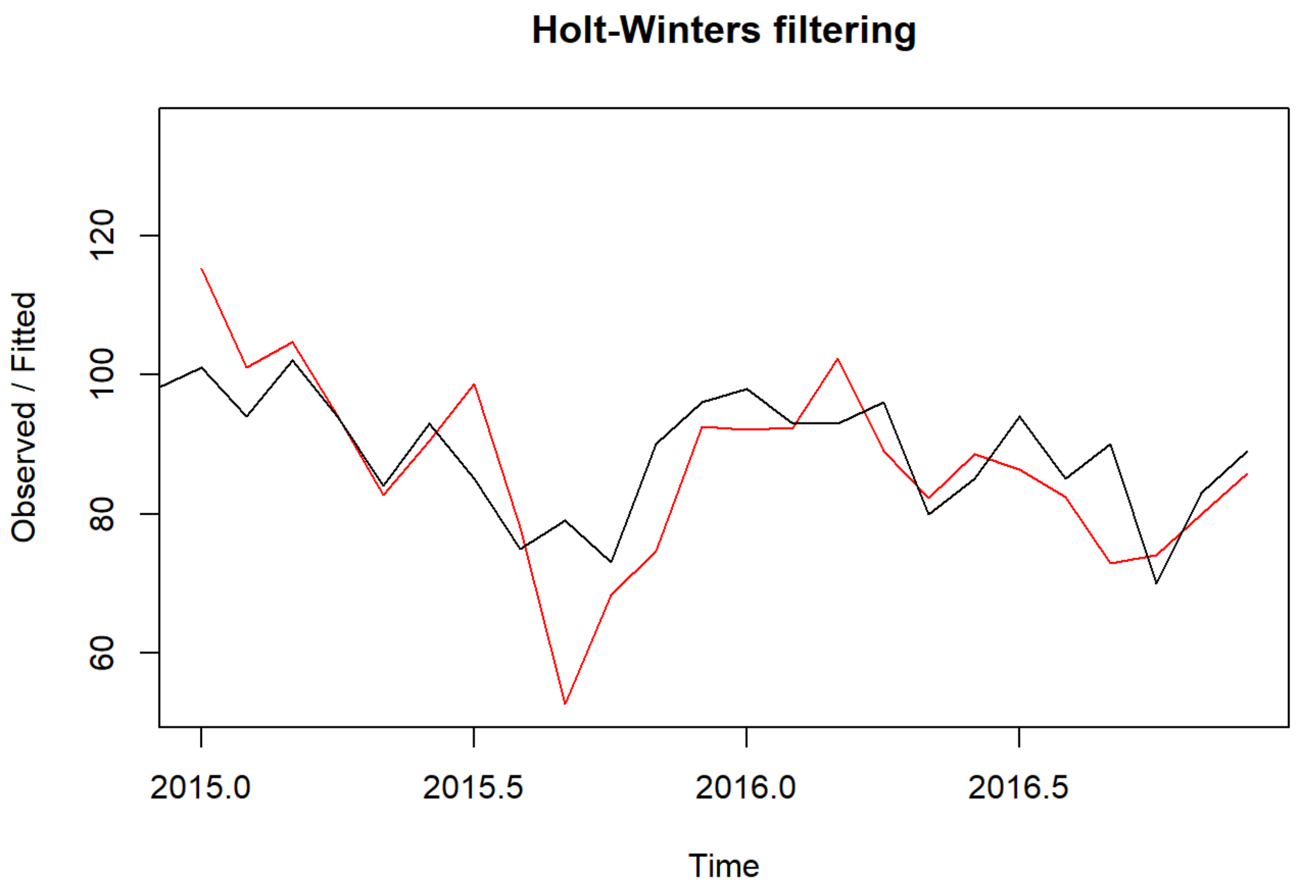


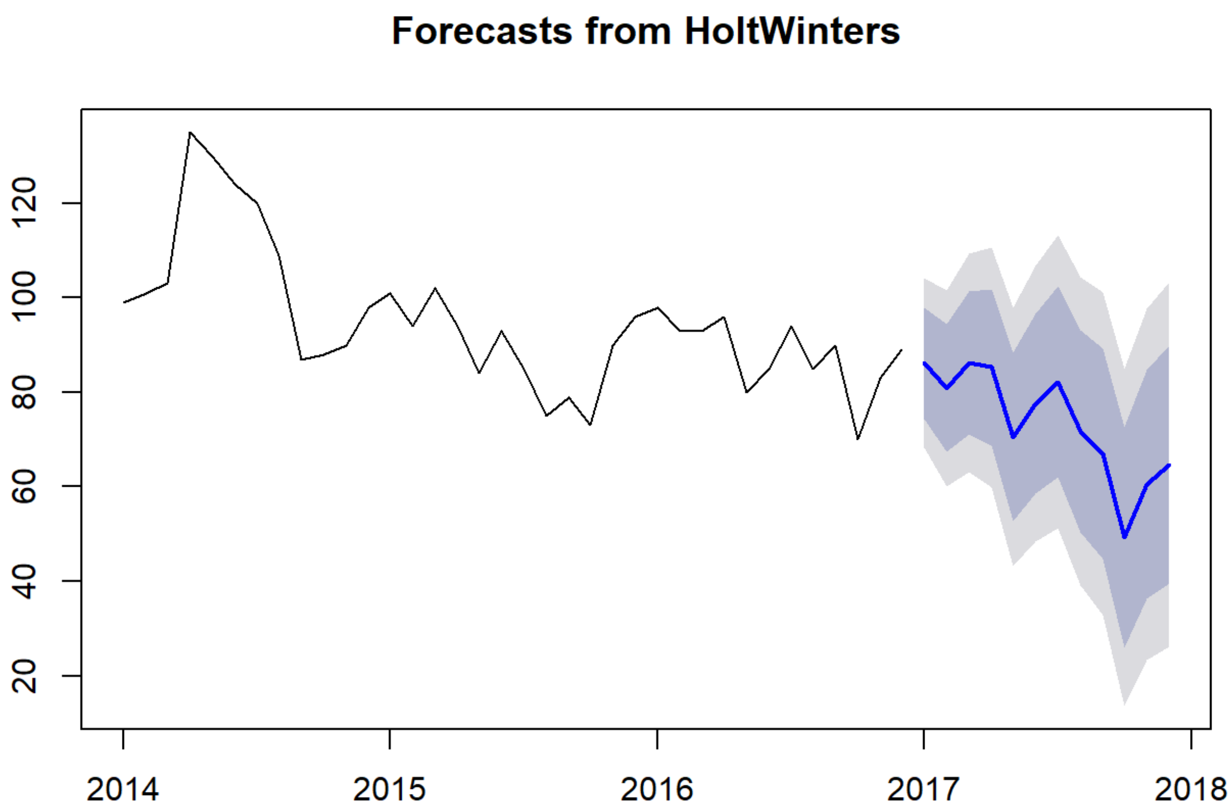
Decomposition of additive time series
observed
trend
seasonal
random
Time

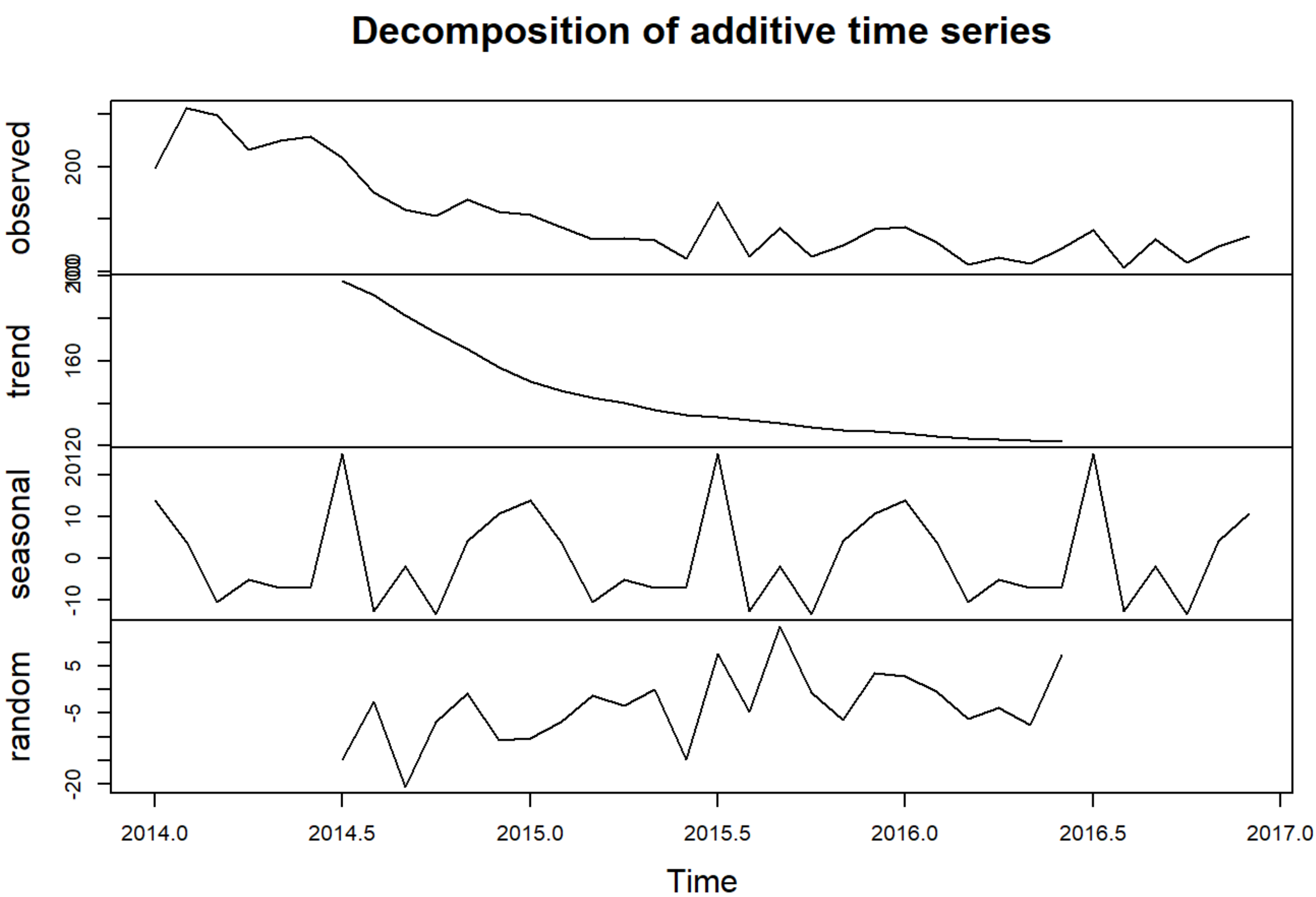



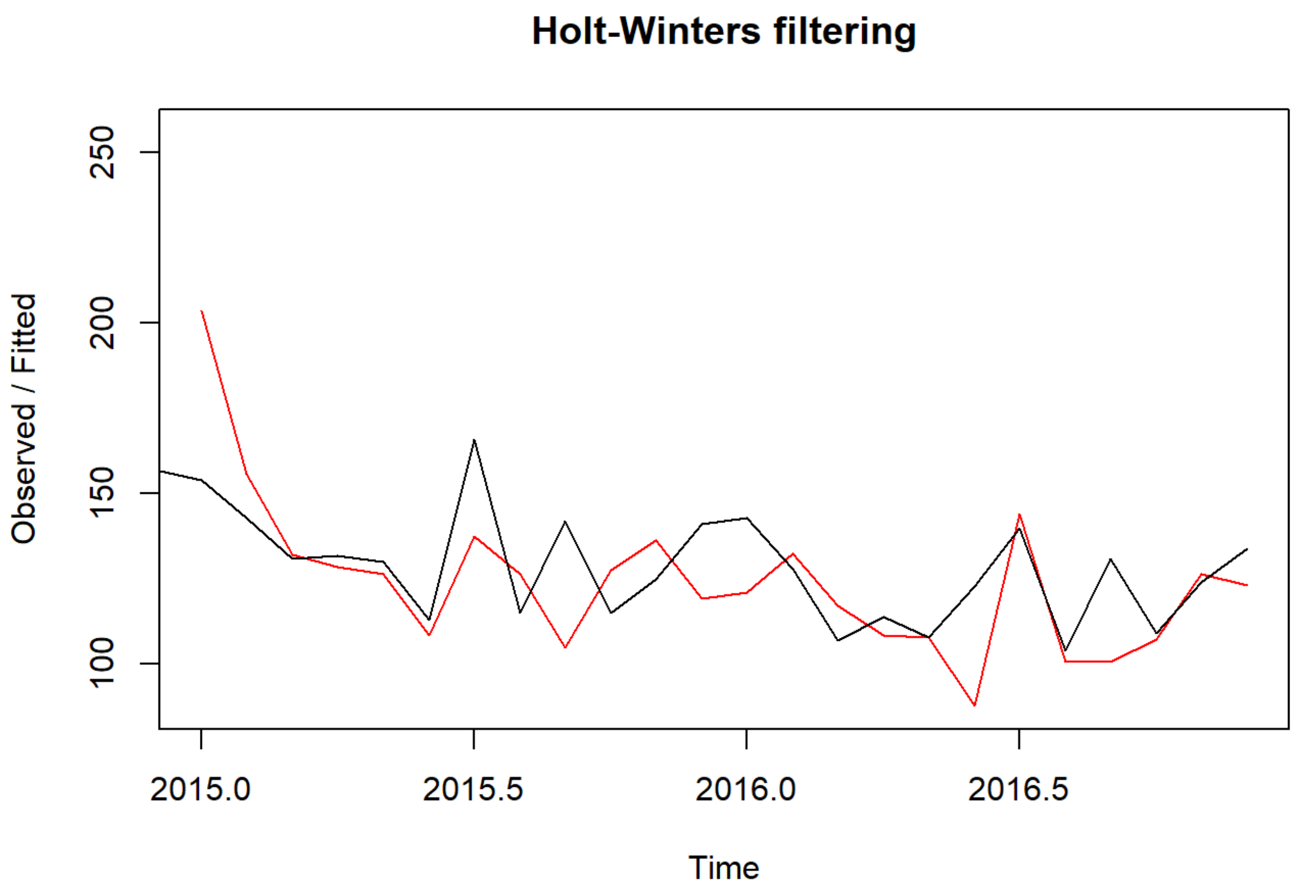
viewers
ACF
Lag


Series train_A[[i]]
Partial ACF
0.6
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag

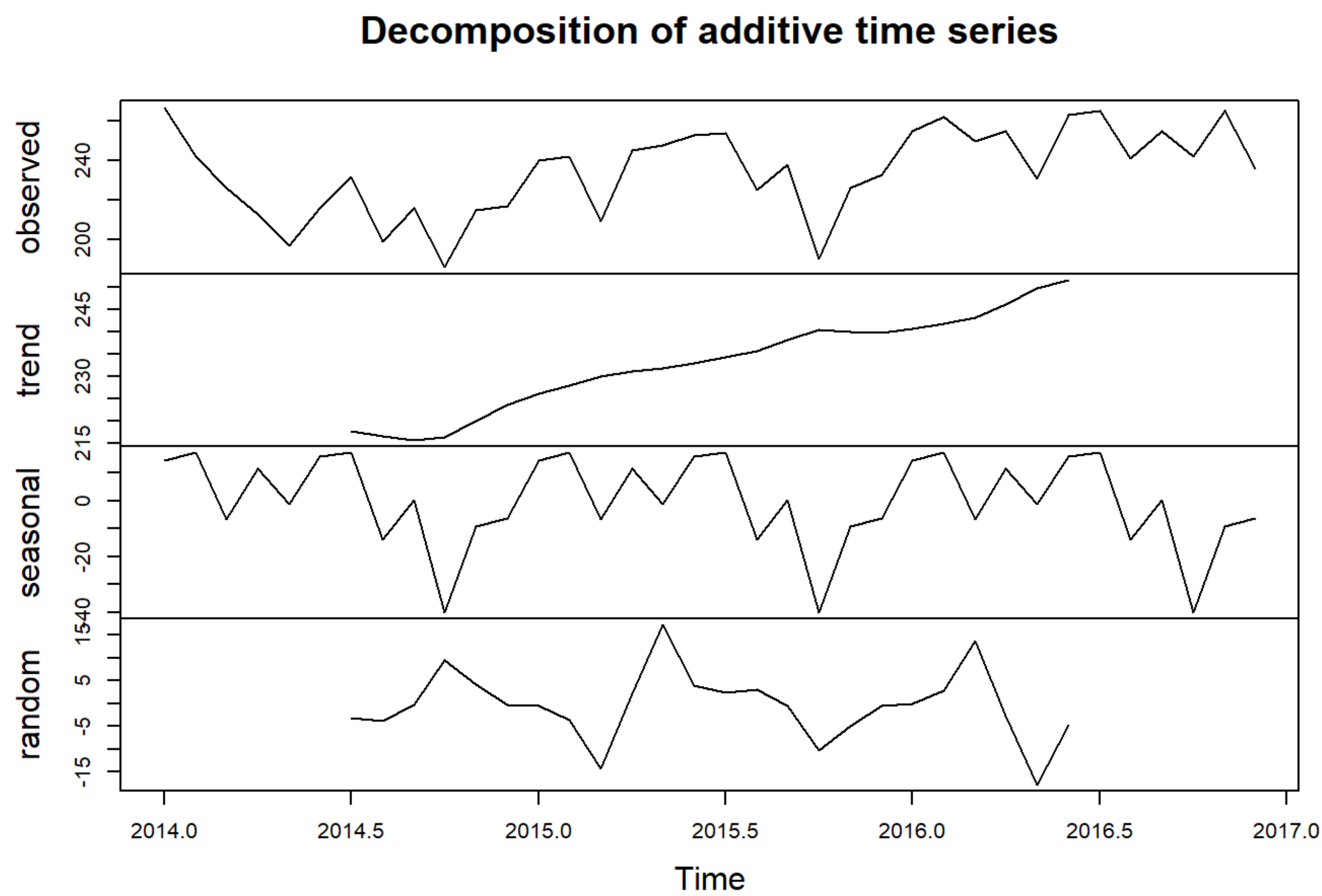

Holt-Winters filtering
Observed / Fitted
120
100
80
60
2015.0
2015.5
2016.0
2016.5
Time


Forecasts from HoltWinters
20
40
60
80
100
120
2014
2015
2016
2017
2018

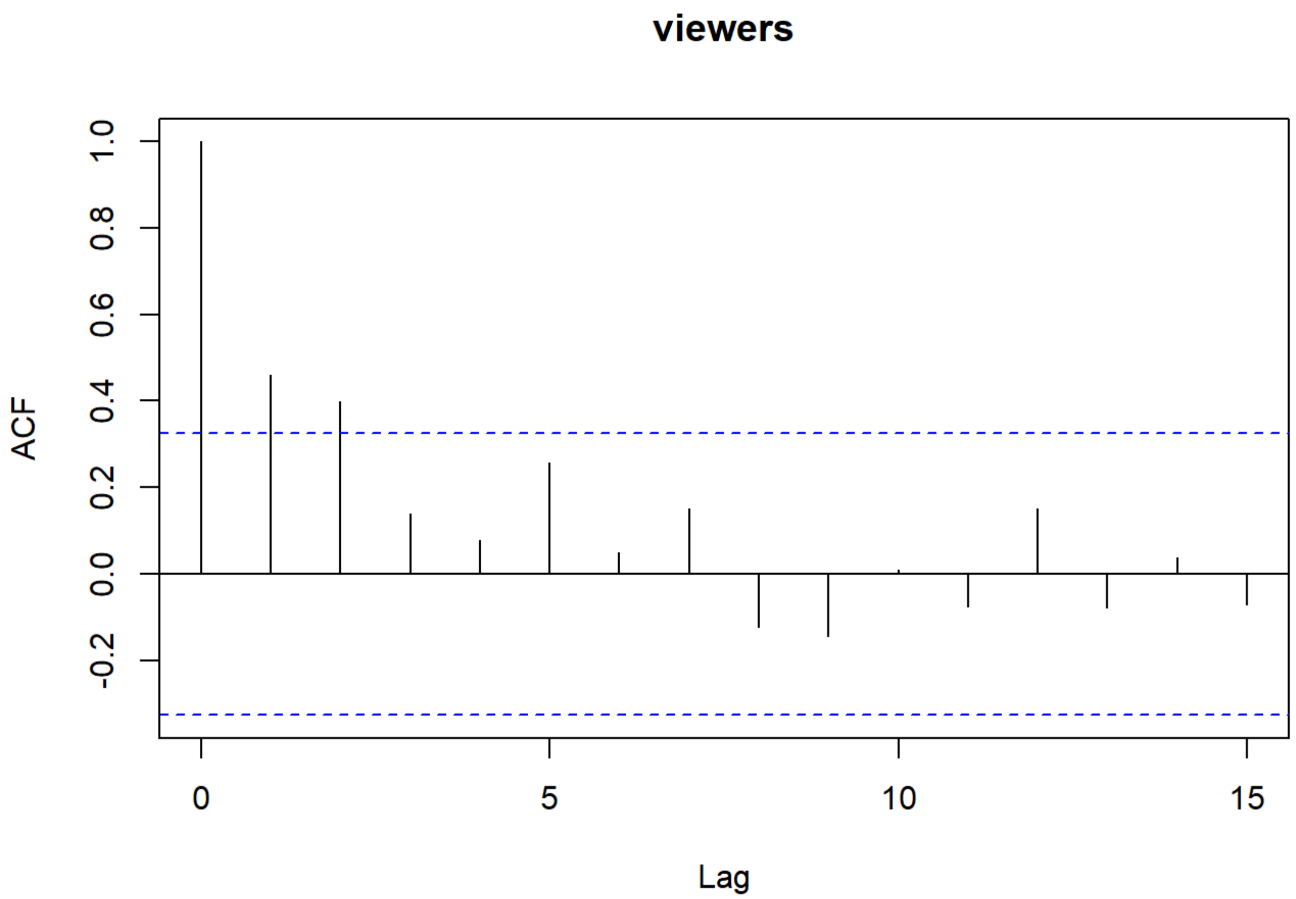

Decomposition of additive time series
observed
trend
seasonal
random
200
160
120
20
10
0
-10
5
-5
-20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

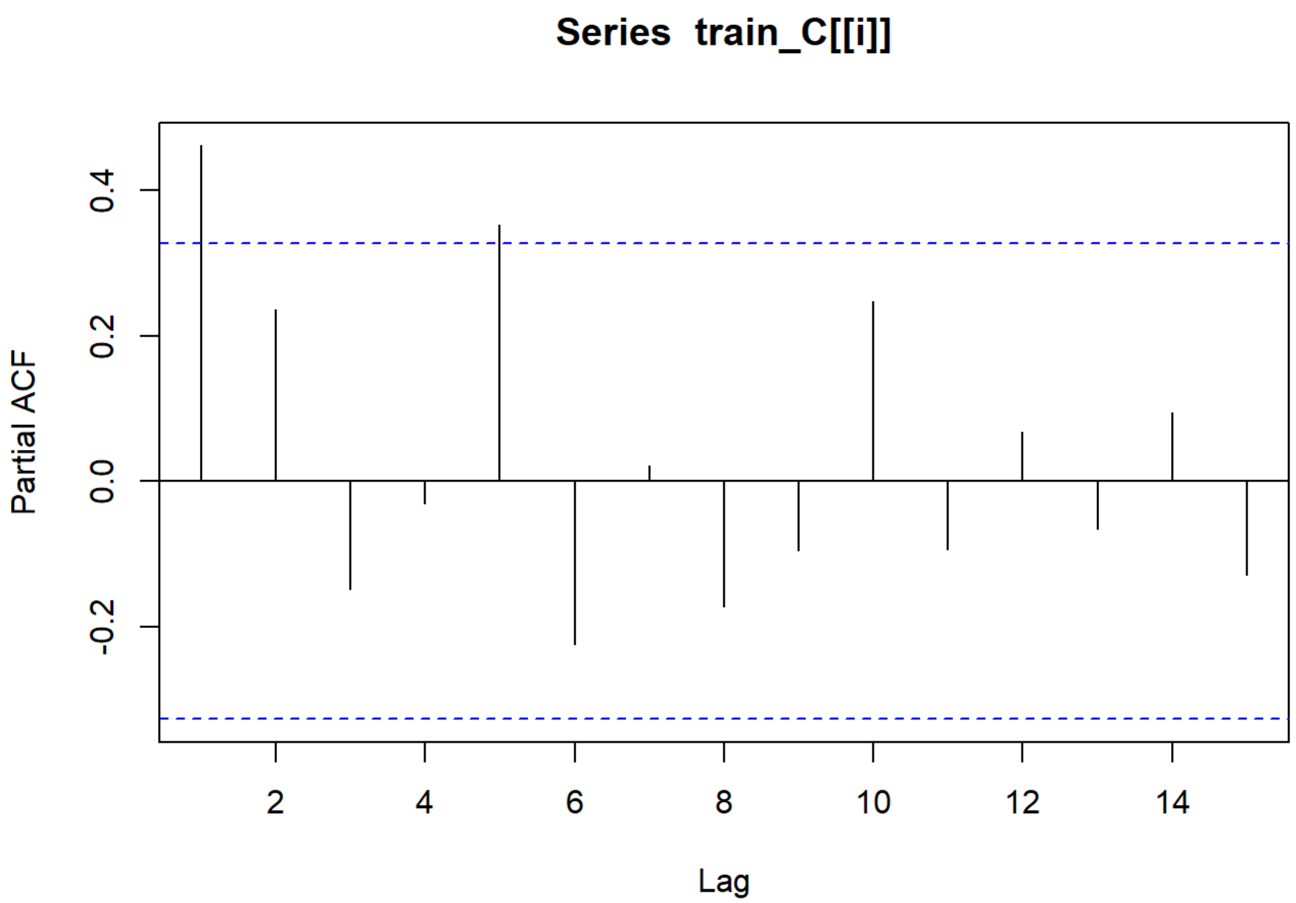


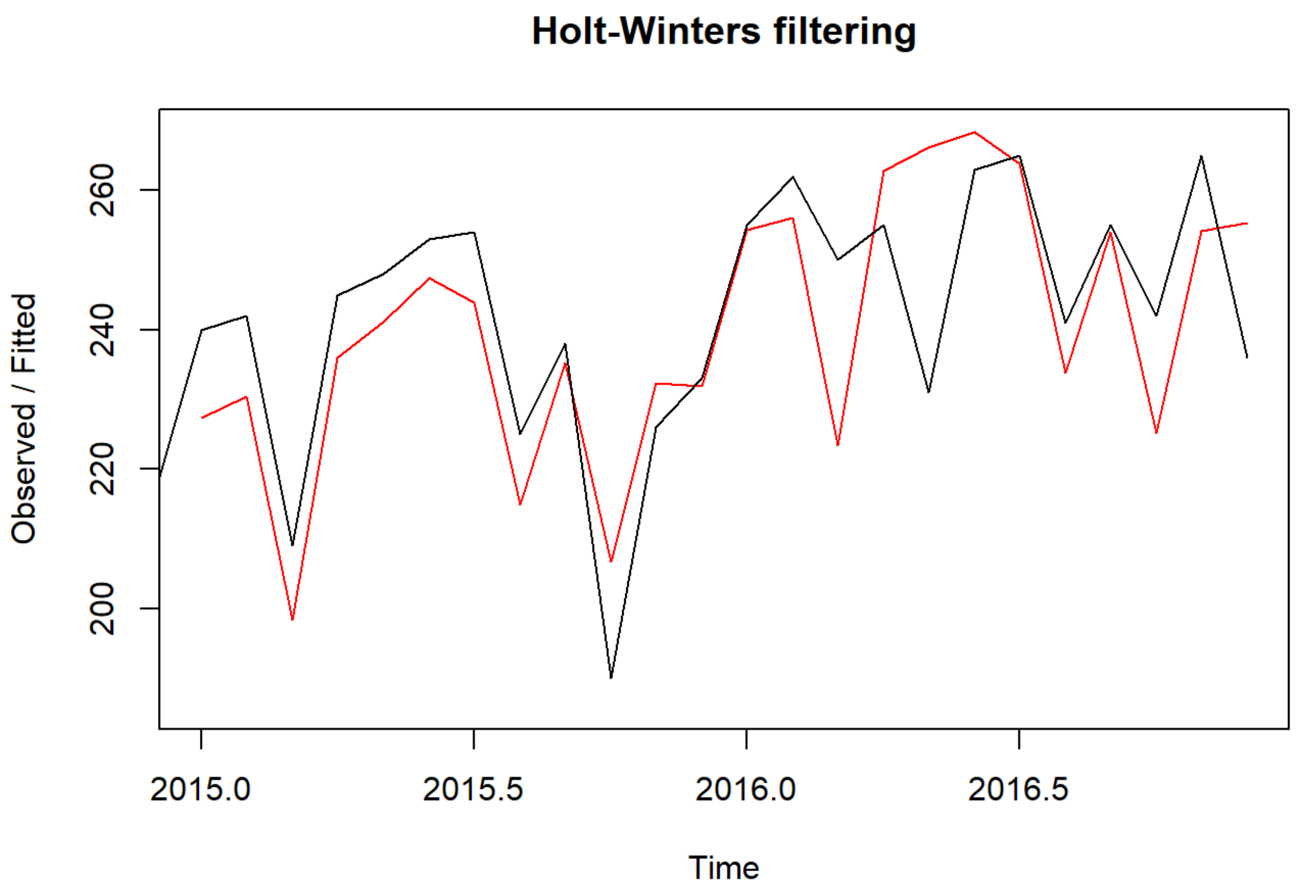
Holt-Winters filtering
Observed / Fitted
250
200
150
100
2015.0
2015.5
2016.0
2016.5
Time

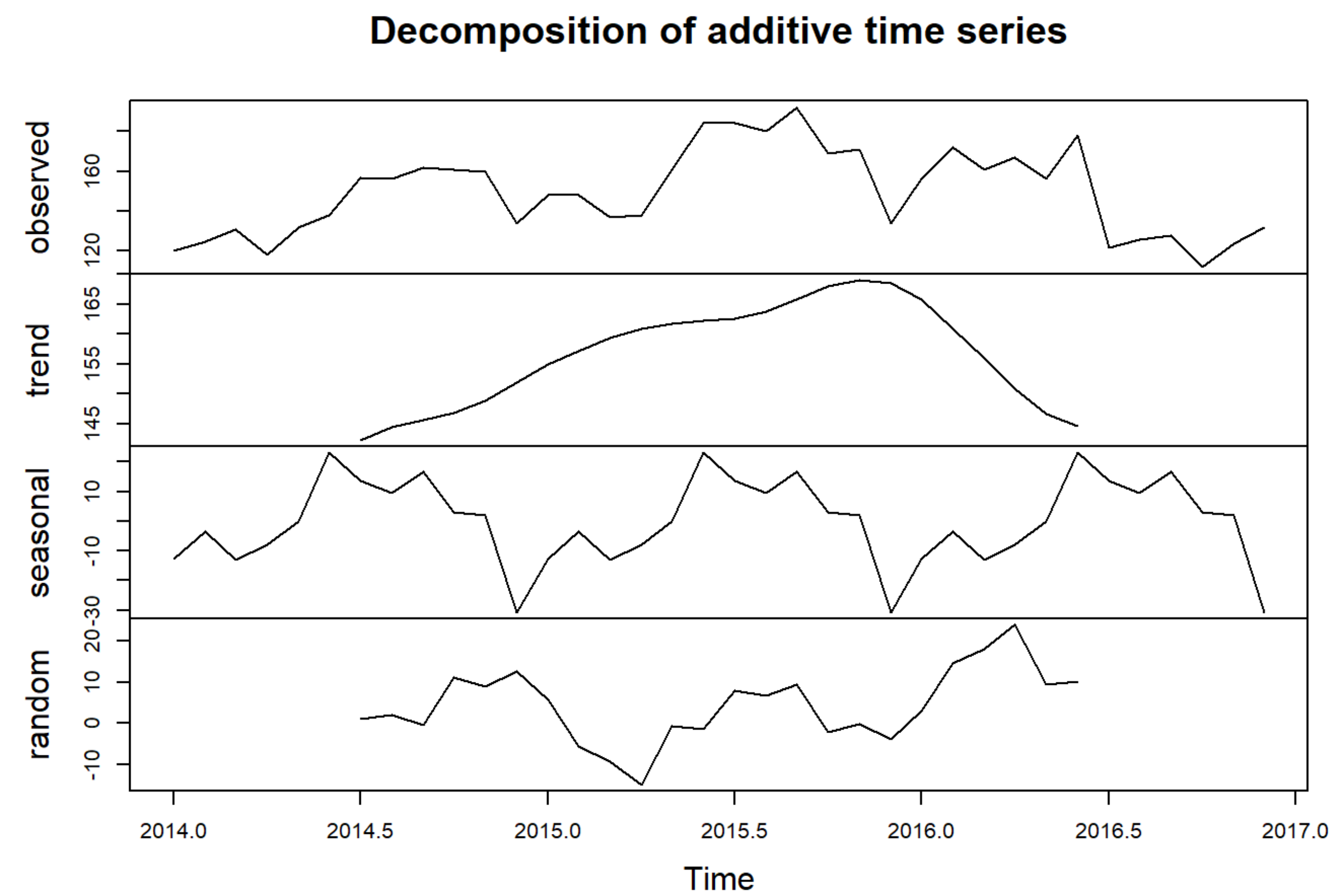



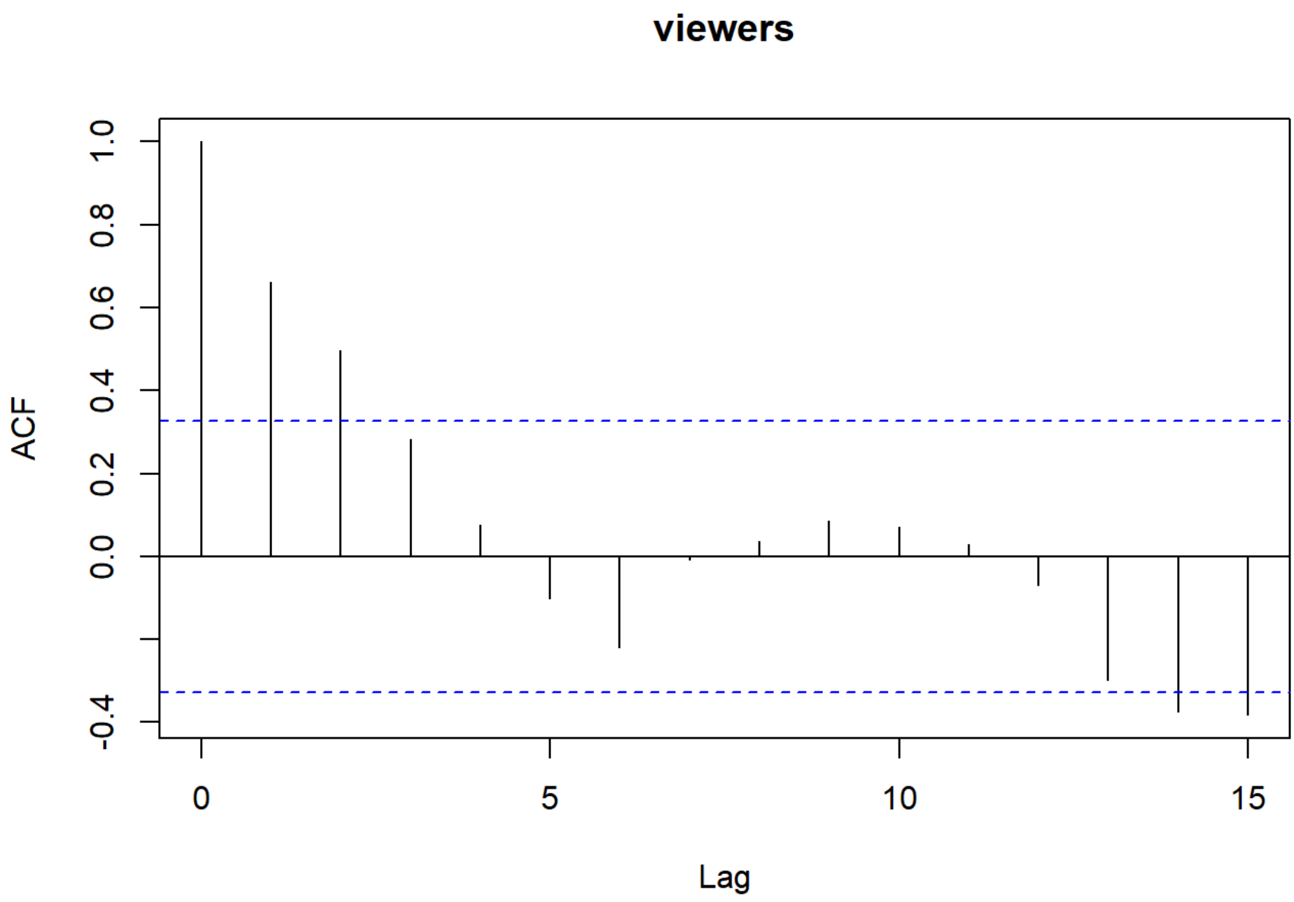
Decomposition of additive time series
observed
trend
seasonal
random
240
200
245
230
215
0
-20
-40
15
5
-5
-15
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

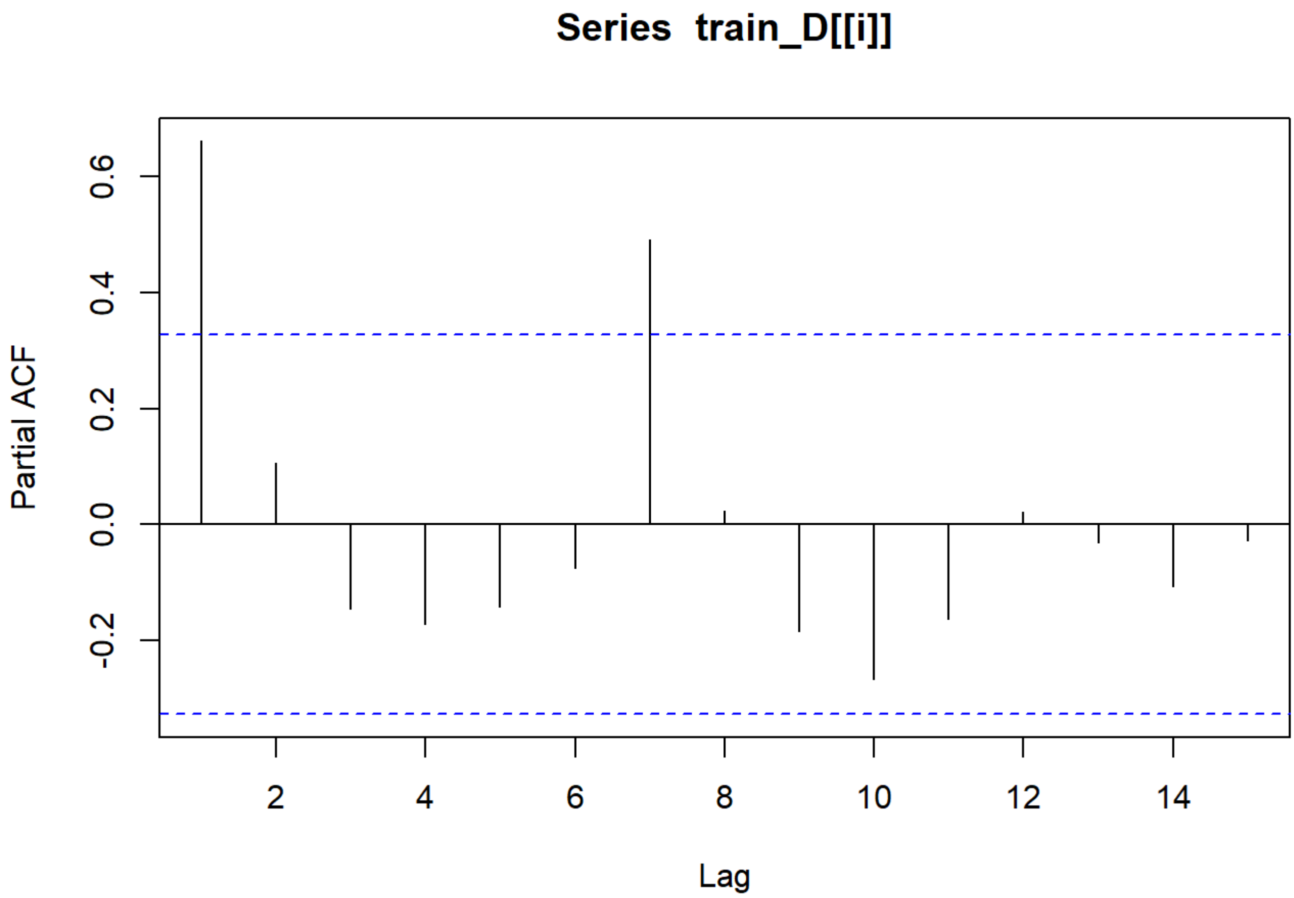

viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

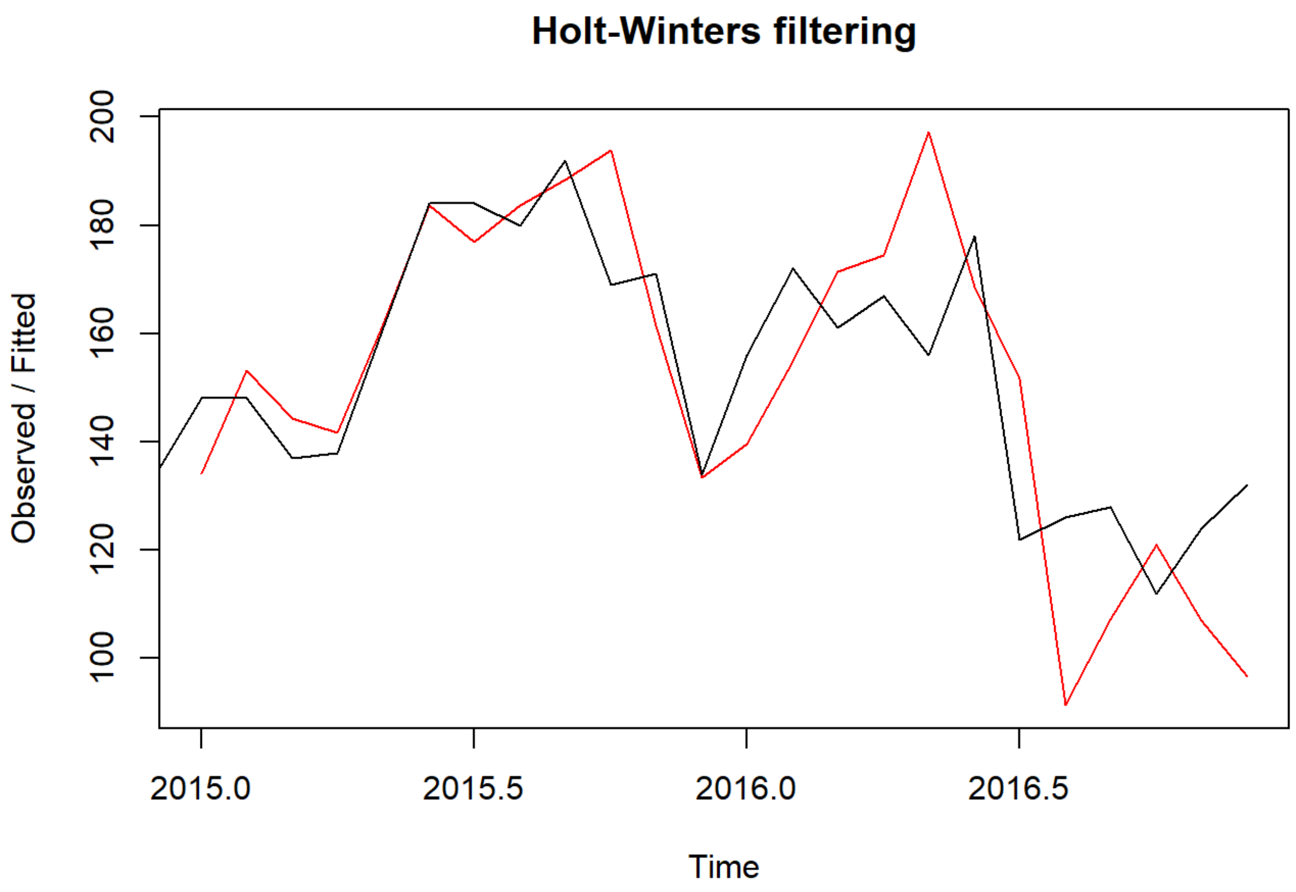

Series train_C[[i]]
Partial ACF
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag

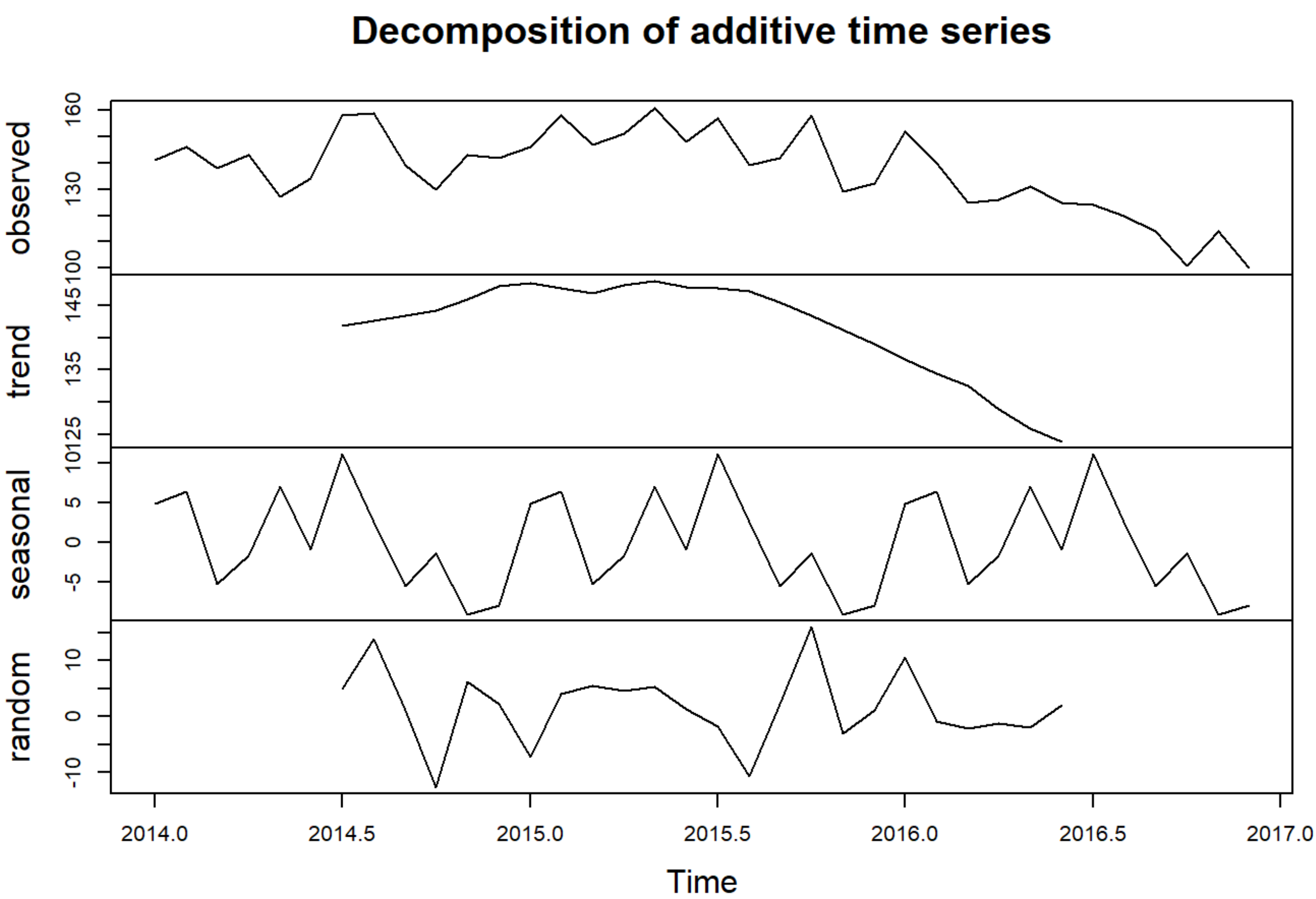

Holt-Winters filtering
Observed / Fitted
200
220
240
260
2015.0
2015.5
2016.0
2016.5
Time

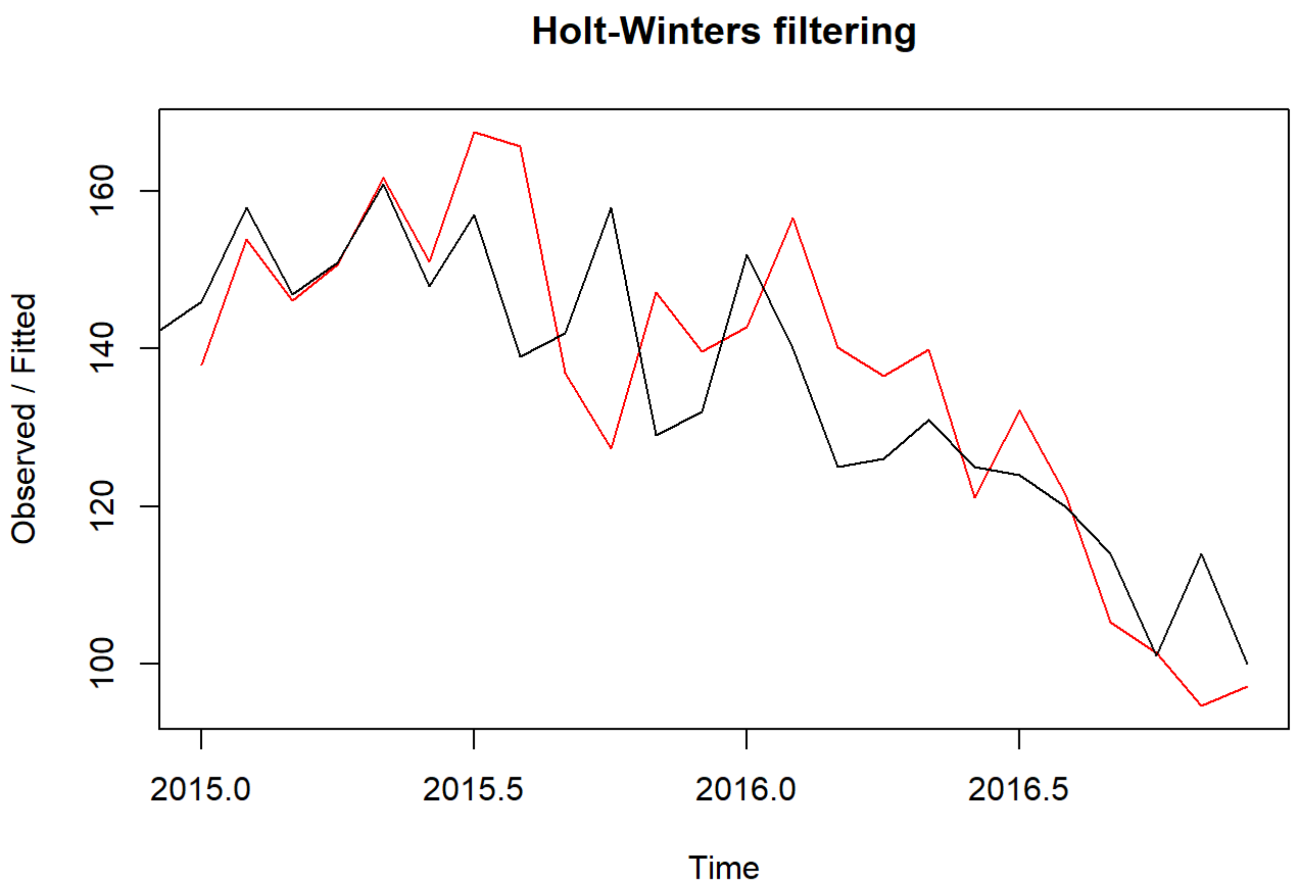

Decomposition of additive time series
observed
120
160
trend
145
155
165
seasonal
-30
-10
10
random
-10
0
10
20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time


viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.4
0
5
10
15
Lag

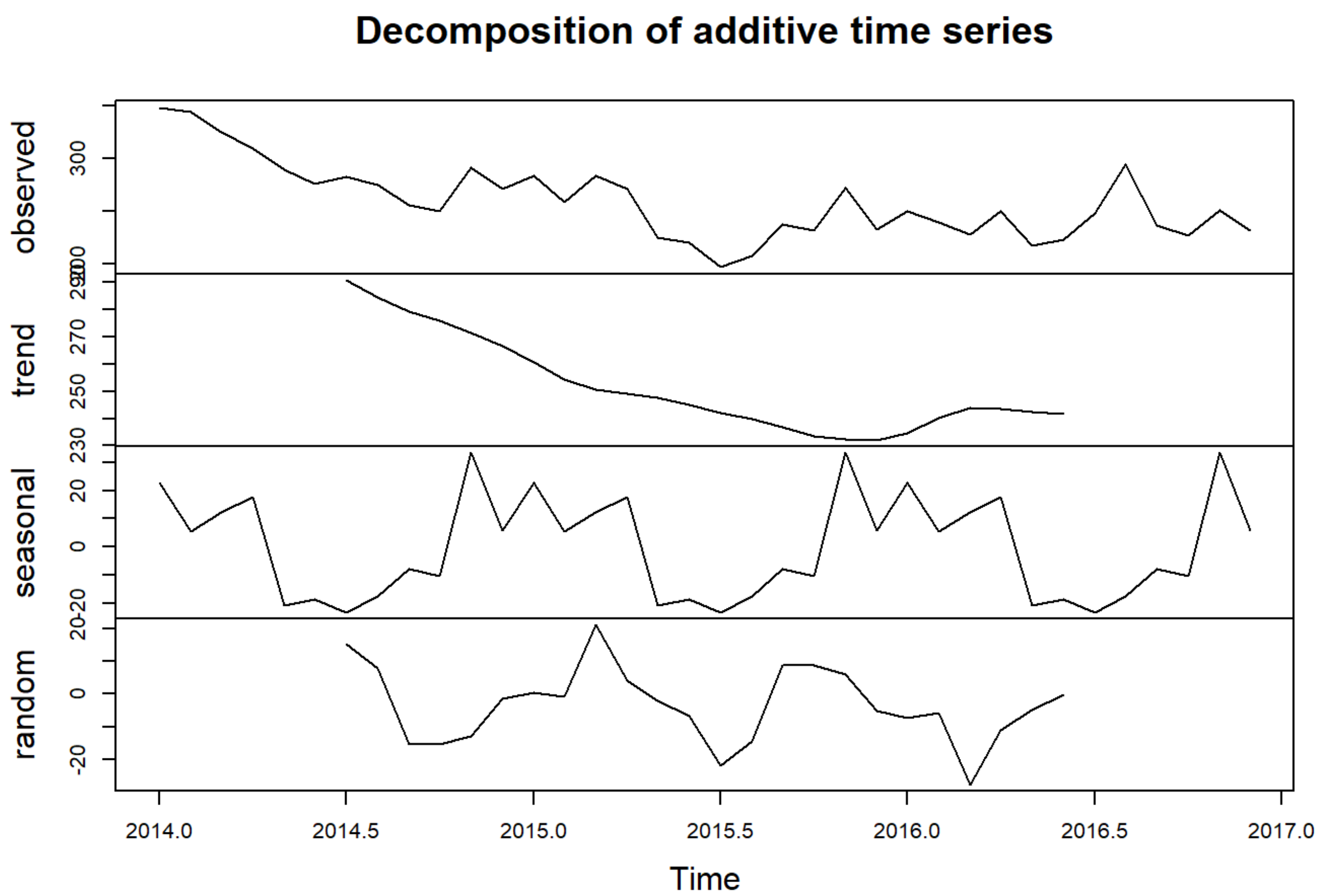

Series train_D[[i]]
Partial ACF
0.6
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag


Holt-Winters filtering
Observed / Fitted
200
180
160
140
120
100
2015.0
2015.5
2016.0
2016.5
Time

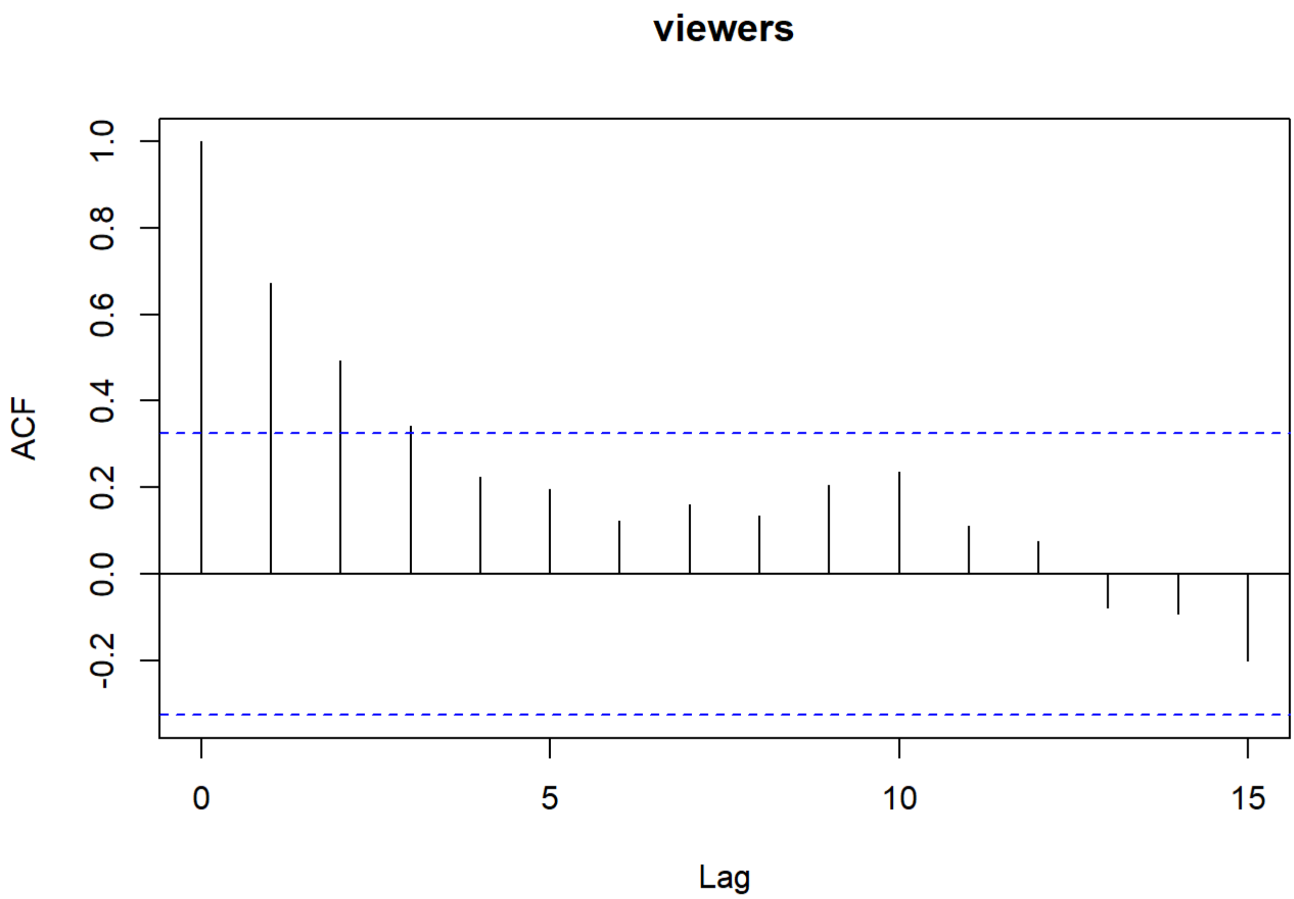

Decomposition of additive time series
observed
trend
seasonal
random
160
130
100
145
135
125
10
5
0
-5
10
0
-10
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

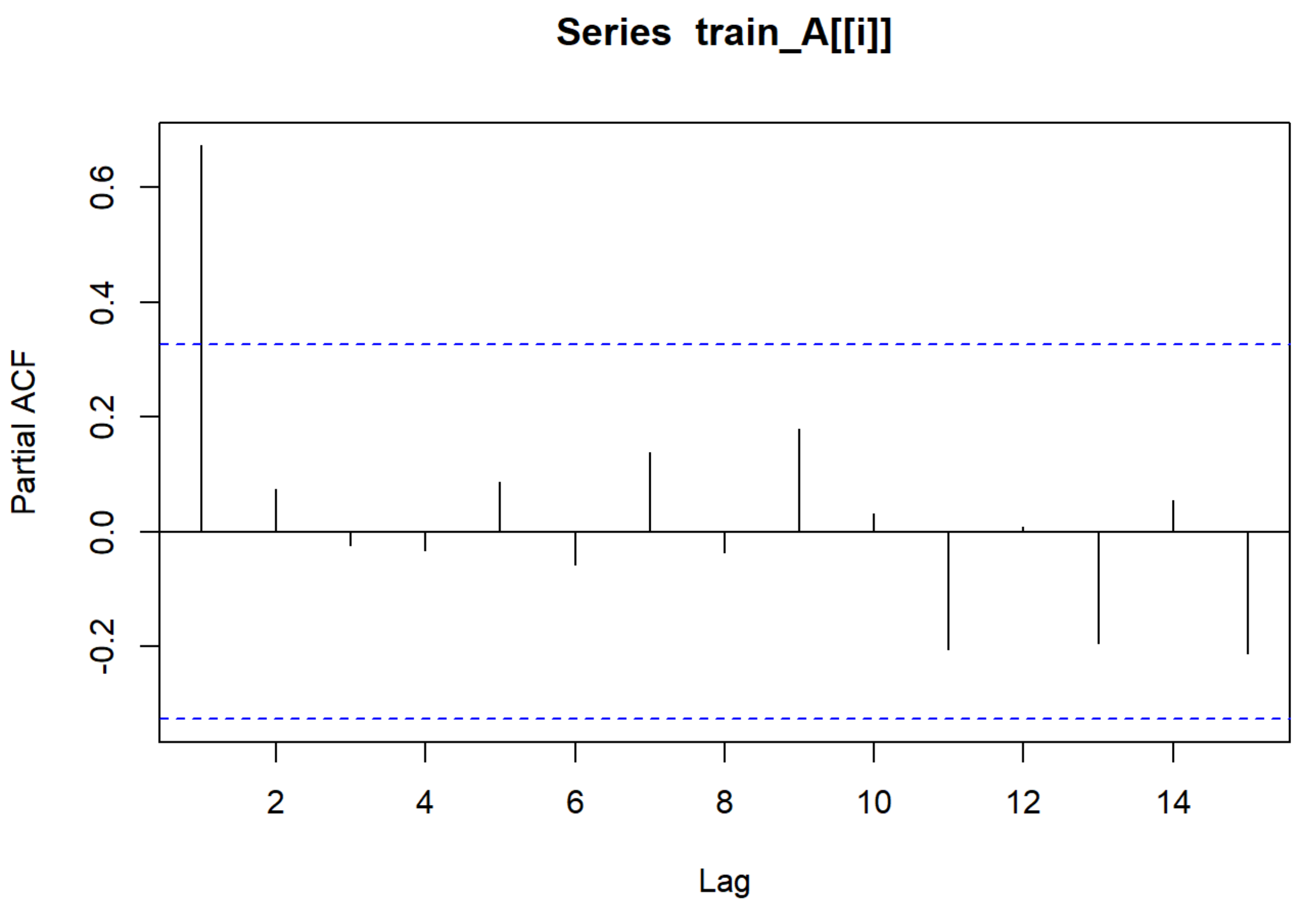


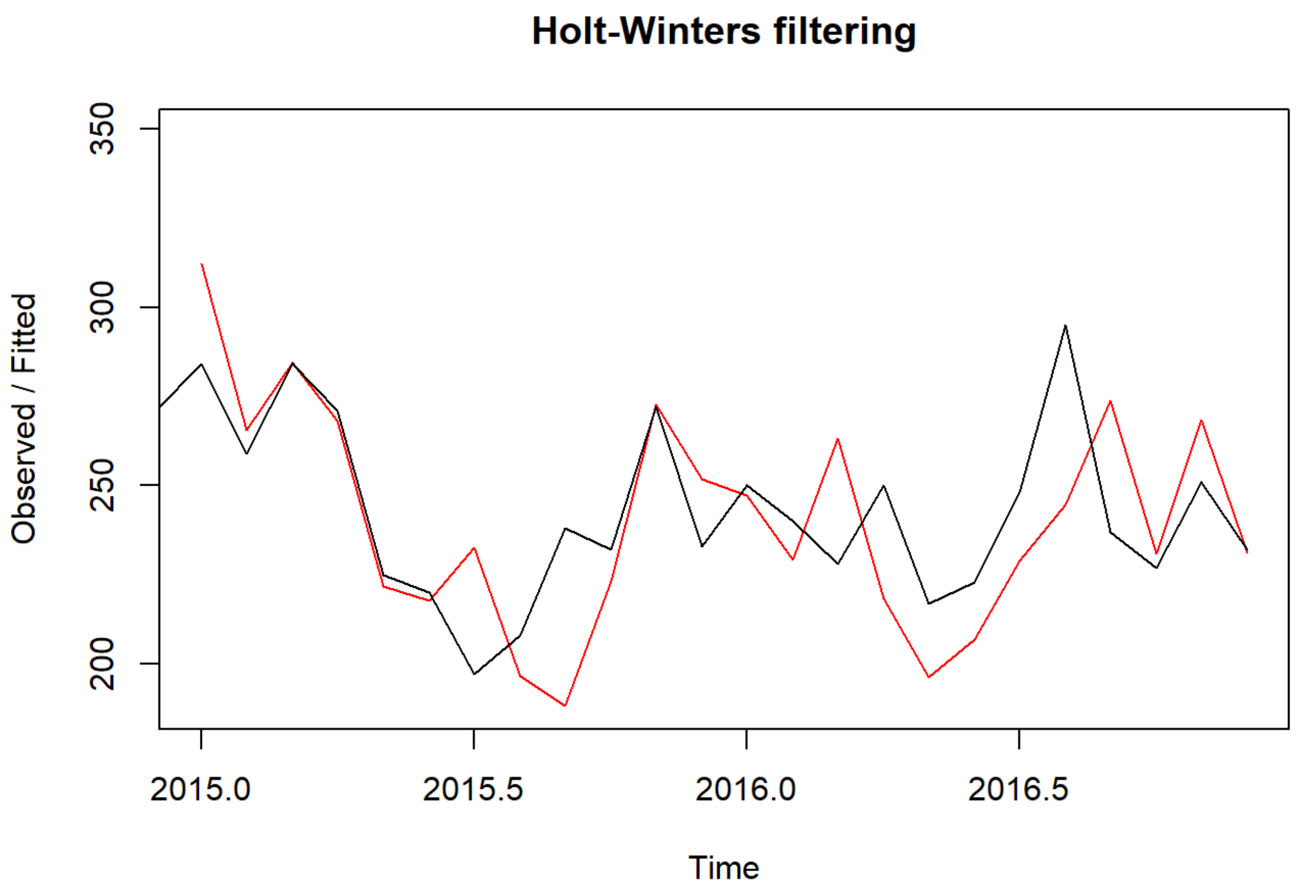
Holt-Winters filtering
Observed / Fitted
160
140
120
100
2015.0
2015.5
2016.0
2016.5
Time

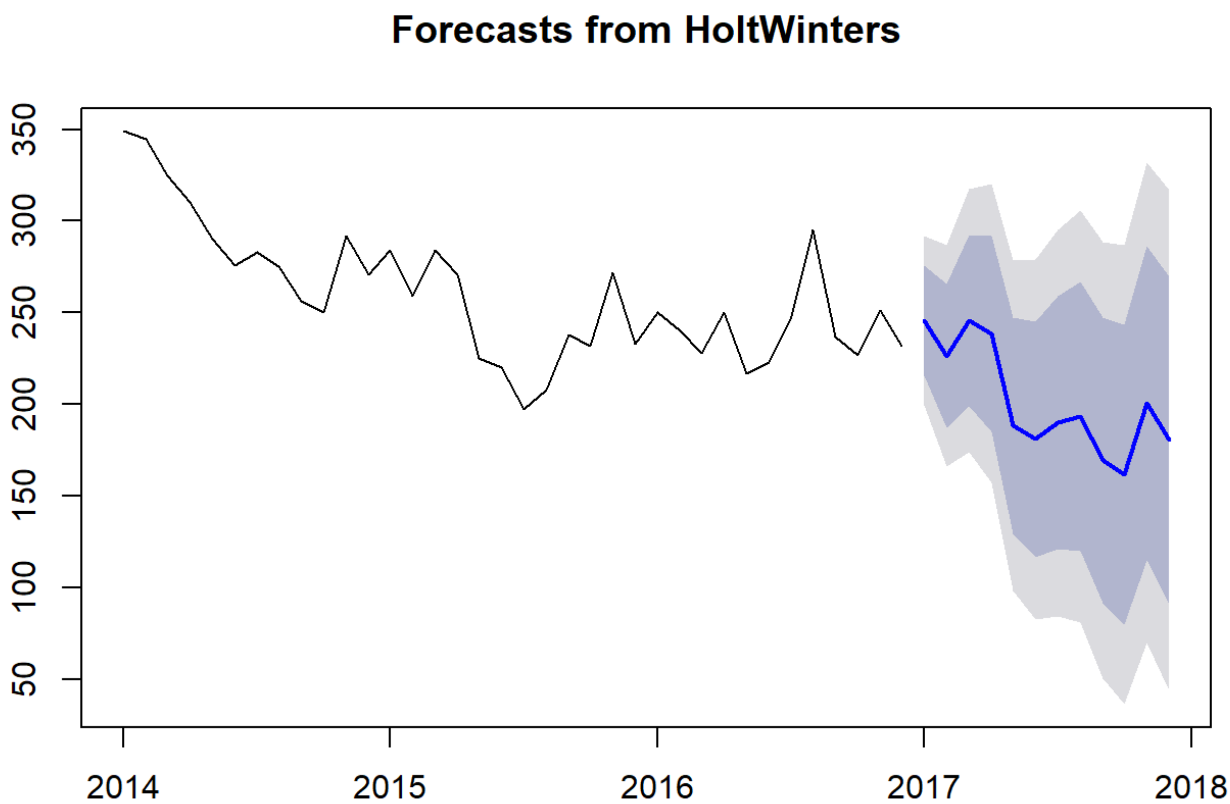



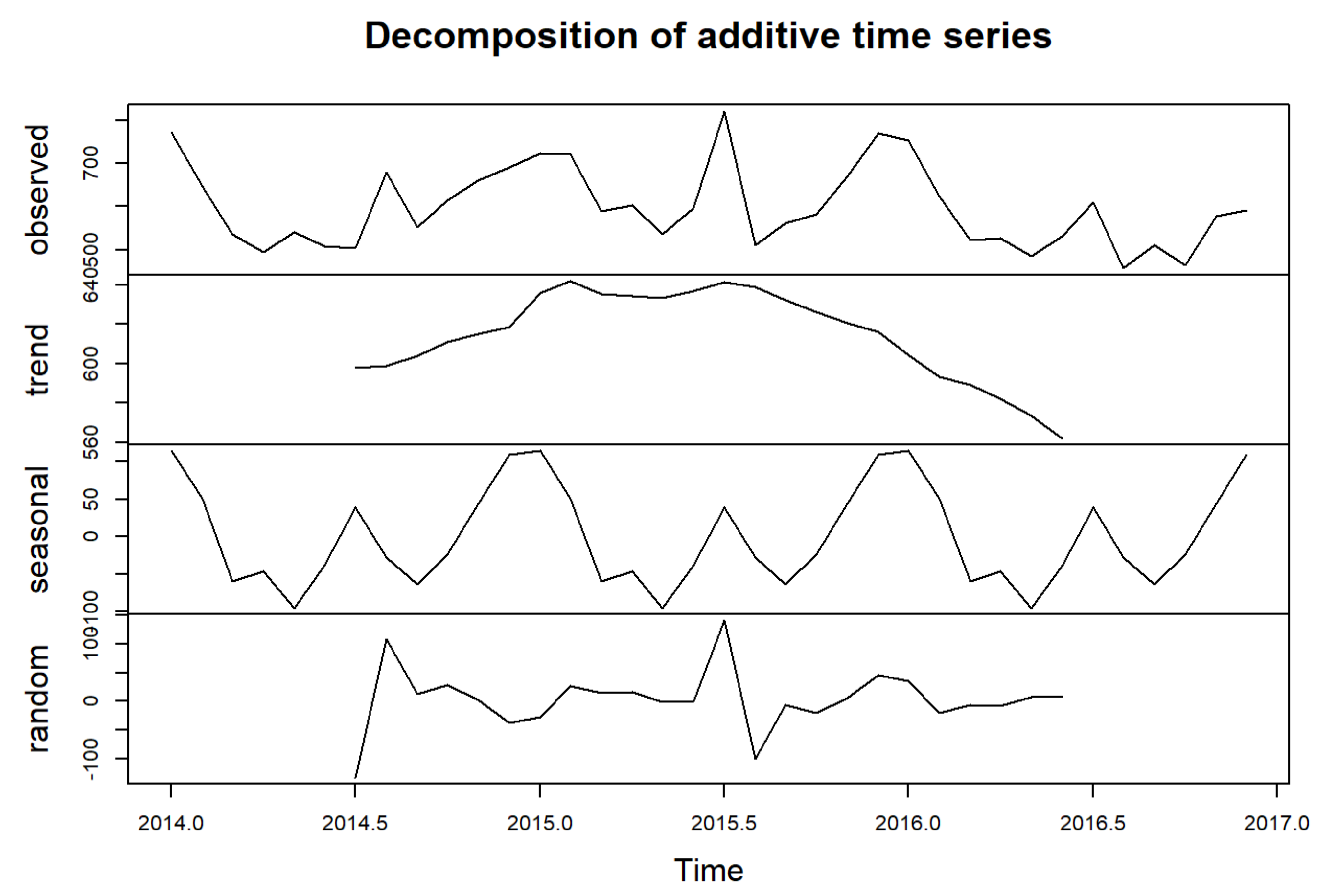
Decomposition of additive time series
observed
trend
seasonal
random
300
200
290
270
250
230
20
0
-20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time


viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

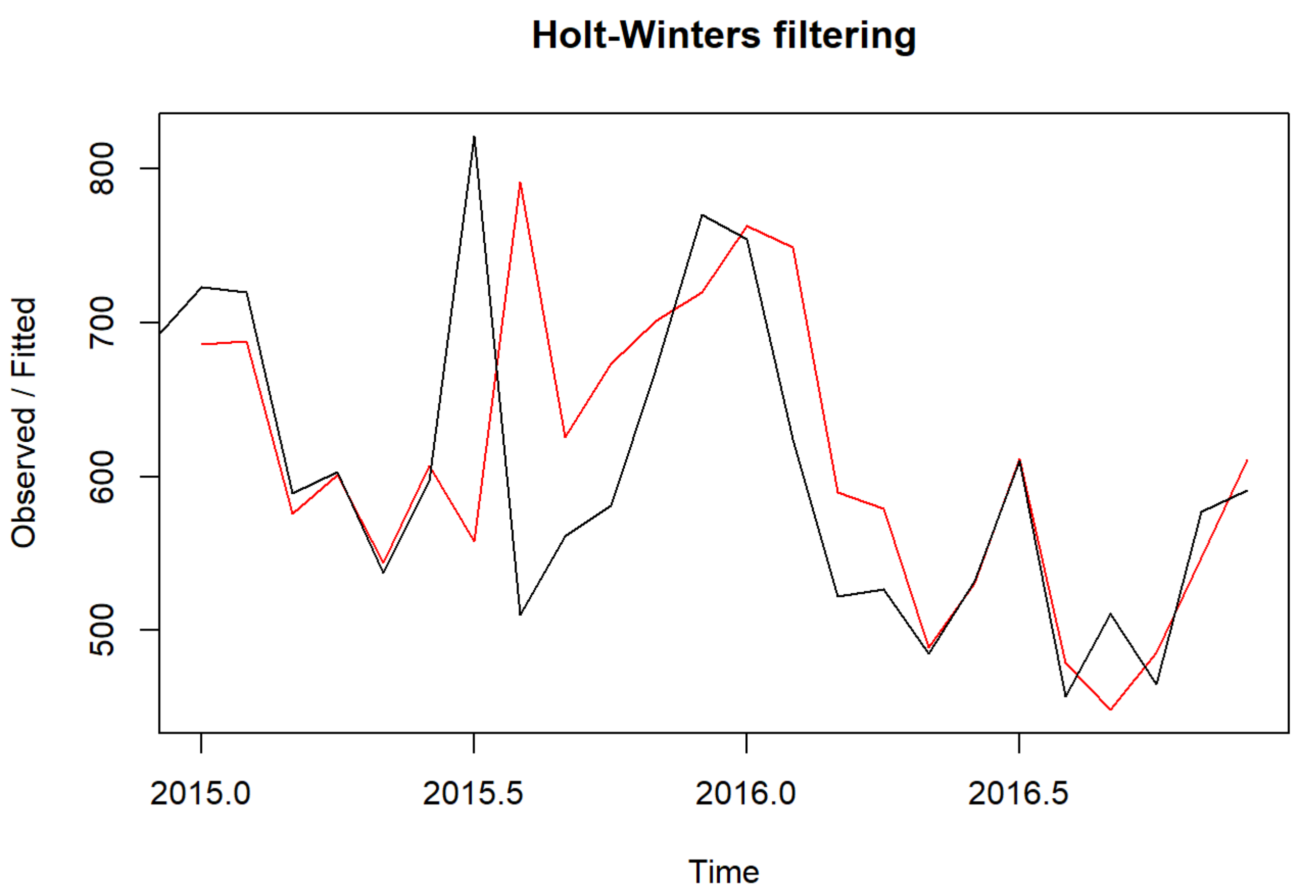

Series train_A[[i]]
Partial ACF
0.6
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag


Holt-Winters filtering
Observed / Fitted
350
300
250
200
2015.0
2015.5
2016.0
2016.5
Time

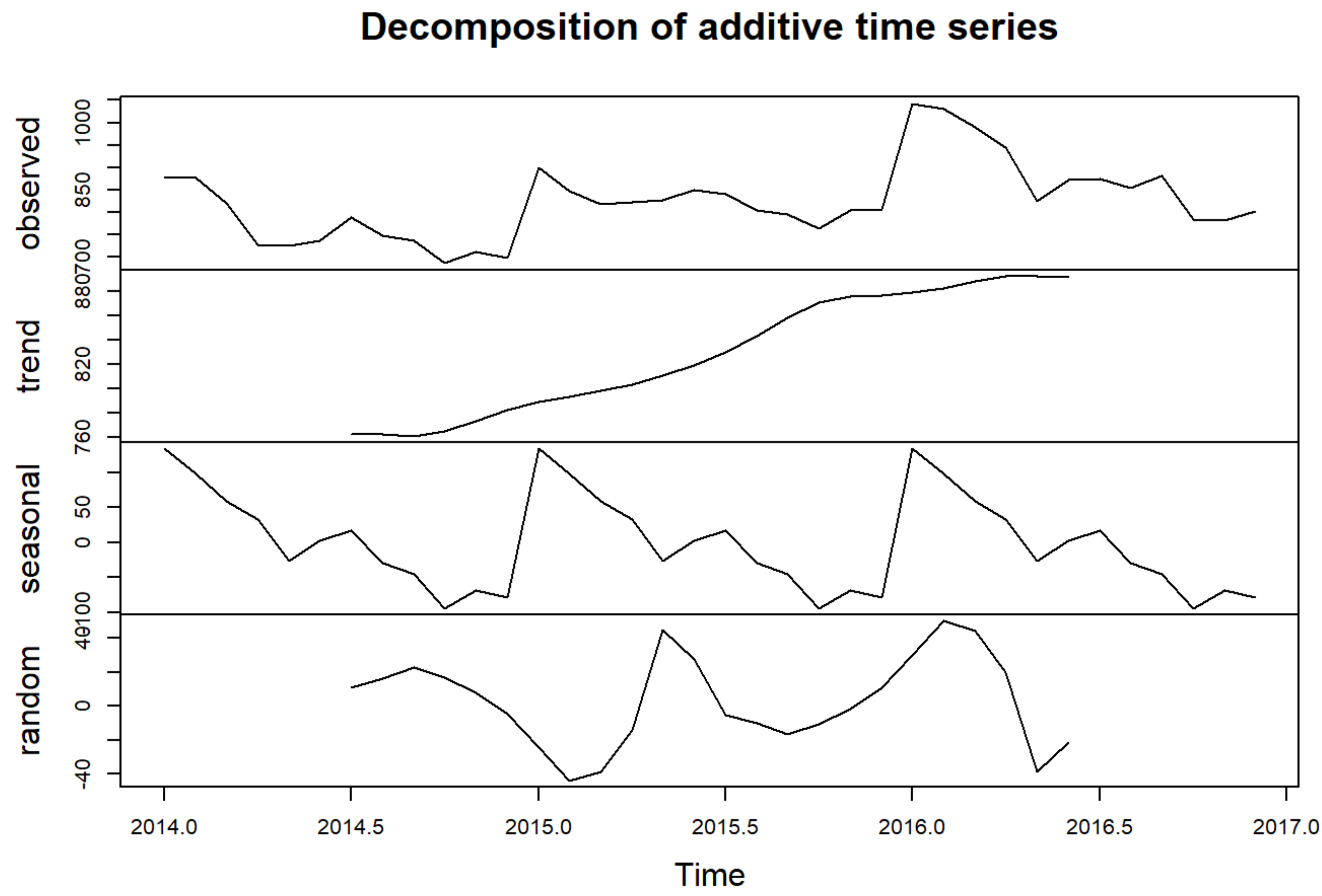

Forecasts from HoltWinters
350
300
250
200
150
100
50
2014
2015
2016
2017
2018

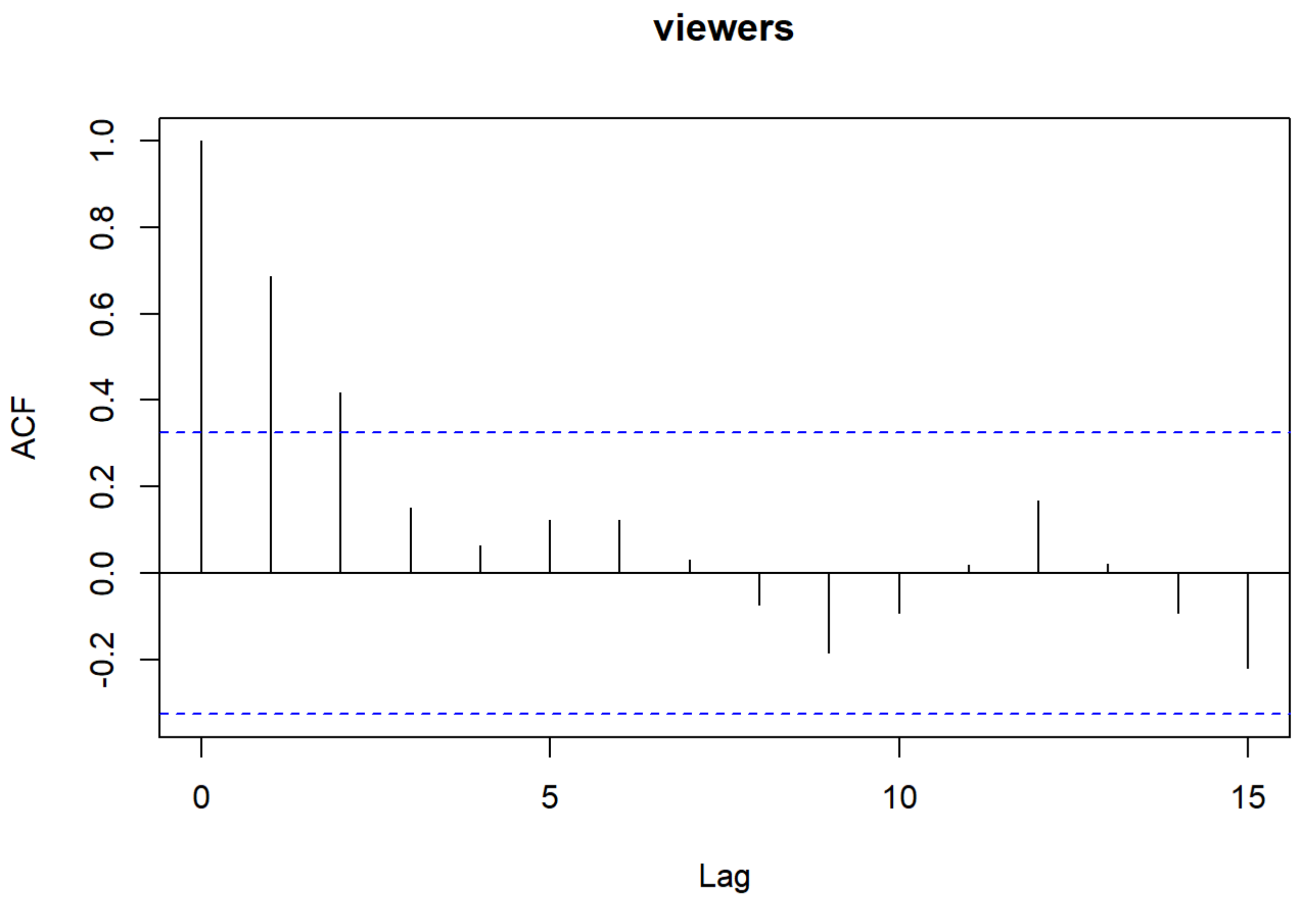


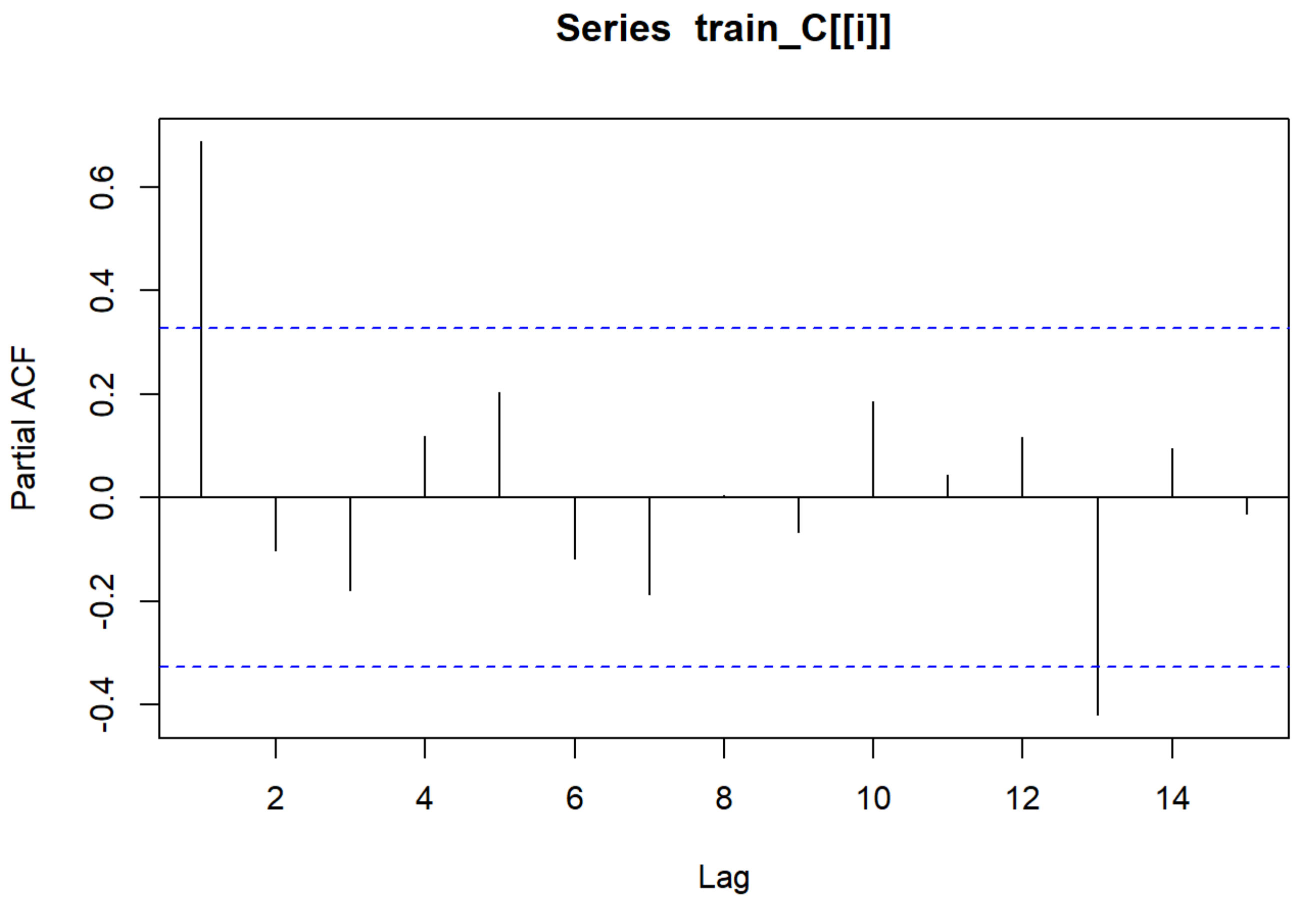
Decomposition of additive time series
observed
trend
seasonal
random
700
500
640
600
560
50
0
-100
100
0
-100
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

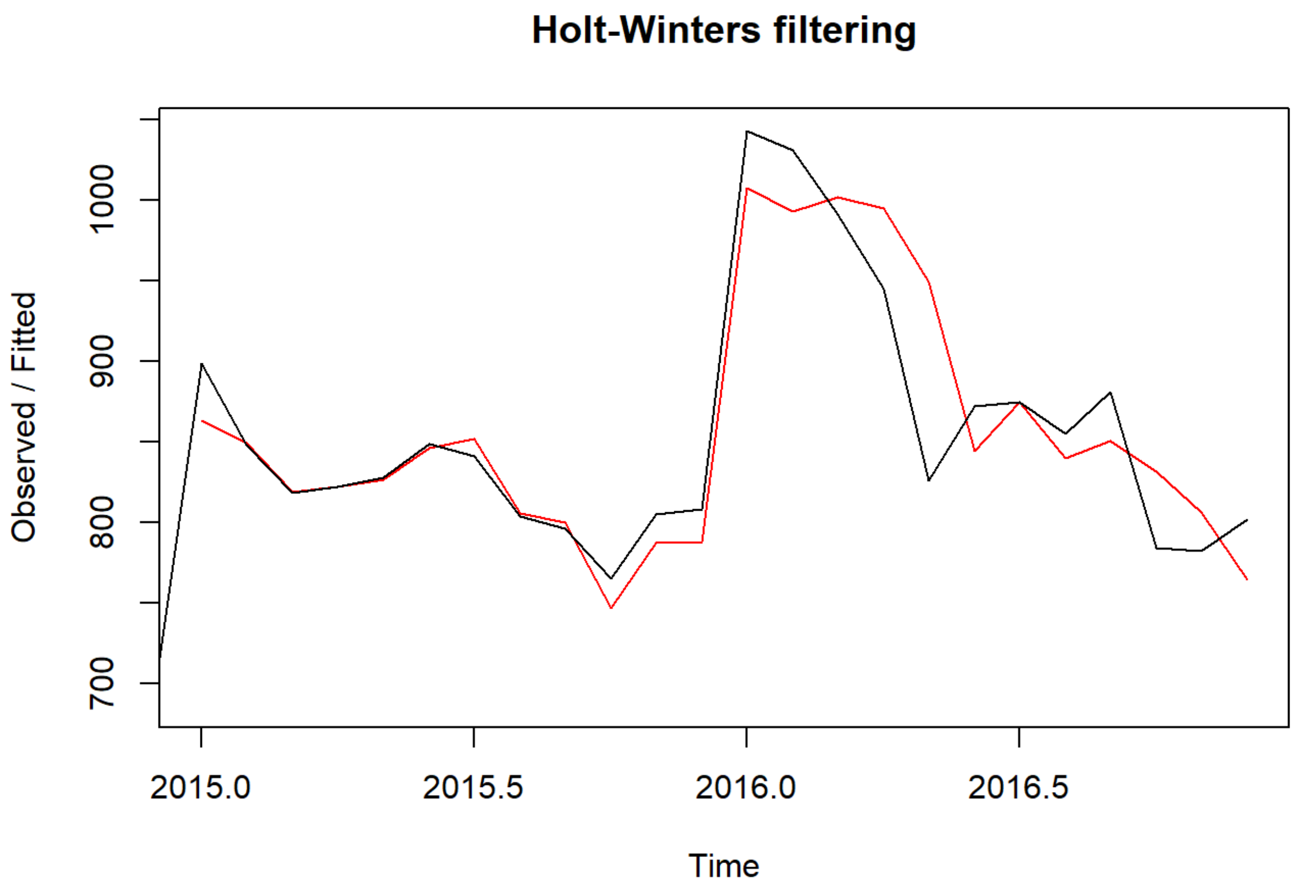



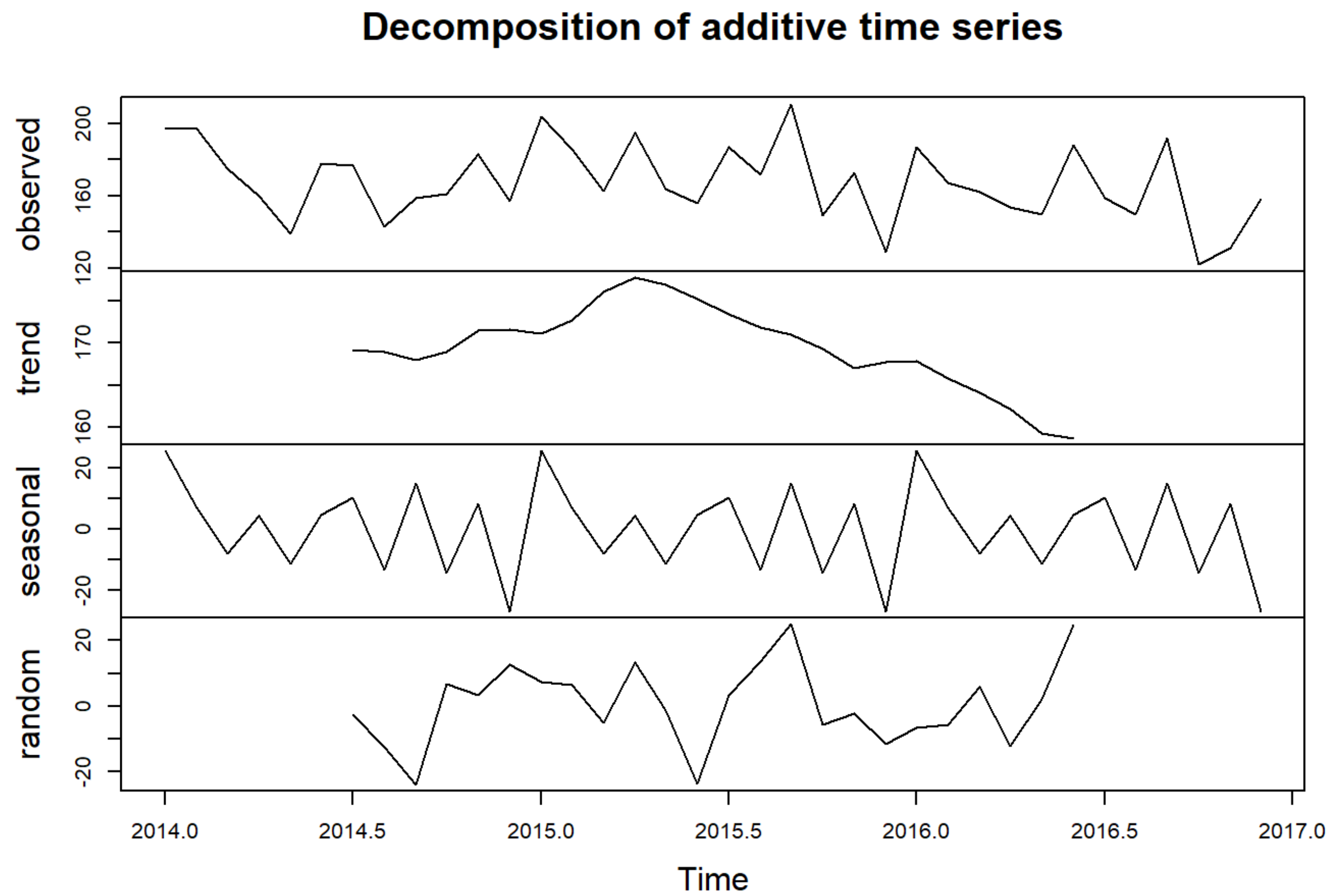
Holt-Winters filtering
Observed / Fitted
800
700
600
500
2015.0
2015.5
2016.0
2016.5
Time


Decomposition of additive time series
observed
trend
seasonal
random
Time
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0

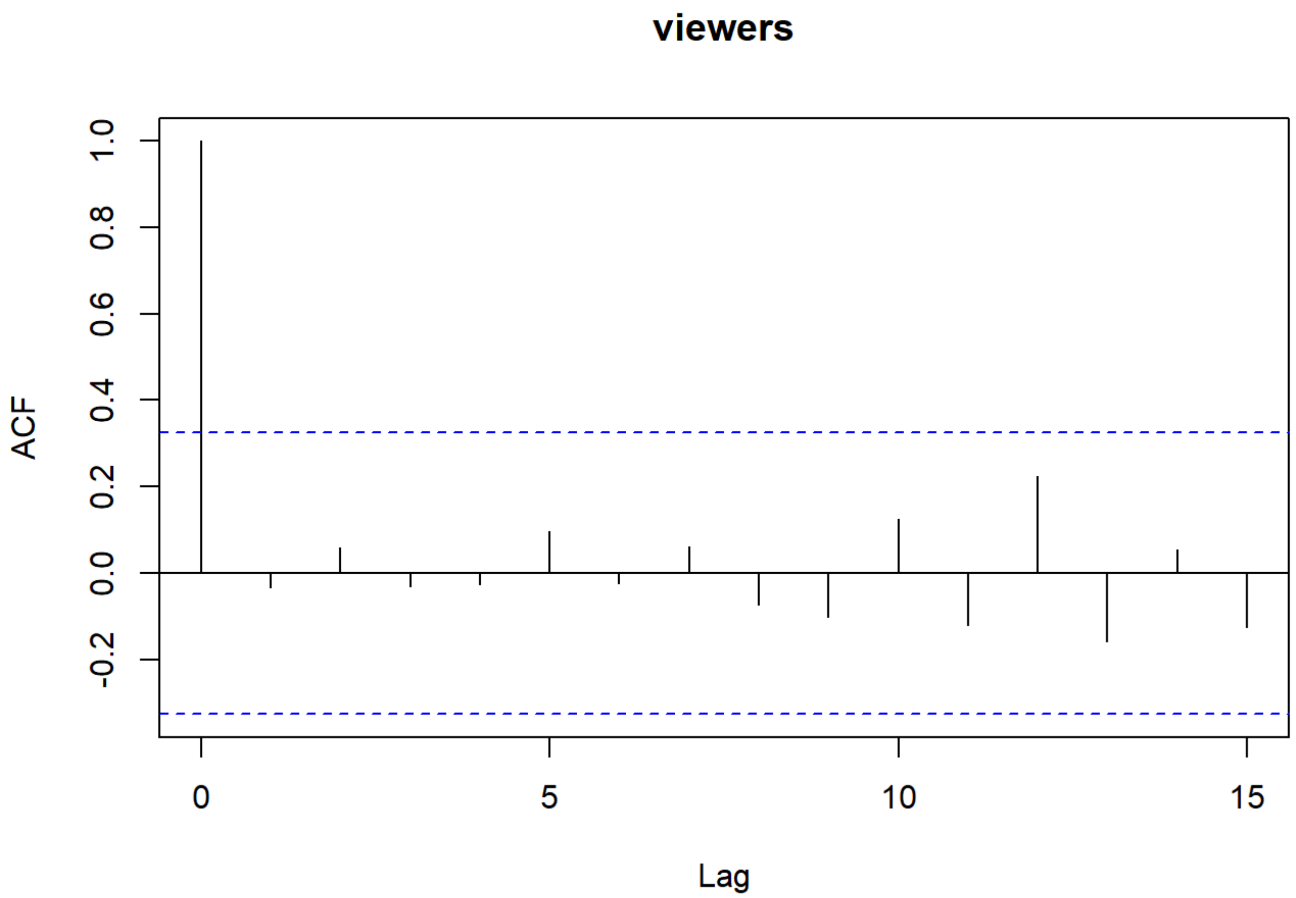

viewers
ACF
Lag


Series train_C[[i]]
Partial ACF
Lag
0.6
0.4
0.2
0.0
-0.2
-0.4
2
4
6
8
10
12
14

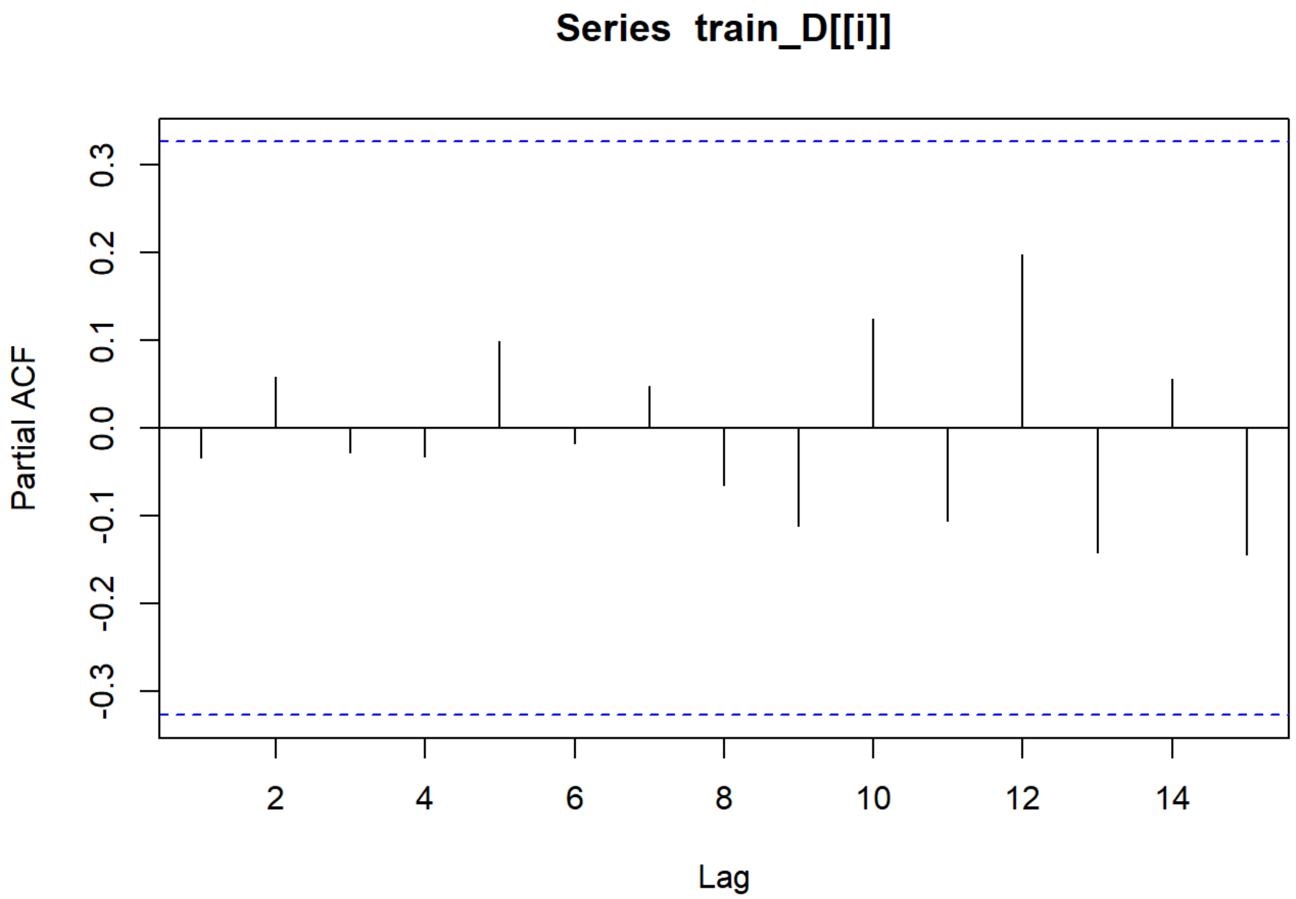

Holt-Winters filtering
Observed / Fitted
Time
1000
900
800
700
2015.0
2015.5
2016.0
2016.5

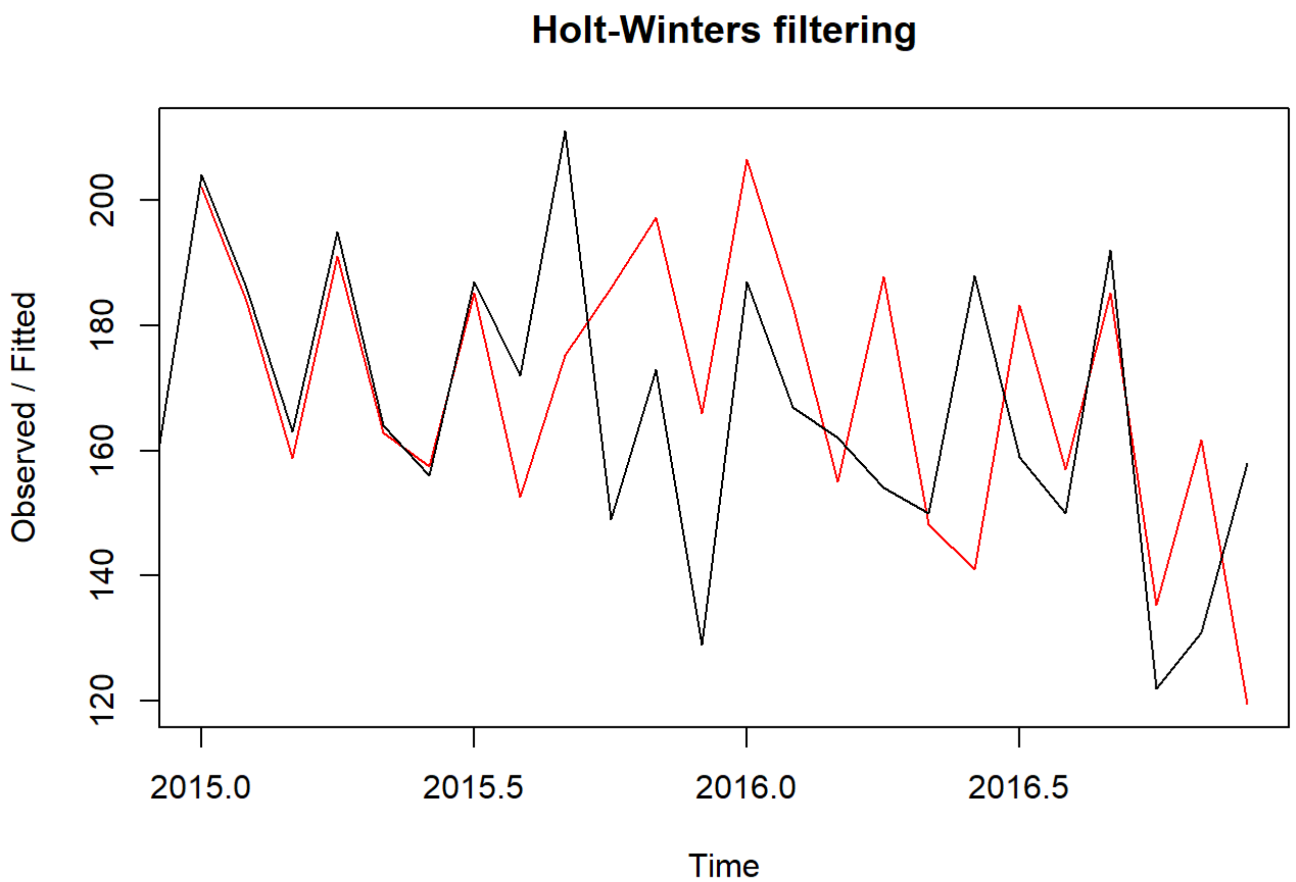


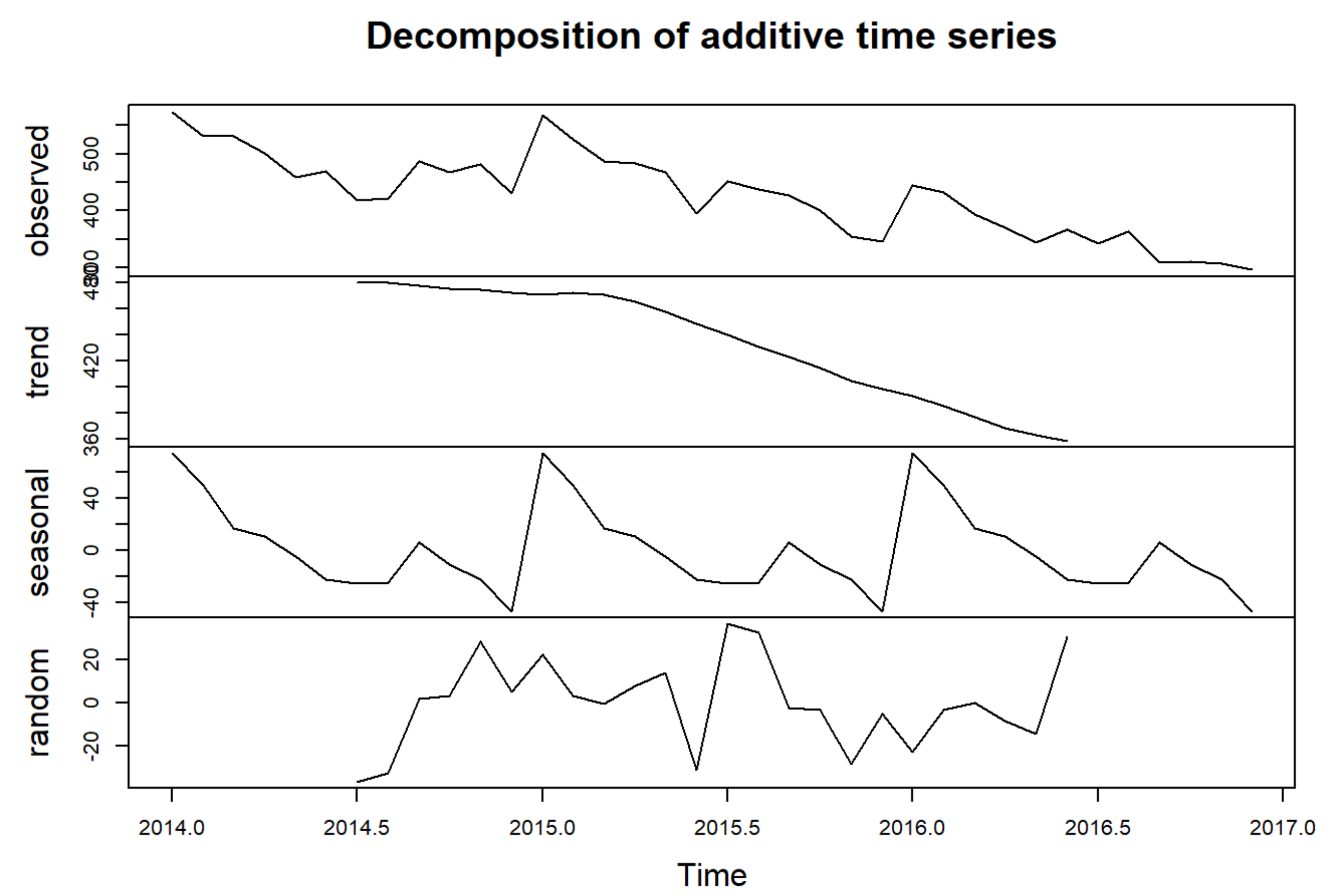
Decomposition of additive time series
observed
trend
seasonal
random
200
160
120
170
160
20
0
-20
20
0
-20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

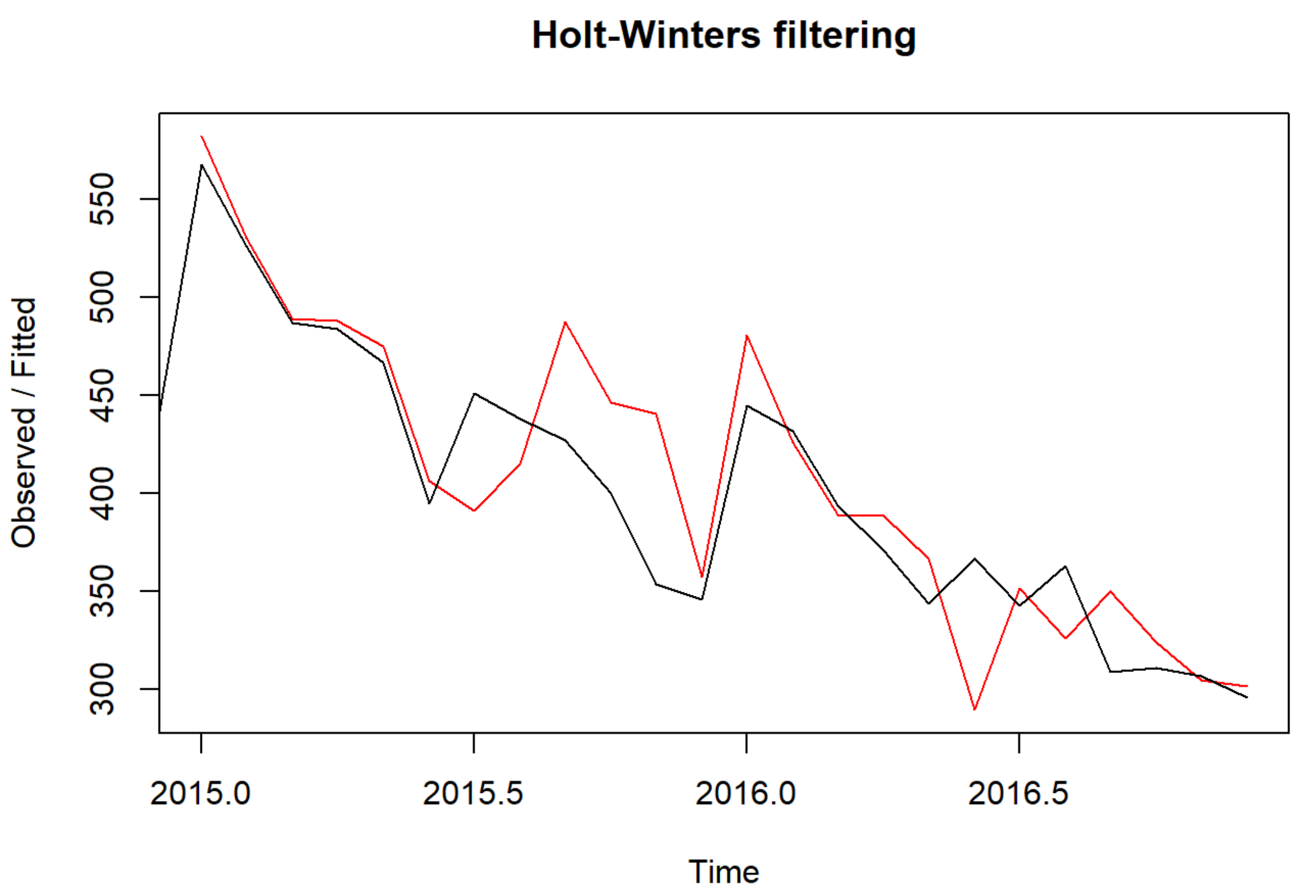



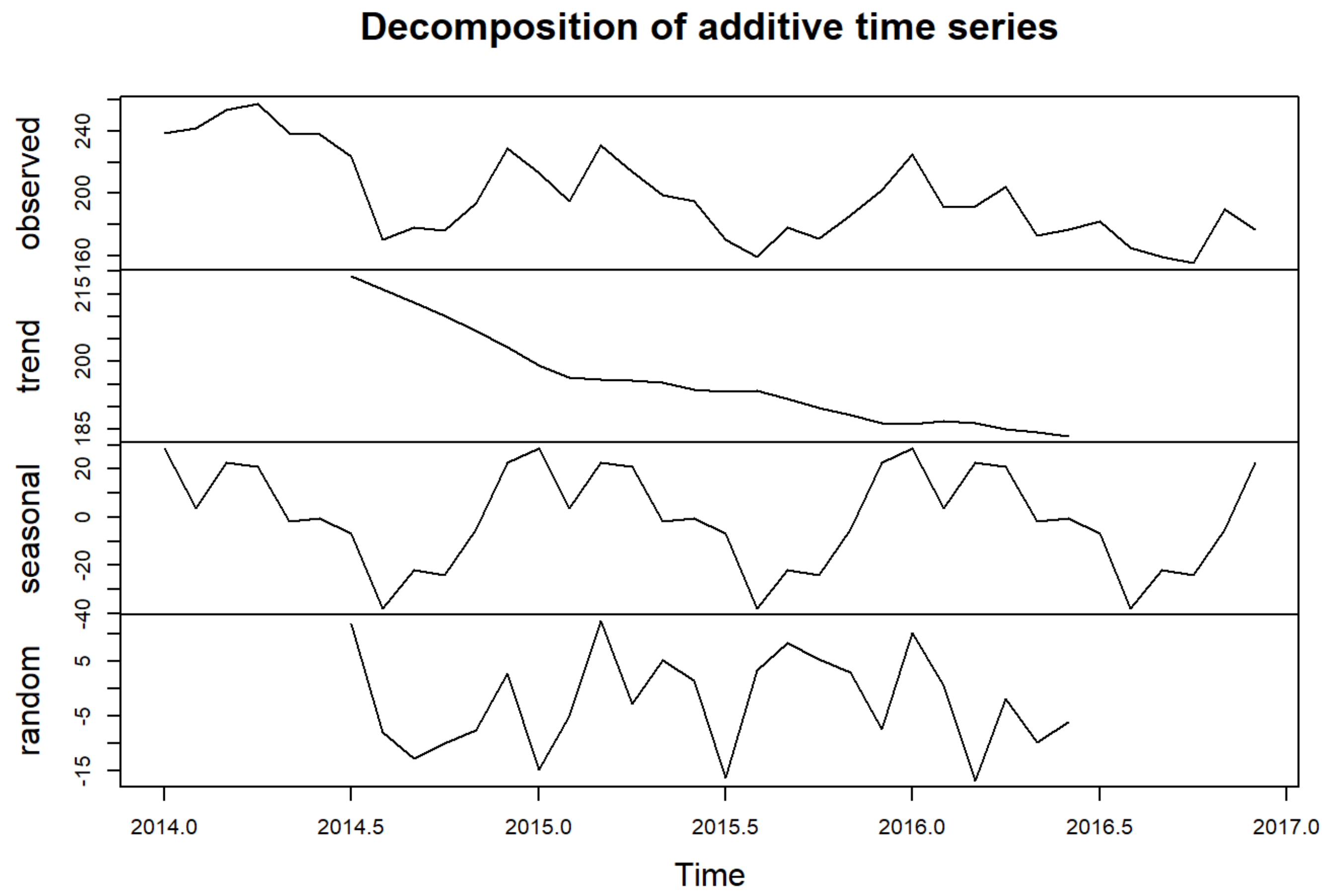
viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag


Series train_D[[i]]
Partial ACF
Lag
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
2
4
6
8
10
12
14

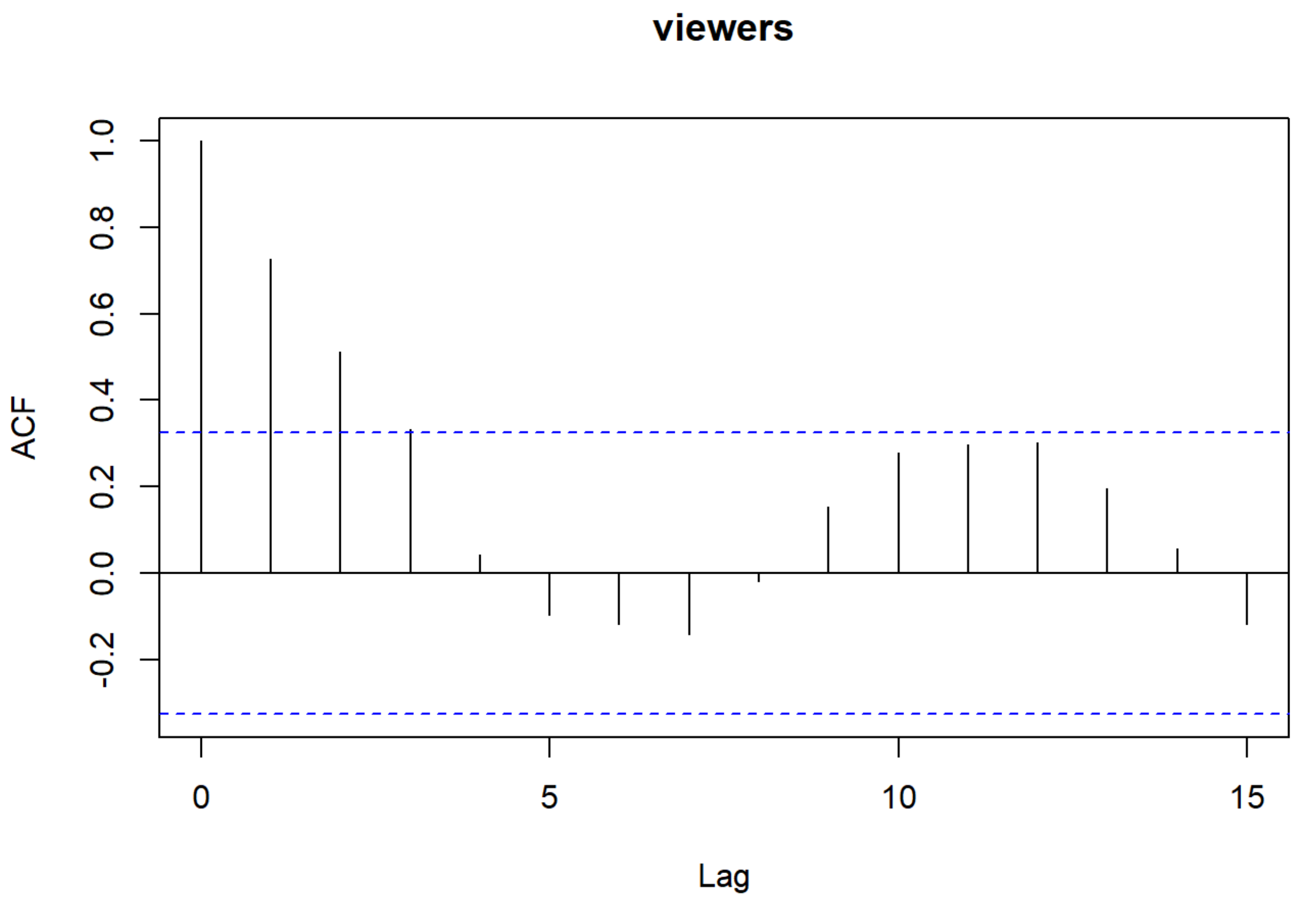

Holt-Winters filtering
Observed / Fitted
Time
200
180
160
140
120
2015.0
2015.5
2016.0
2016.5


Decomposition of additive time series
observed
trend
seasonal
random
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

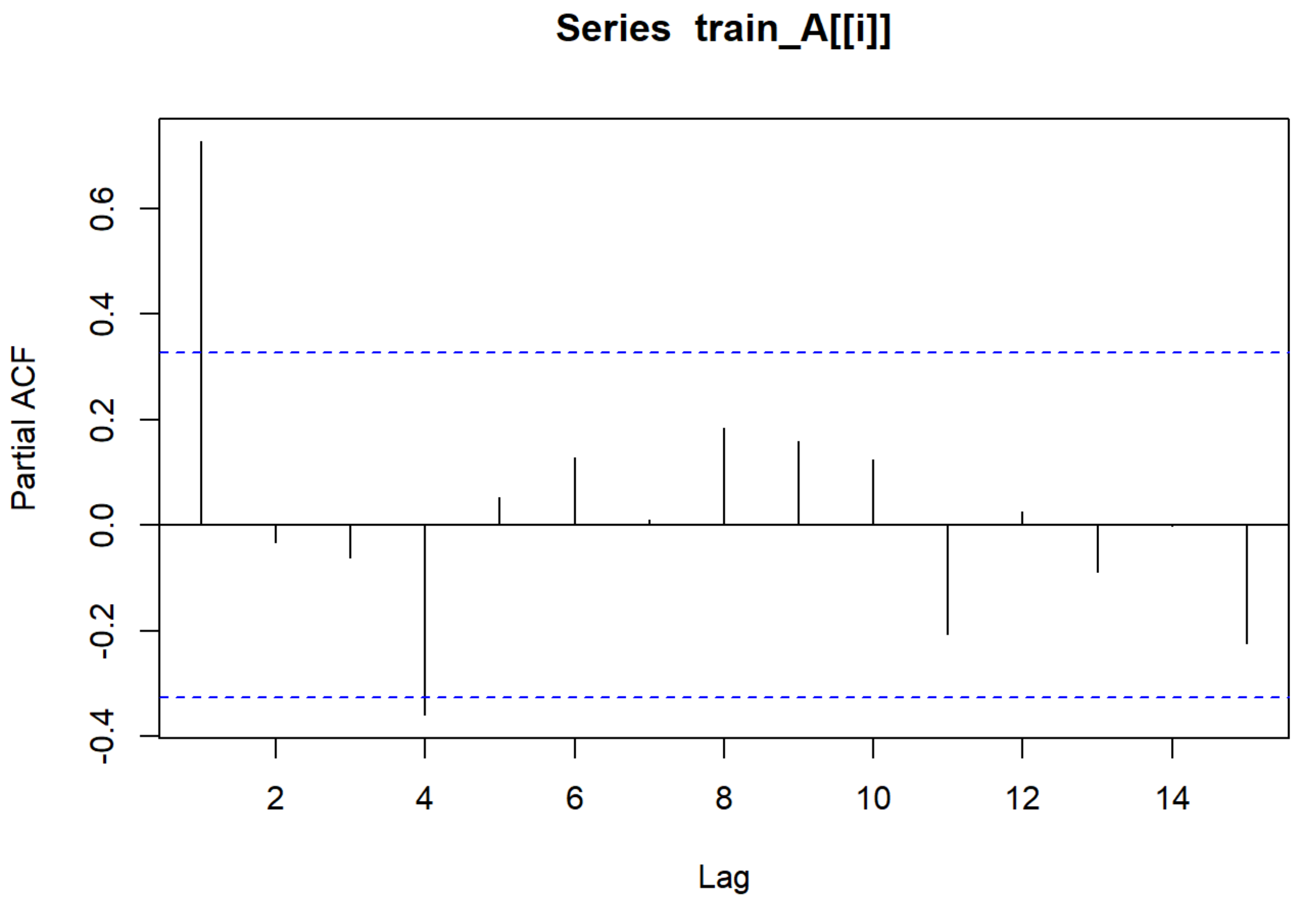

Holt-Winters filtering
Observed / Fitted
300
350
400
450
500
550
2015.0
2015.5
2016.0
2016.5
Time



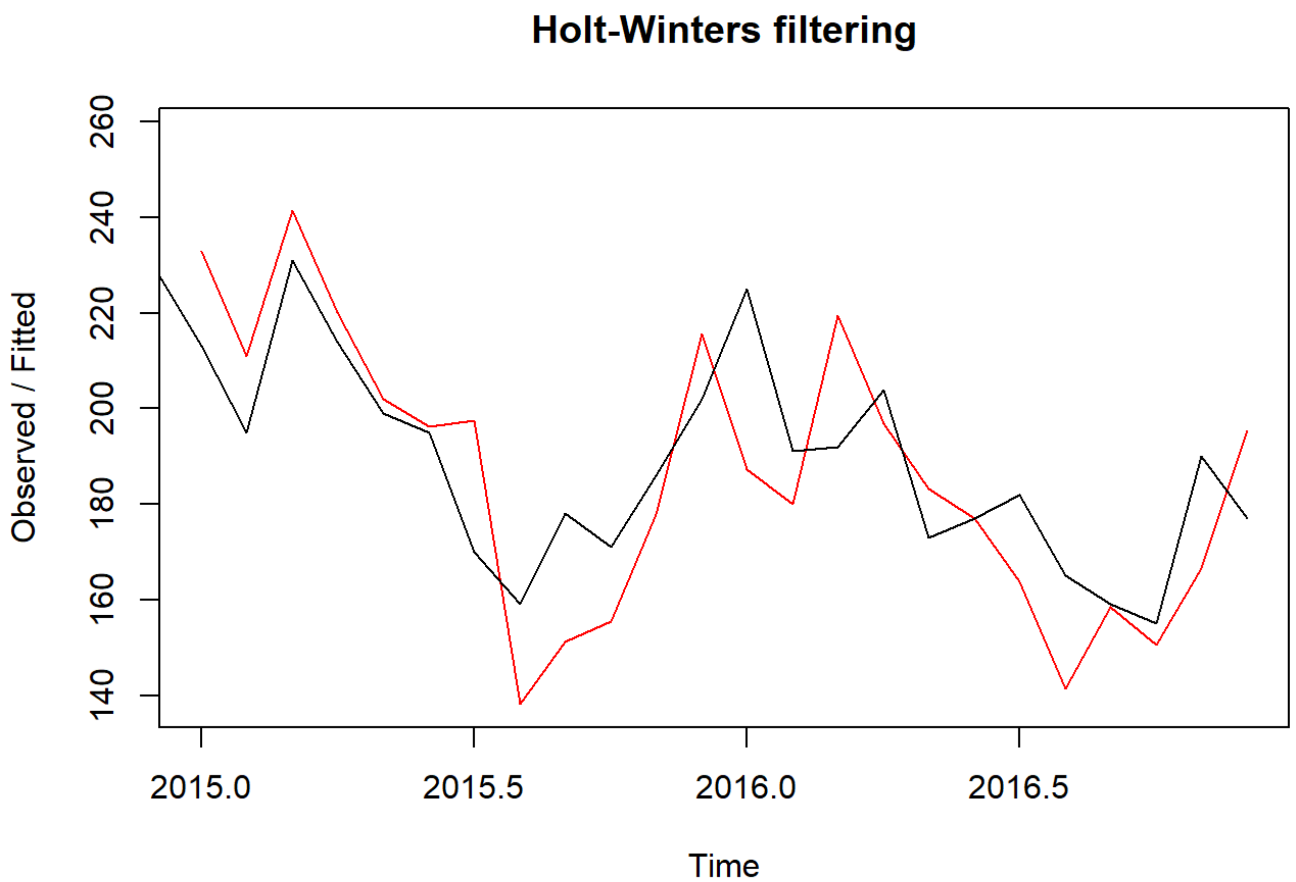
Decomposition of additive time series
observed
160
200
240
trend
185
200
215
seasonal
-40
-20
0
20
random
-15
-5
5
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

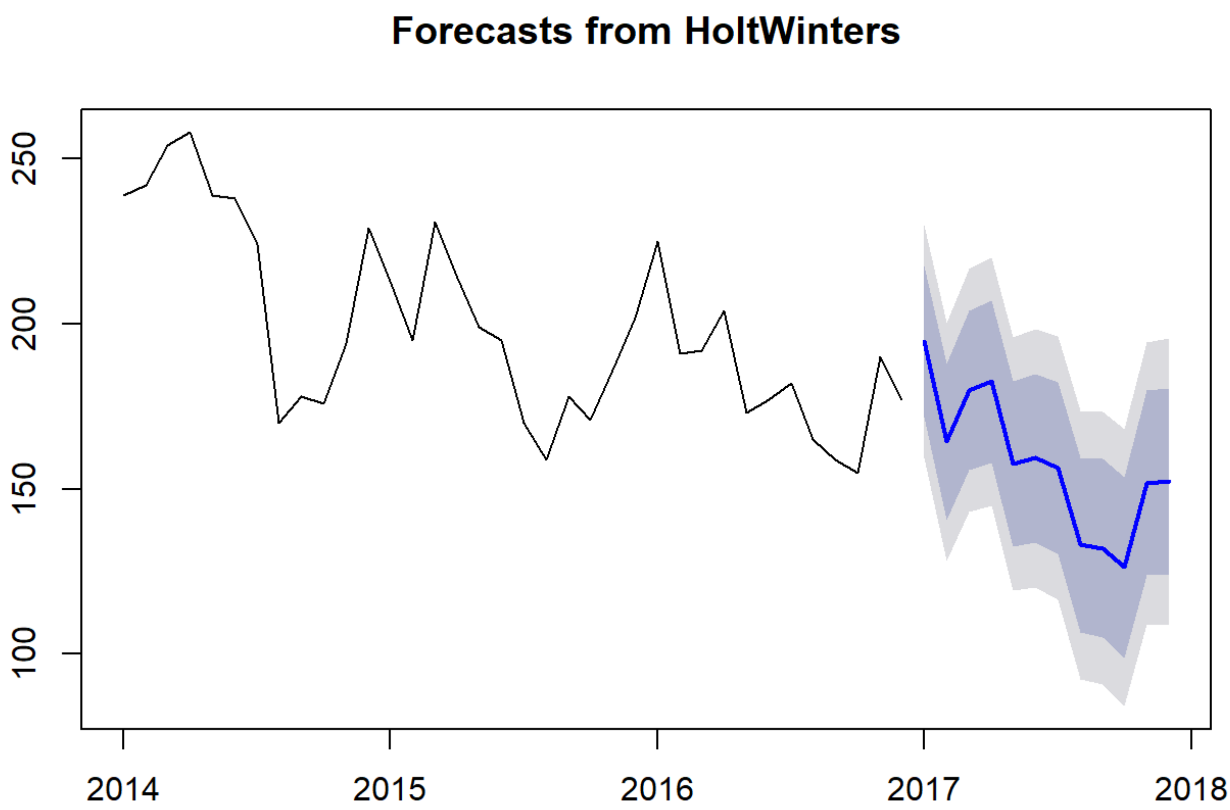
viewers
ACF
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
Lag

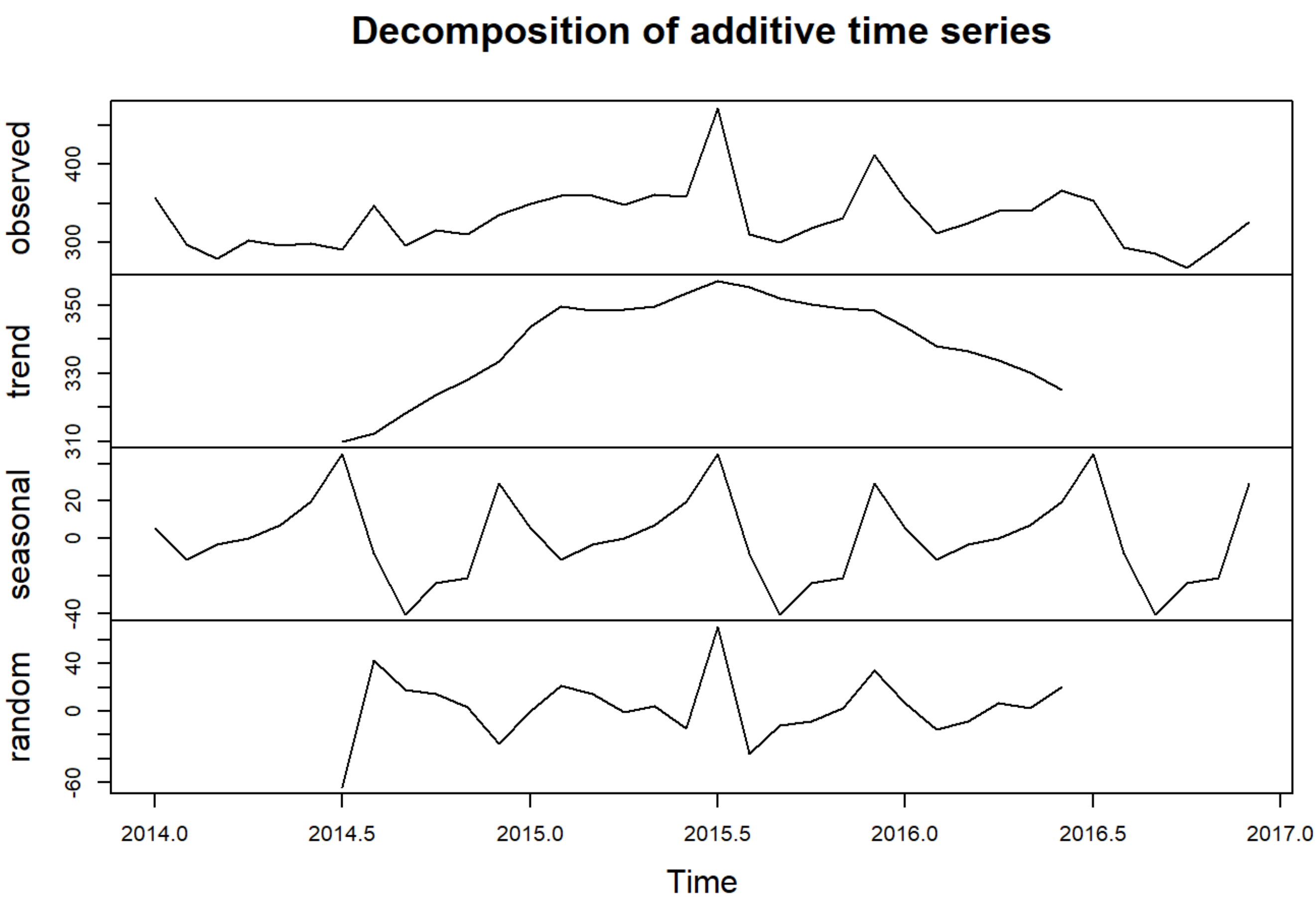


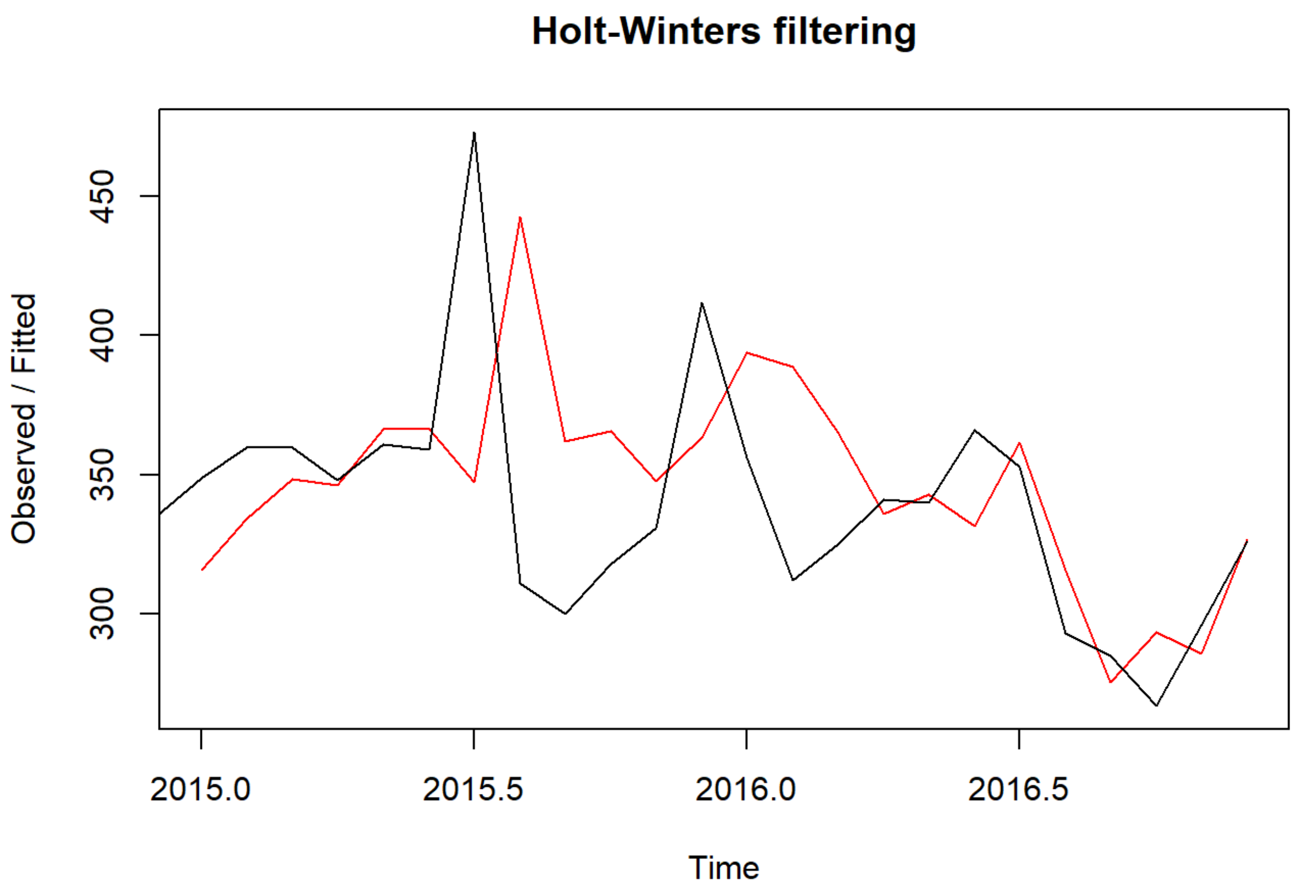
Series train_A[[i]]
Partial ACF
-0.4
-0.2
0.0
0.2
0.4
0.6
2
4
6
8
10
12
14
Lag

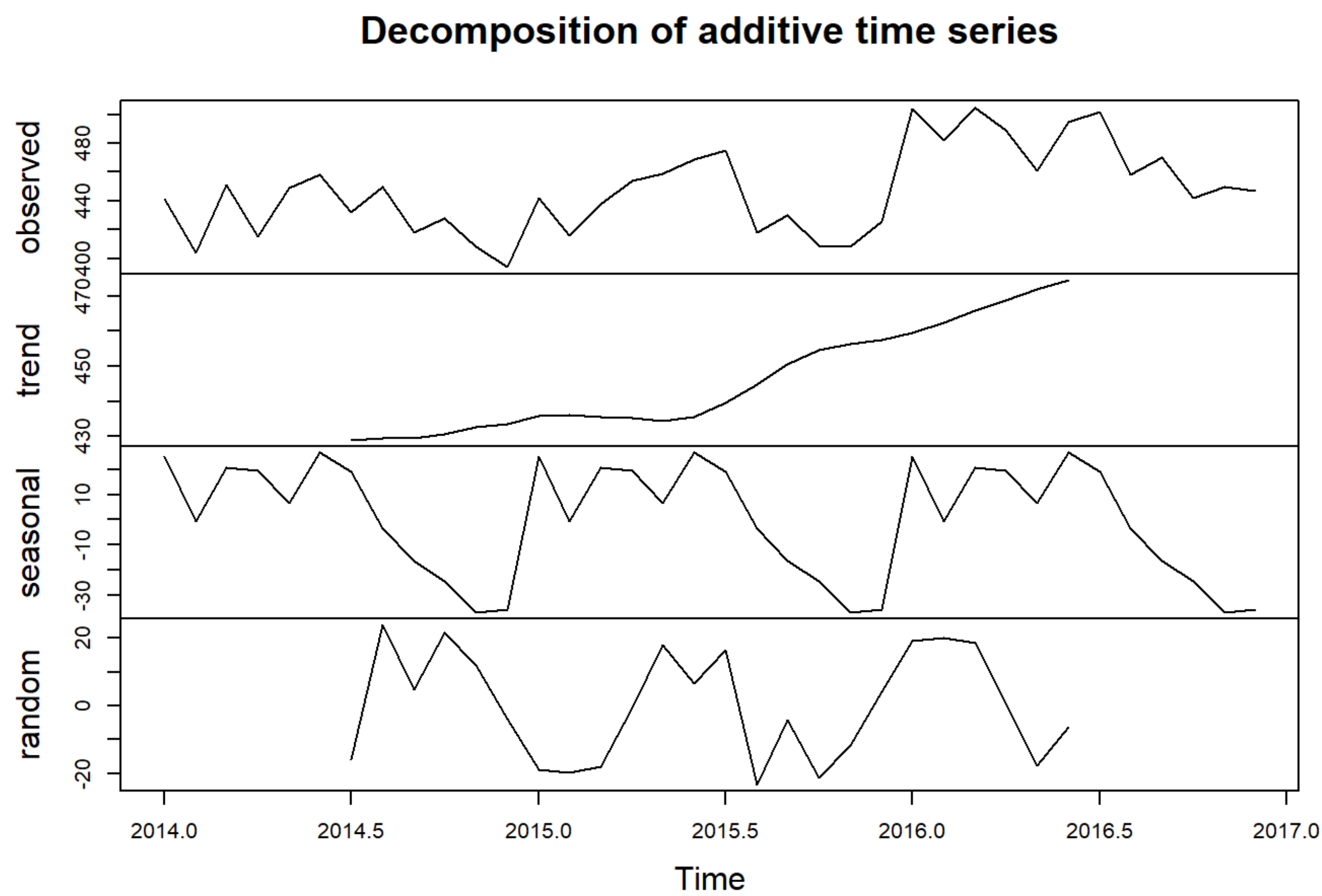
Holt-Winters filtering
Observed / Fitted
140
160
180
200
220
240
260
2015.0
2015.5
2016.0
2016.5
Time


Forecasts from HoltWinters
250
200
150
100
2014
2015
2016
2017
2018

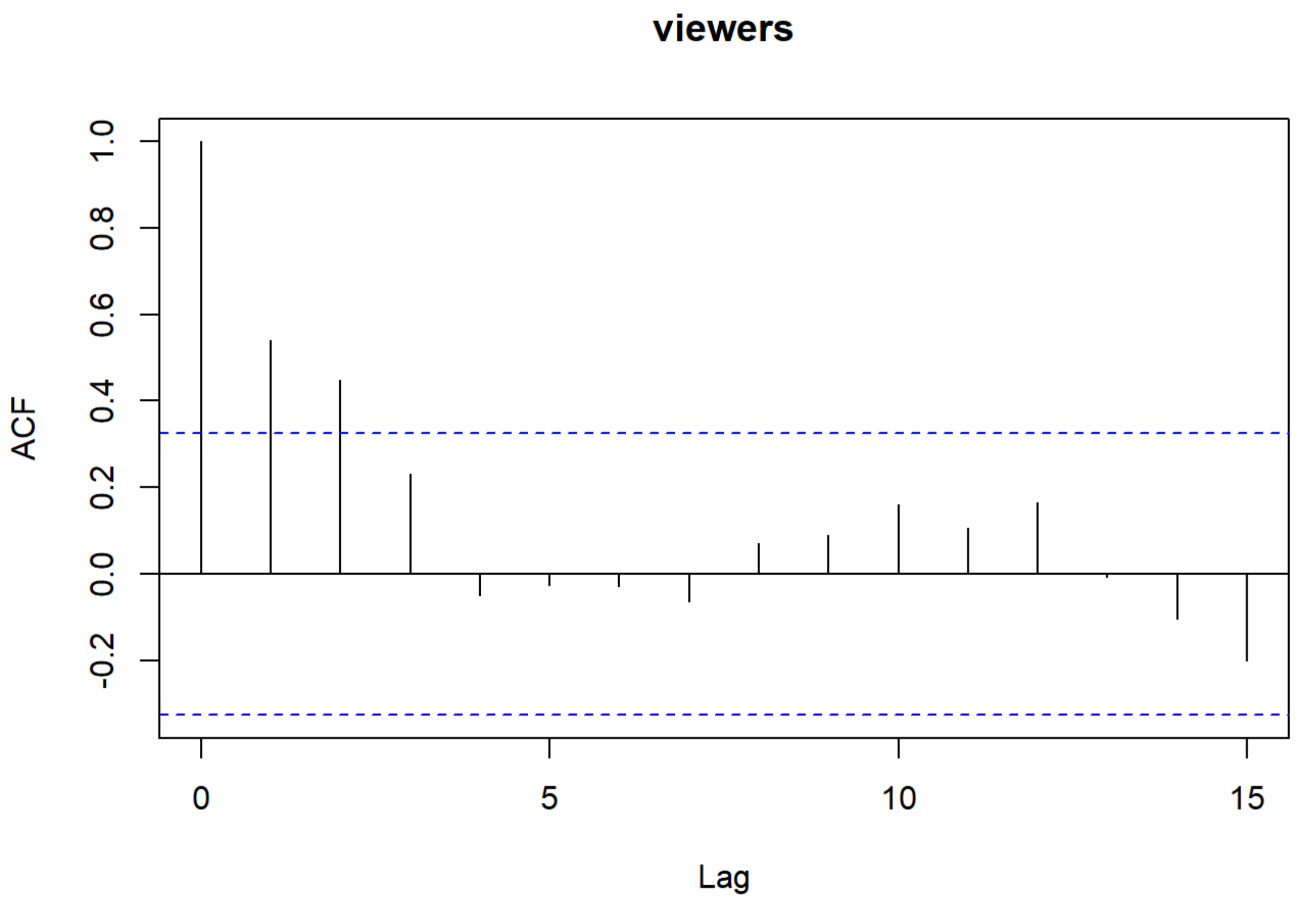

Decomposition of additive time series
observed
trend
seasonal
random
400
300
350
330
310
20
0
-40
40
0
-60
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

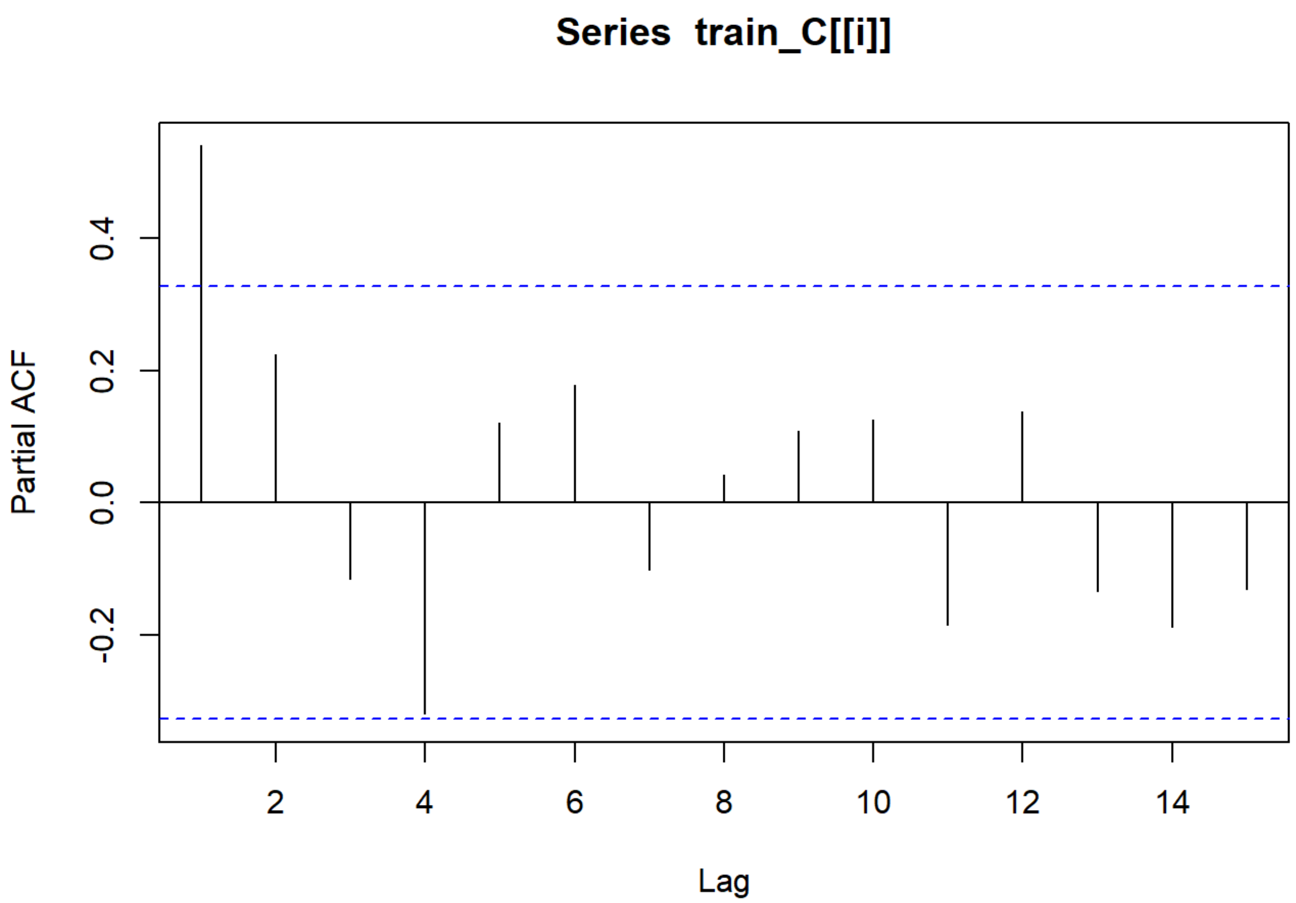


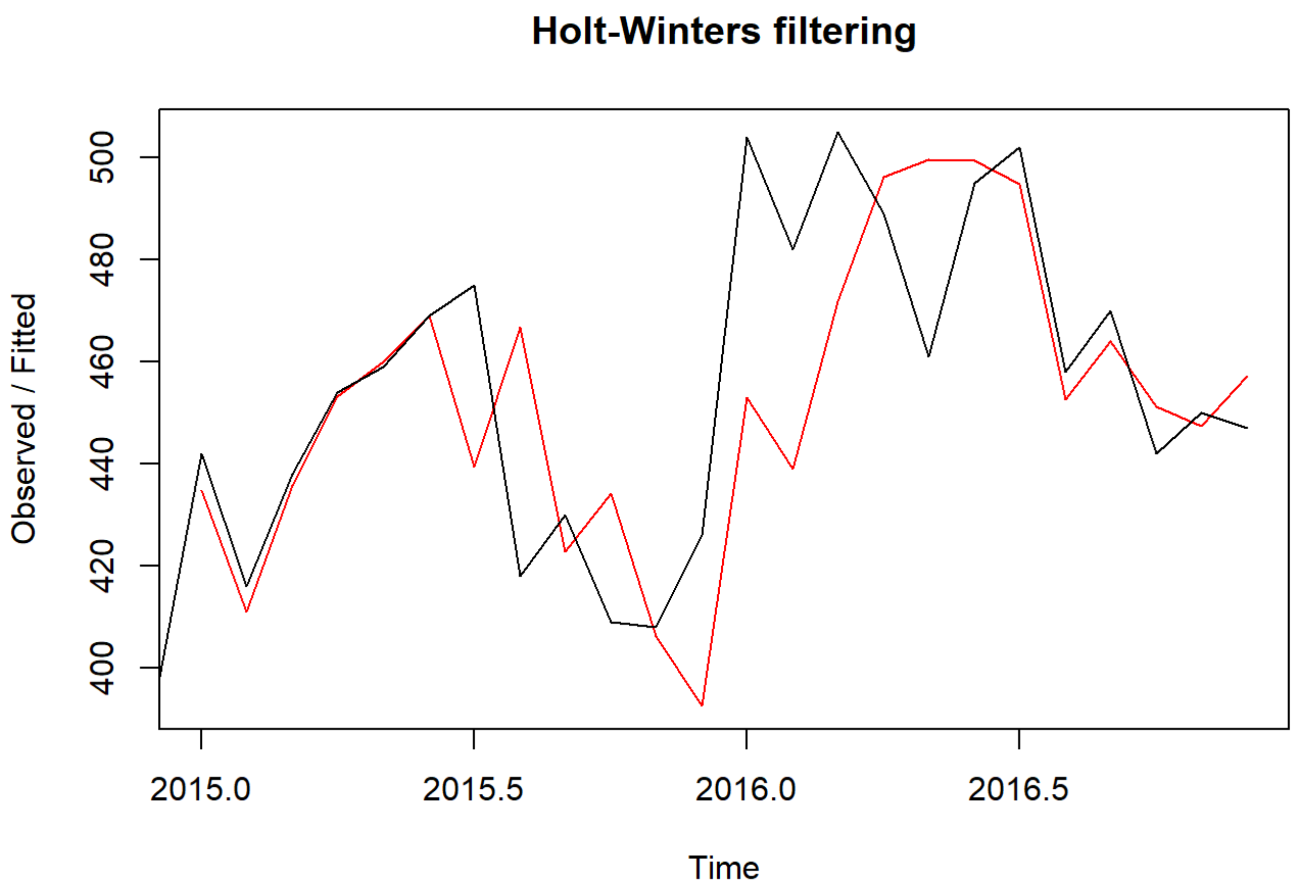
Holt-Winters filtering
Observed / Fitted
300
350
400
450
2015.0
2015.5
2016.0
2016.5
Time

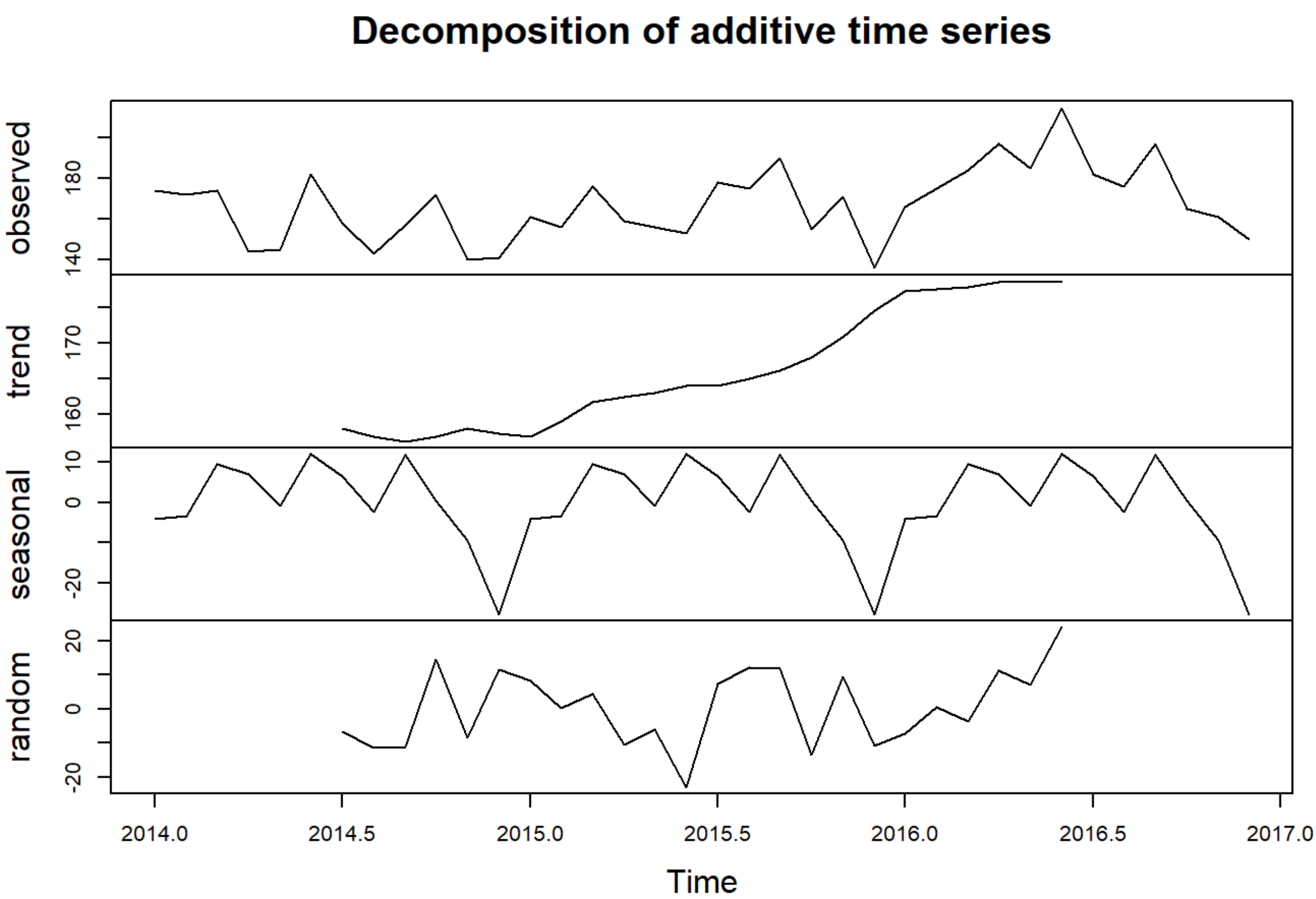



Decomposition of additive time series
observed
400
440
480
trend
430
450
470
seasonal
-30
-10
10
random
-20
0
20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

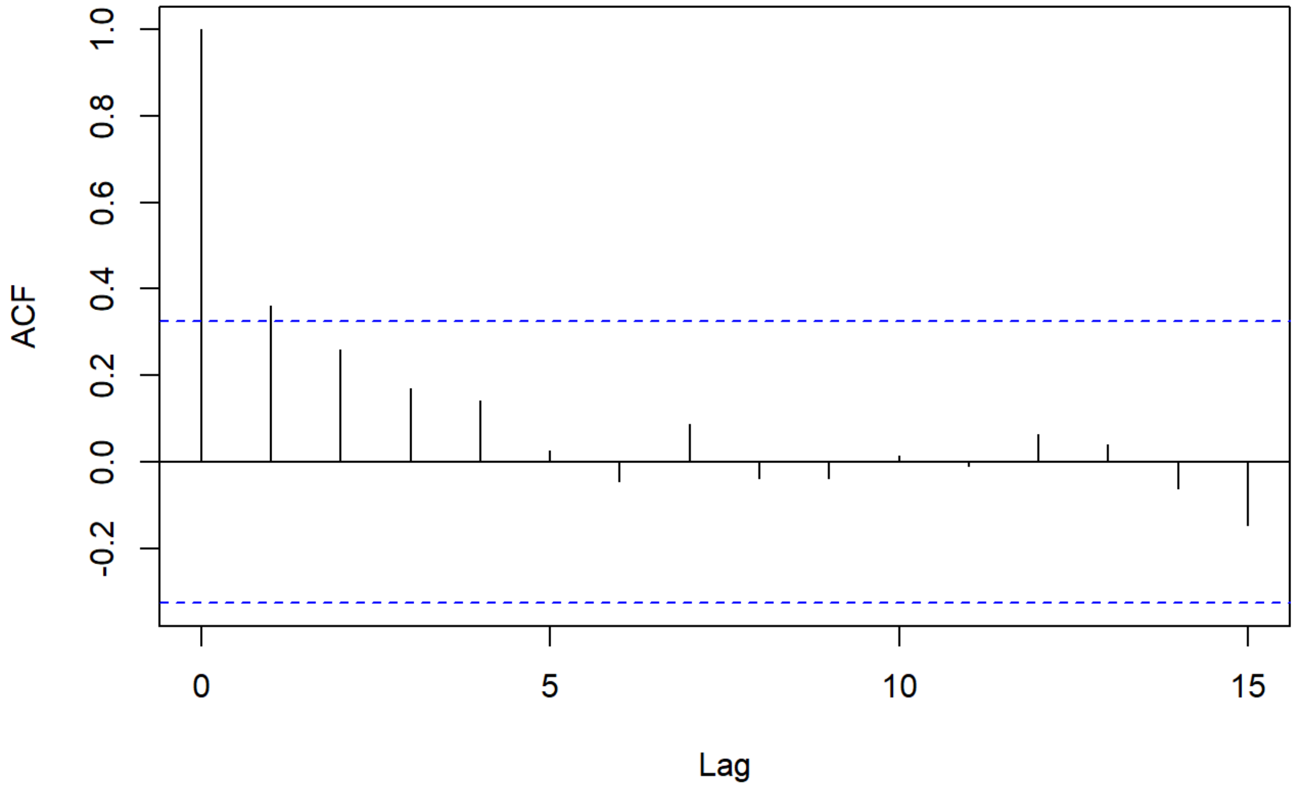

viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag


Series train_C[[i]]
Partial ACF
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag

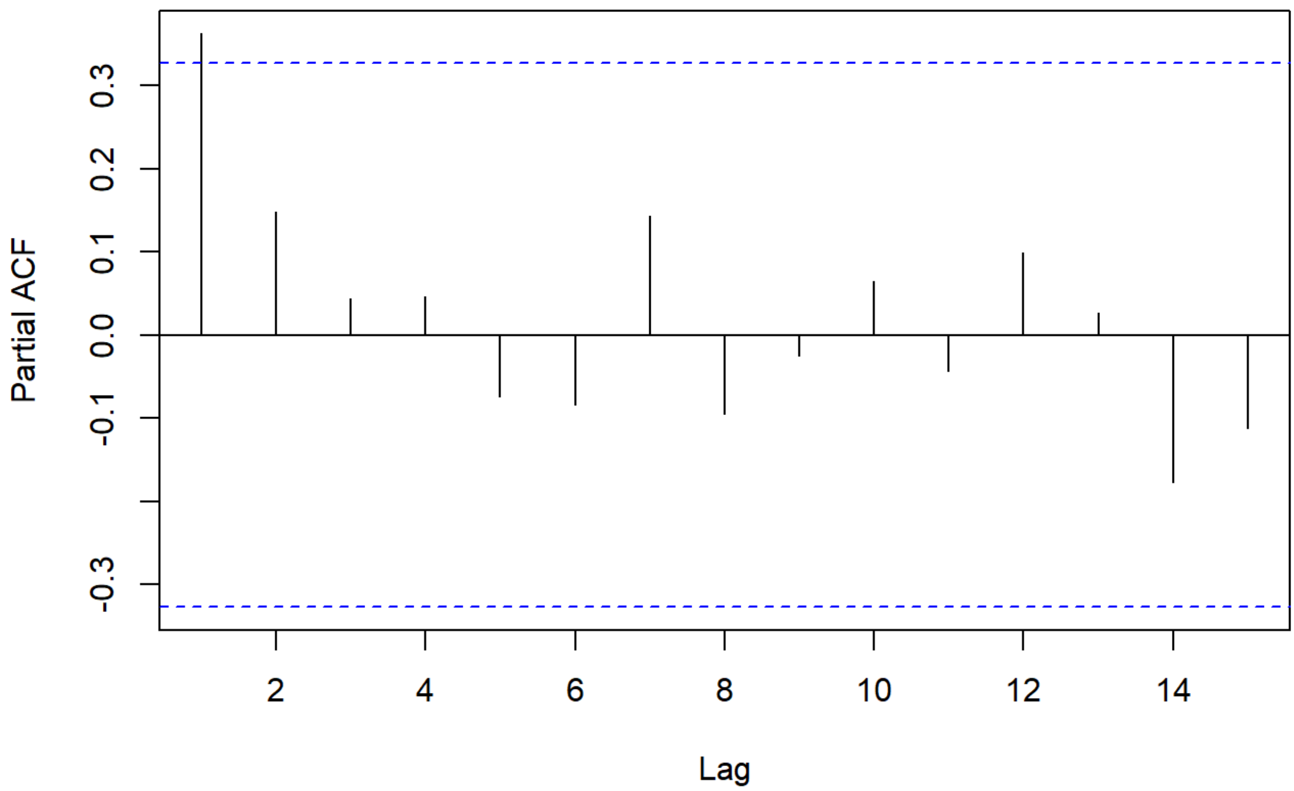

Holt-Winters filtering
Observed / Fitted
400
420
440
460
480
500
2015.0
2015.5
2016.0
2016.5
Time

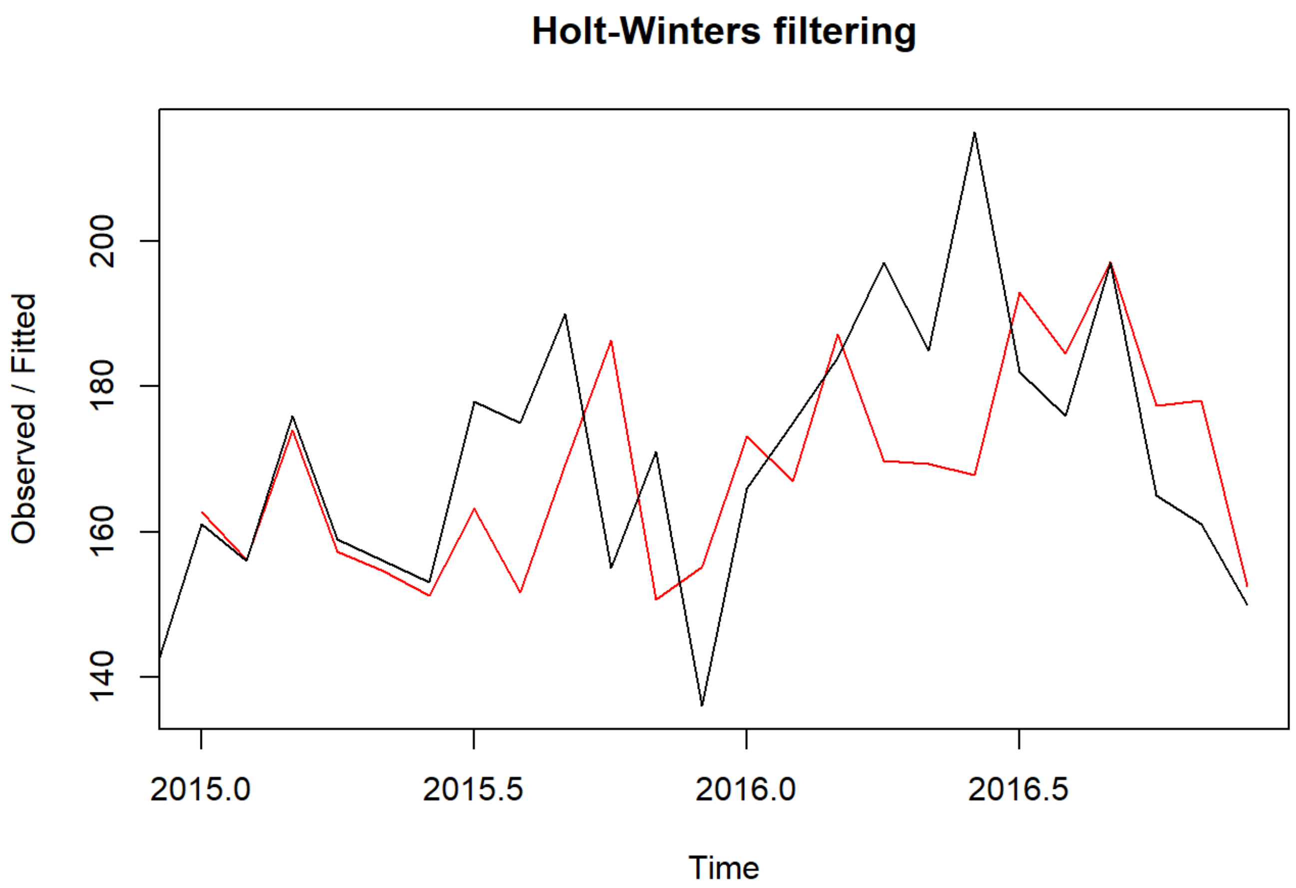

Decomposition of additive time series
observed
140
180
trend
160
170
seasonal
-20
0
10
random
-20
0
20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

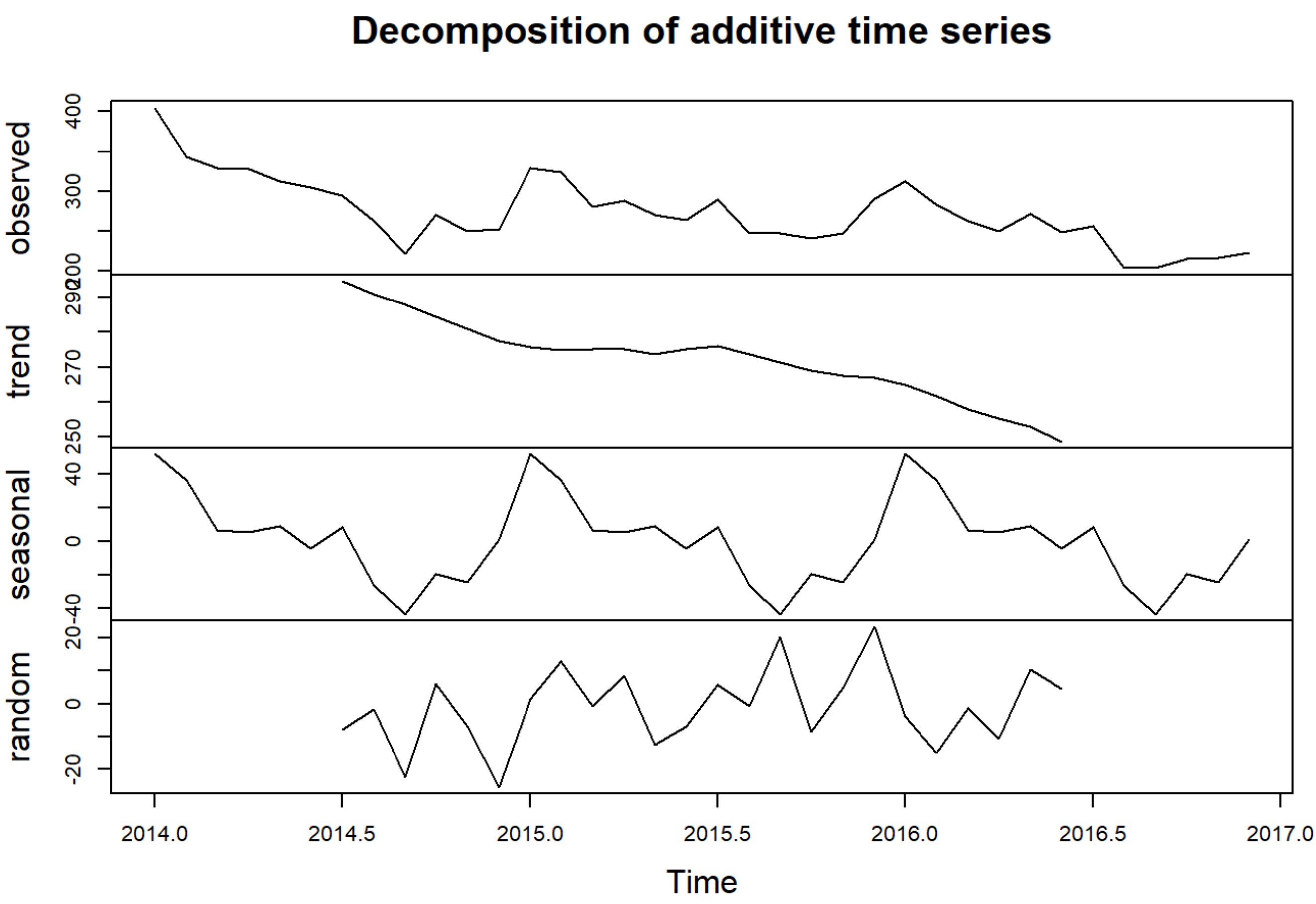
viewers

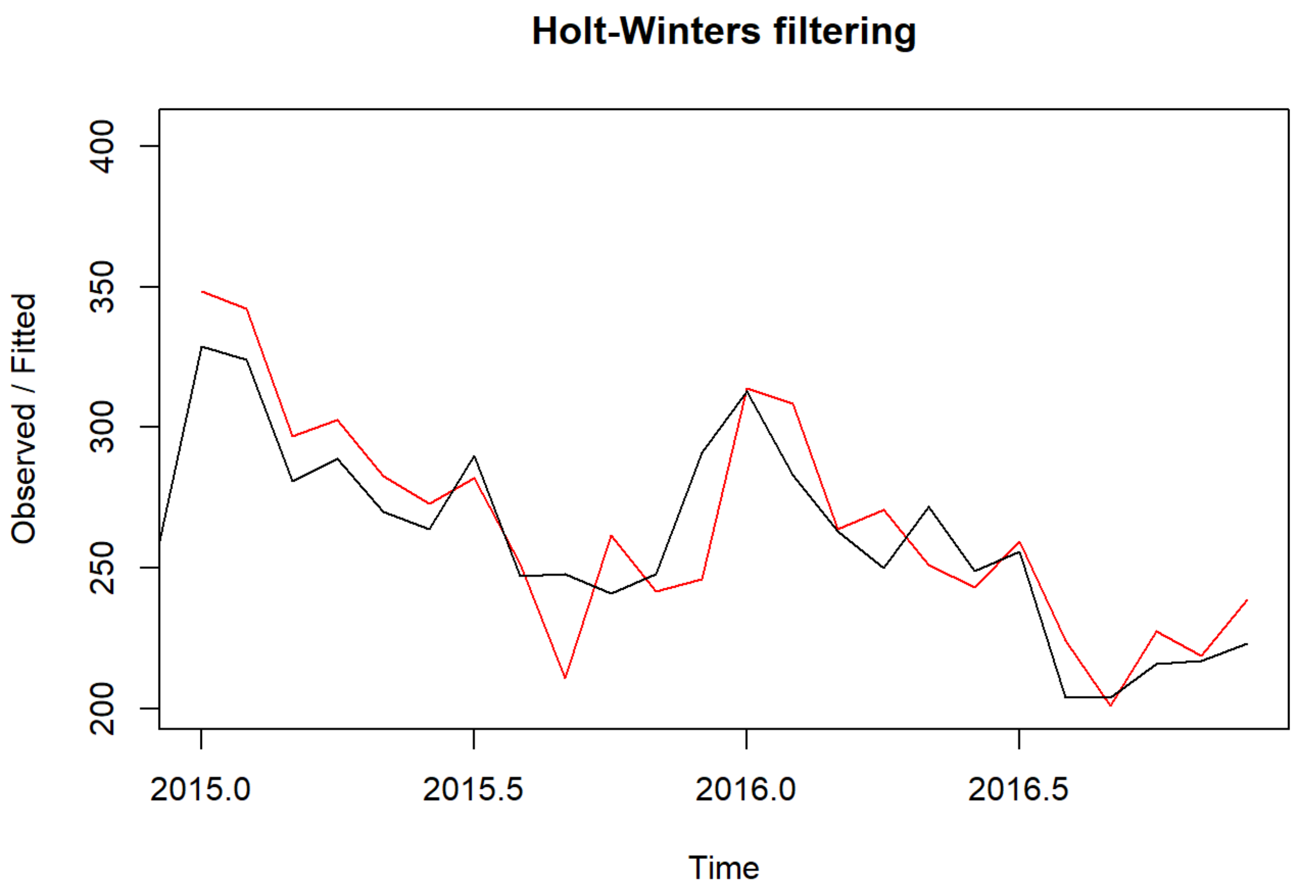


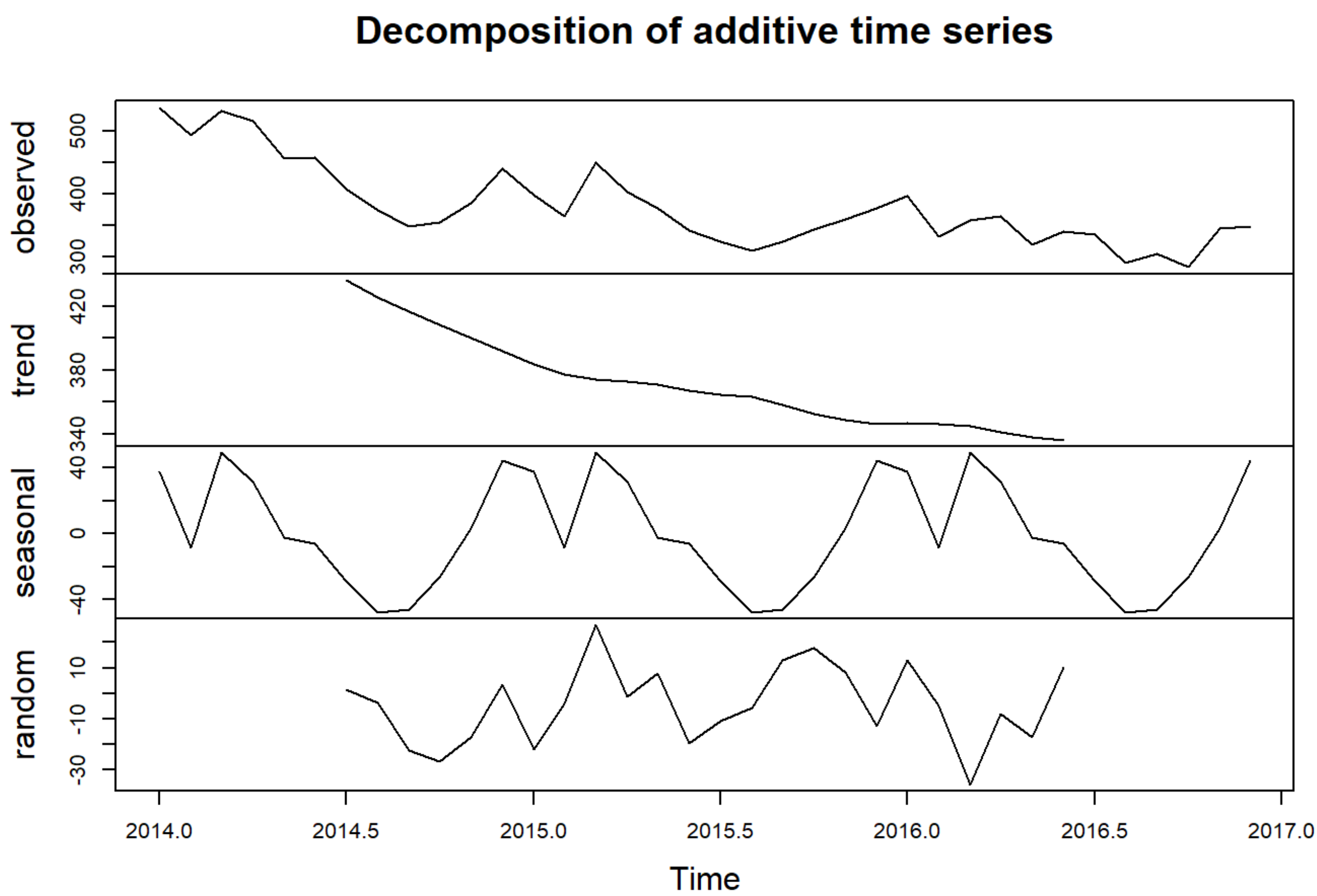

Series train_D[[i]]

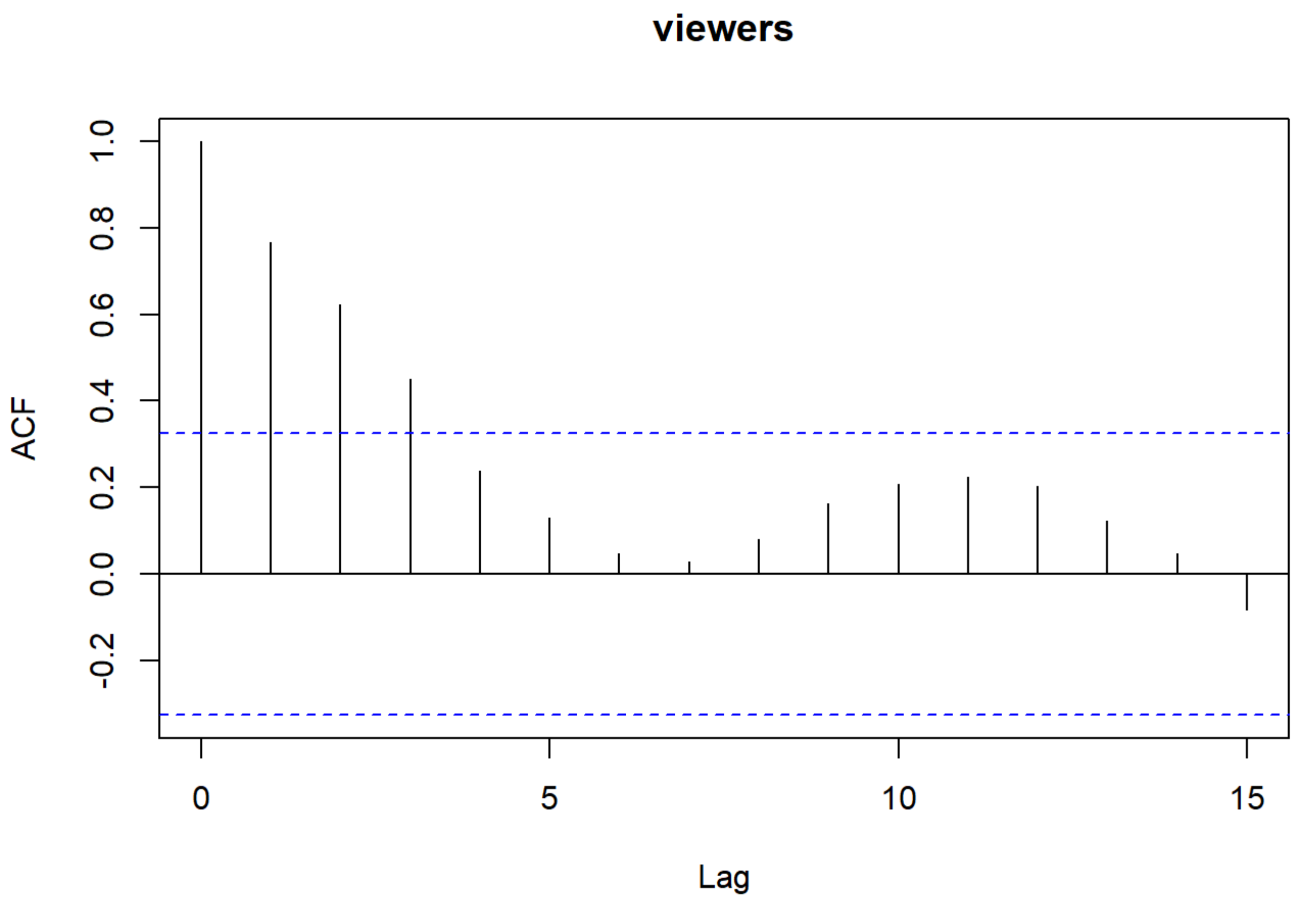



Holt-Winters filtering
Observed / Fitted
140
160
180
200
2015.0
2015.5
2016.0
2016.5
Time

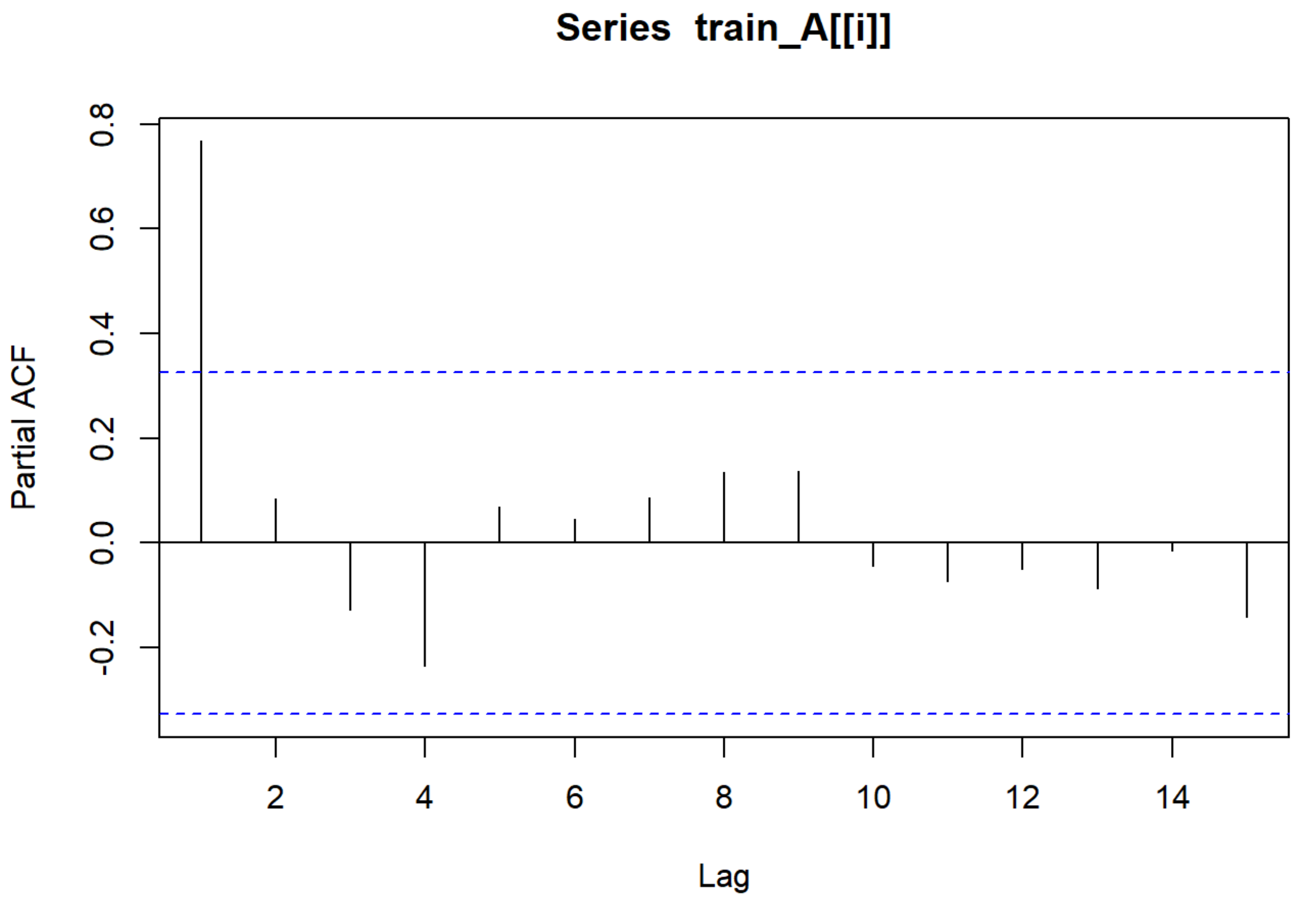

Decomposition of additive time series
observed
trend
seasonal
random
200
300
400
250
270
290
-40
0
40
-20
0
20
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time


Holt-Winters filtering
Observed / Fitted
400
350
300
250
200
2015.0
2015.5
2016.0
2016.5
Time

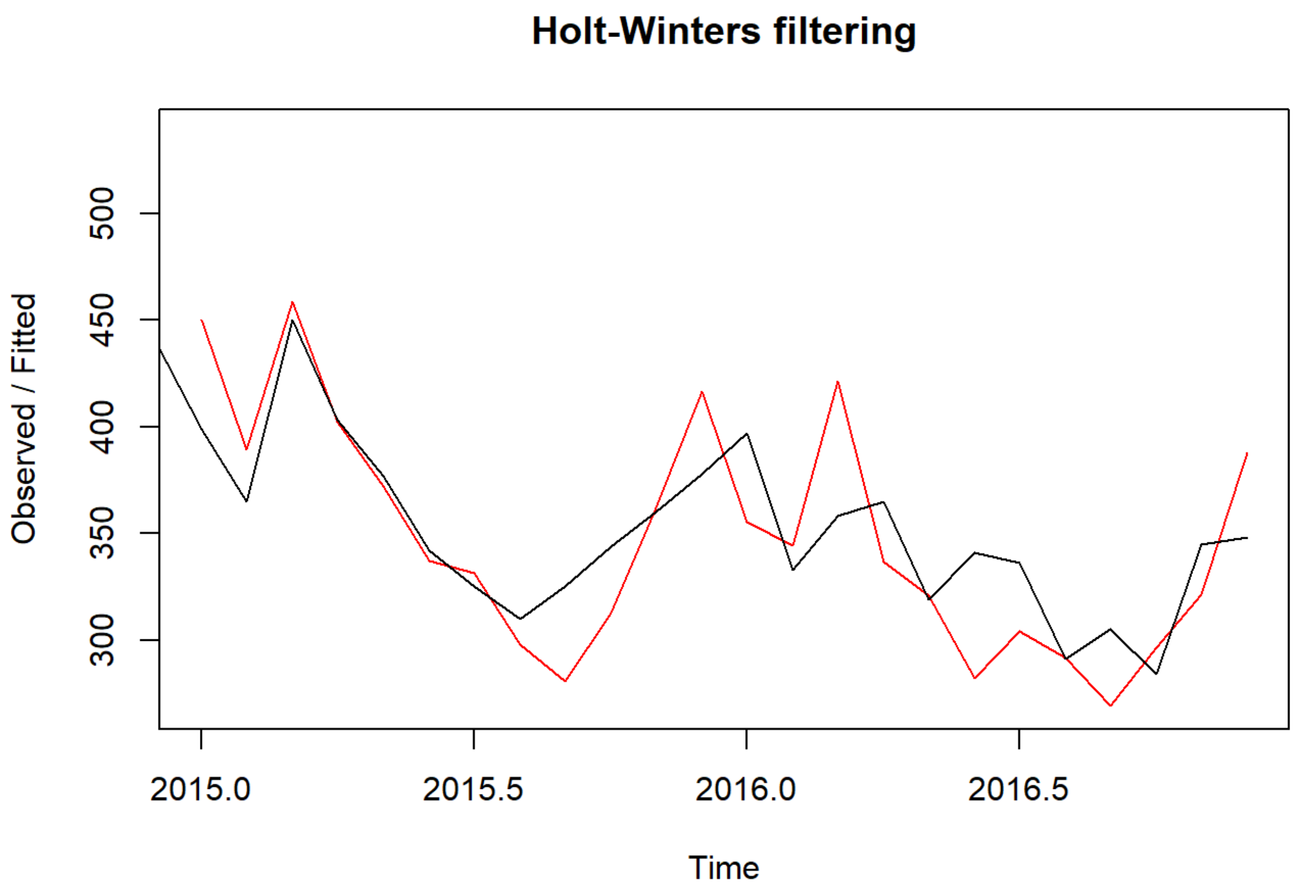

Decomposition of additive time series
observed
500
400
300
trend
420
380
340
seasonal
40
0
-40
random
10
-10
-30
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

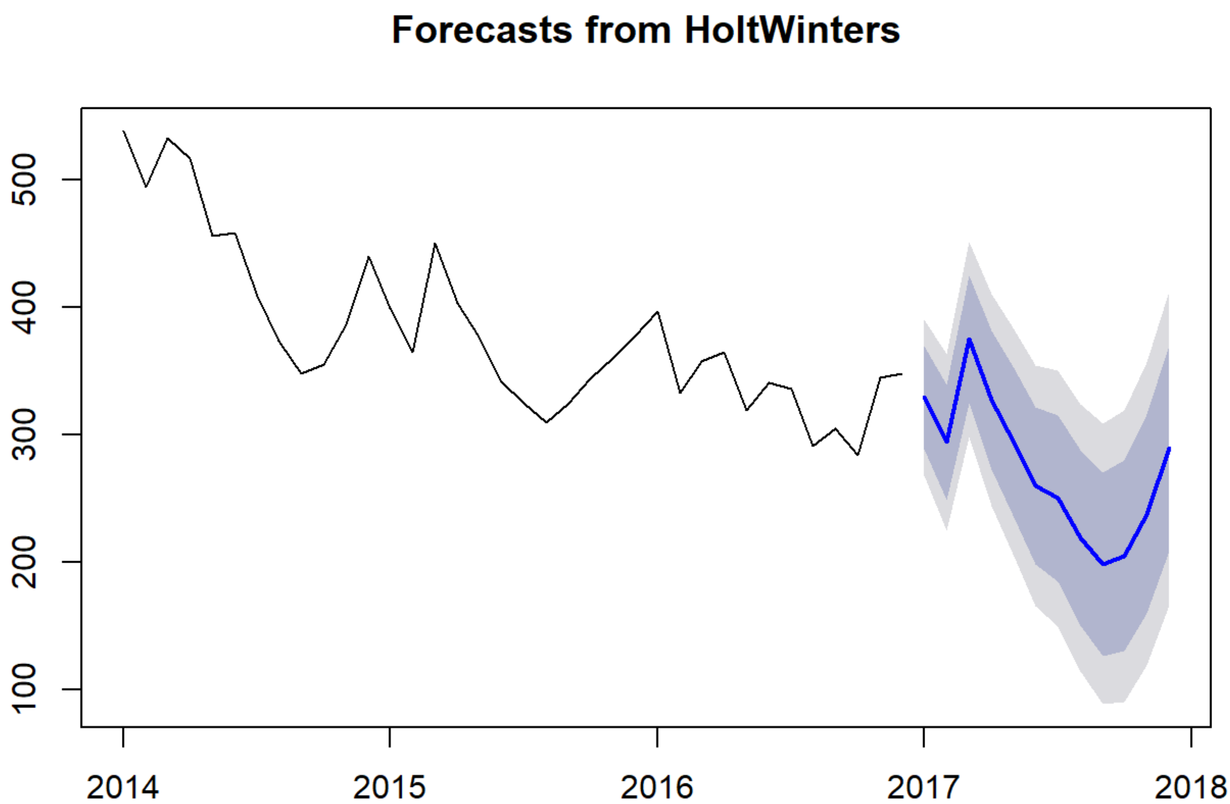


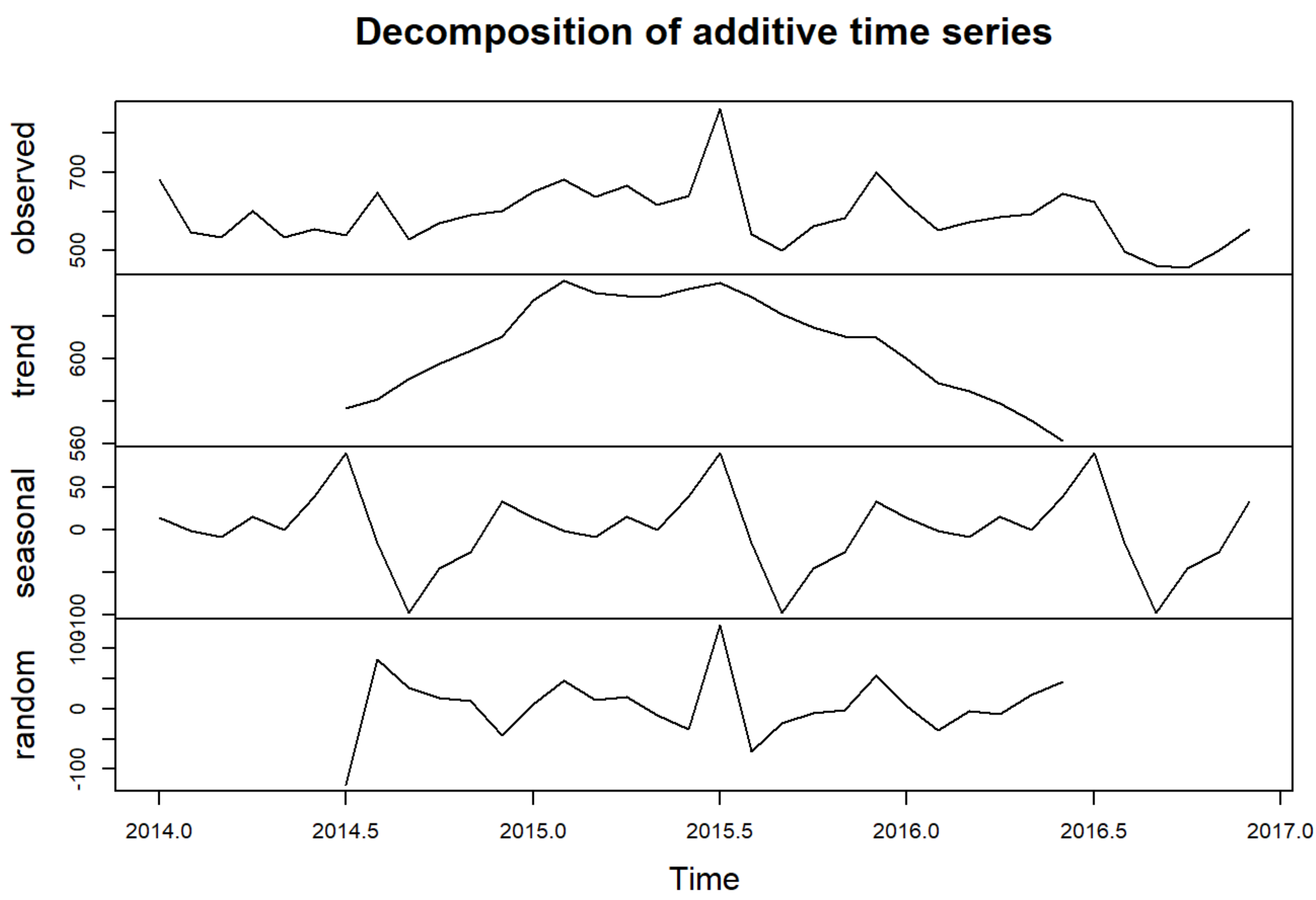
viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

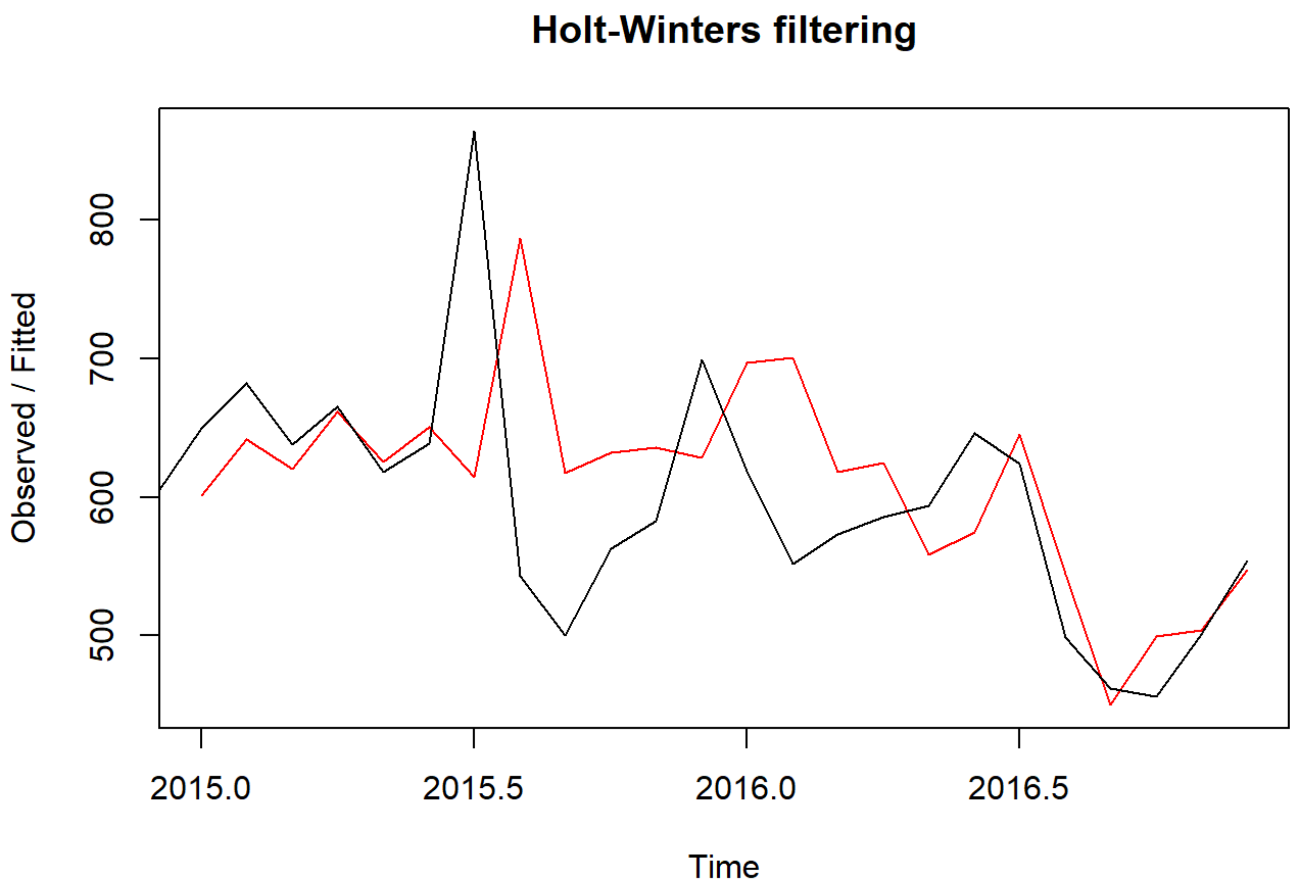



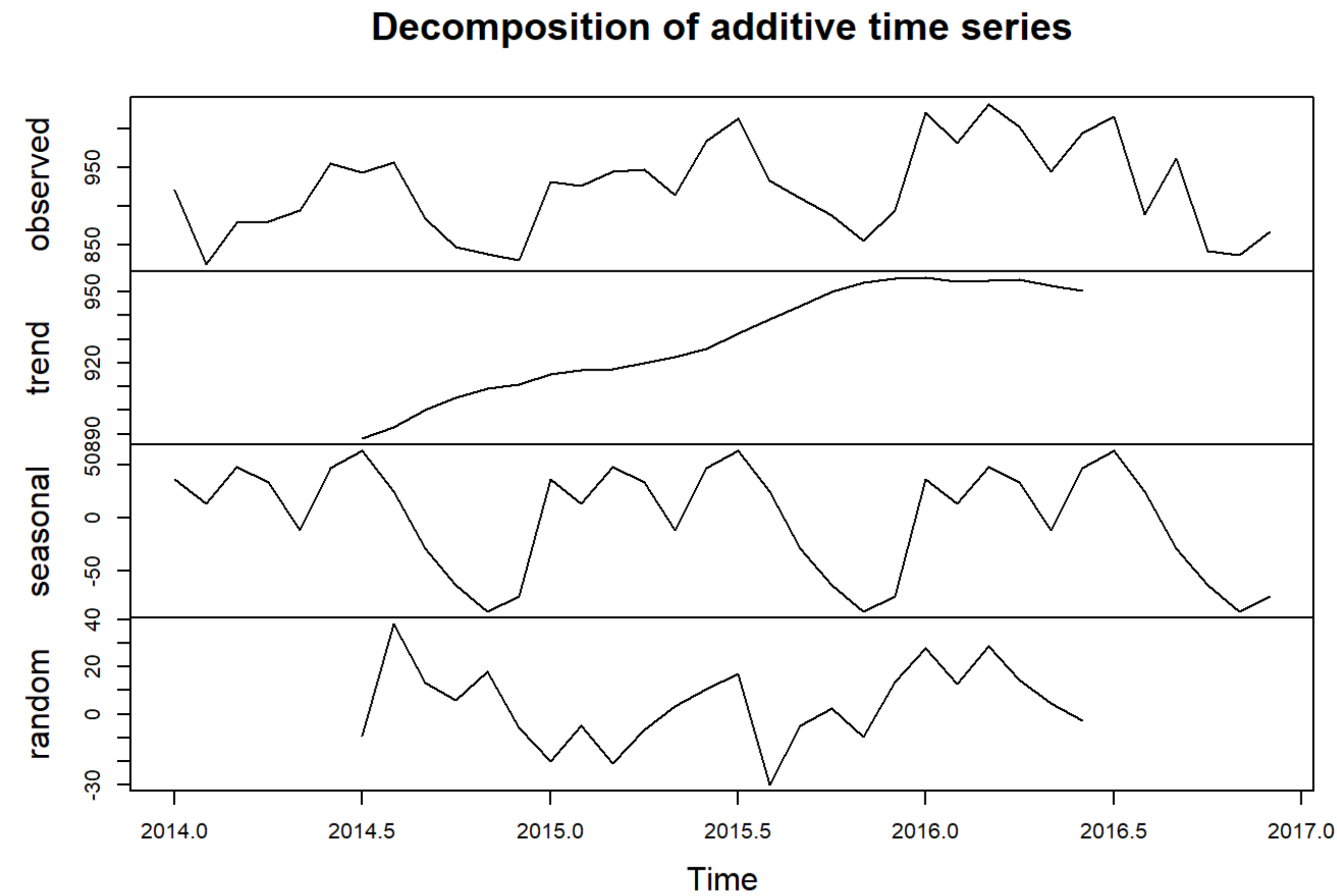
Series train_A[[i]]
Partial ACF
0.8
0.6
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag

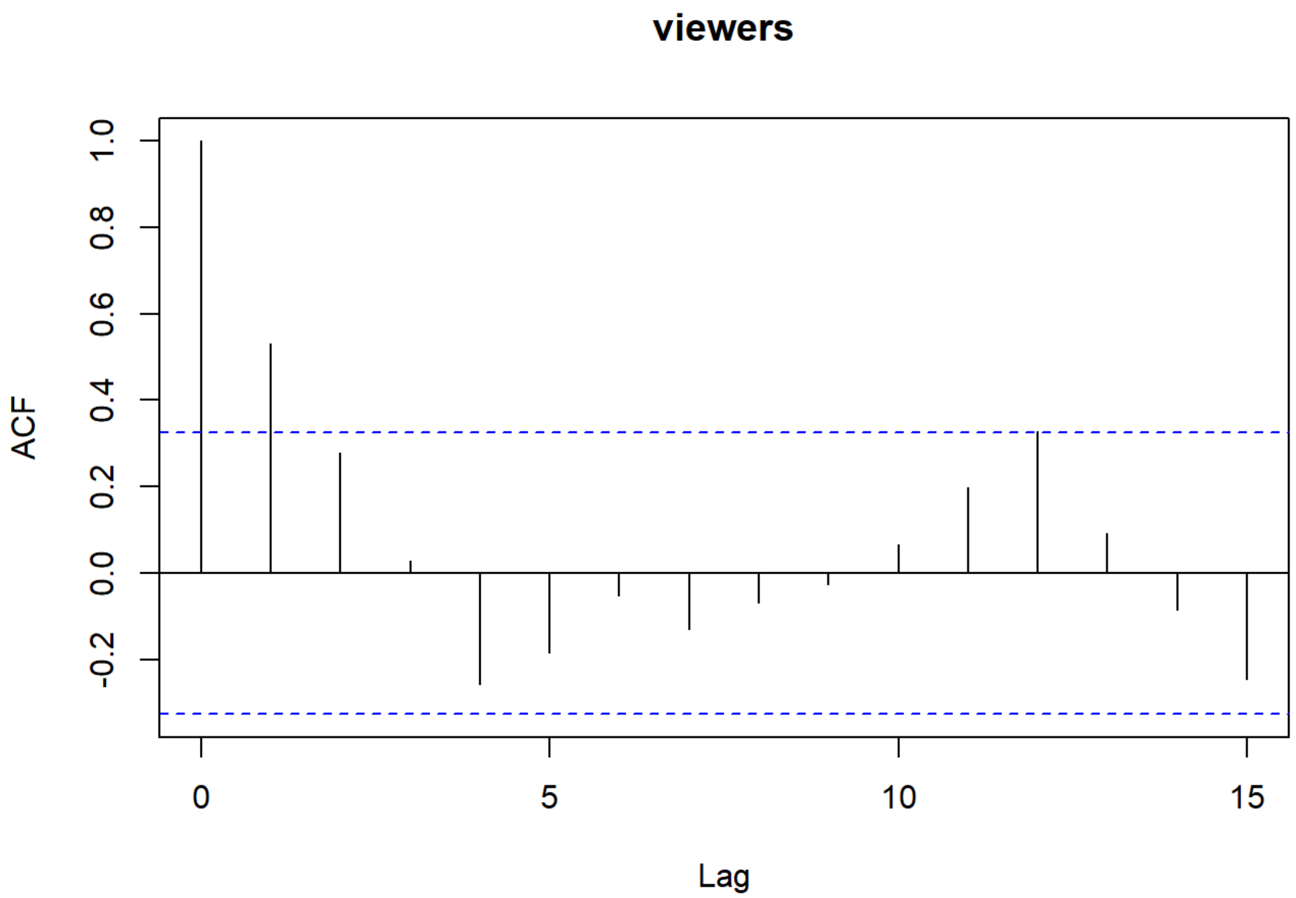

Holt-Winters filtering
Observed / Fitted
300
350
400
450
500
2015.0
2015.5
2016.0
2016.5
Time

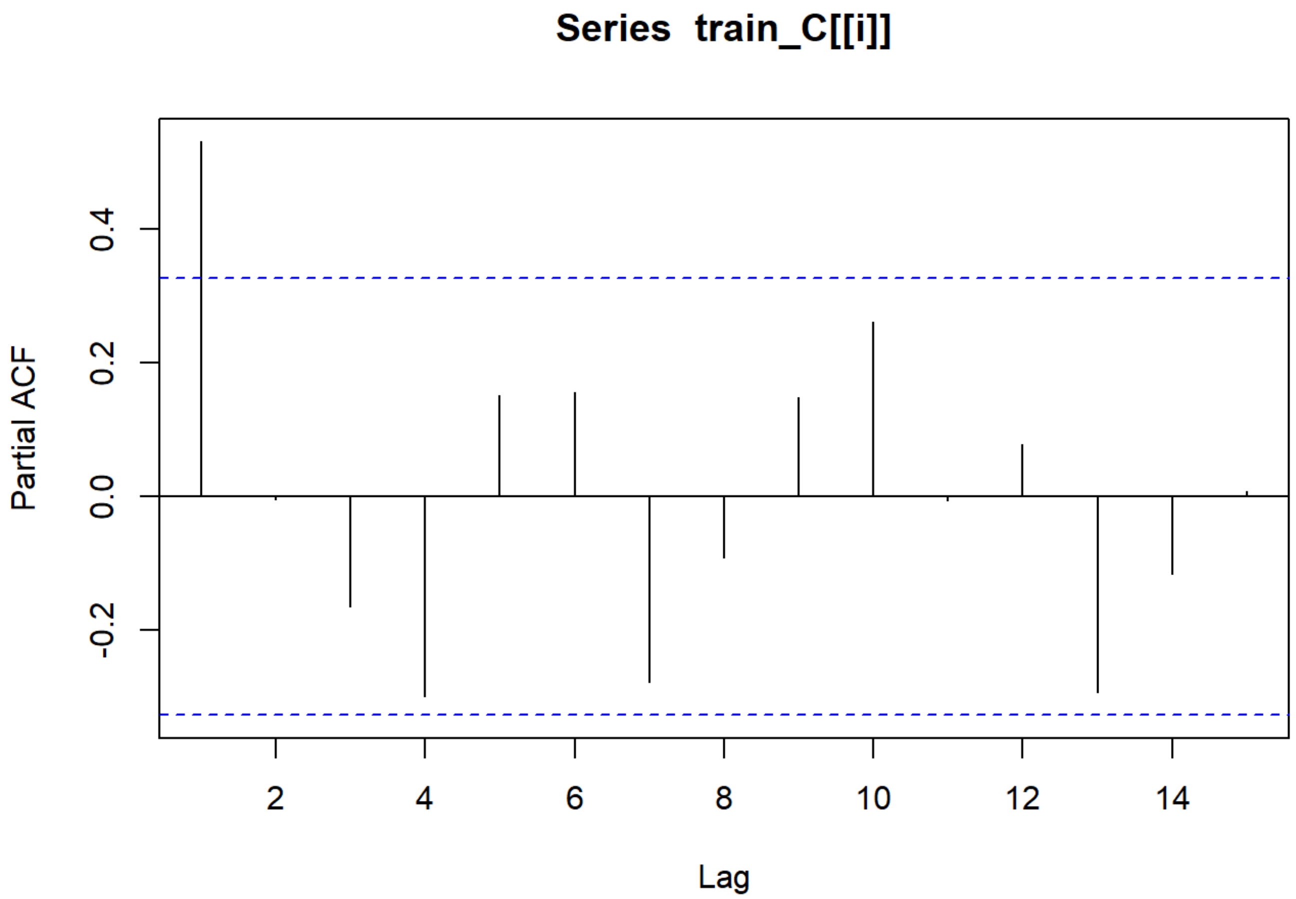

Forecasts from HoltWinters
100
200
300
400
500
2014
2015
2016
2017
2018

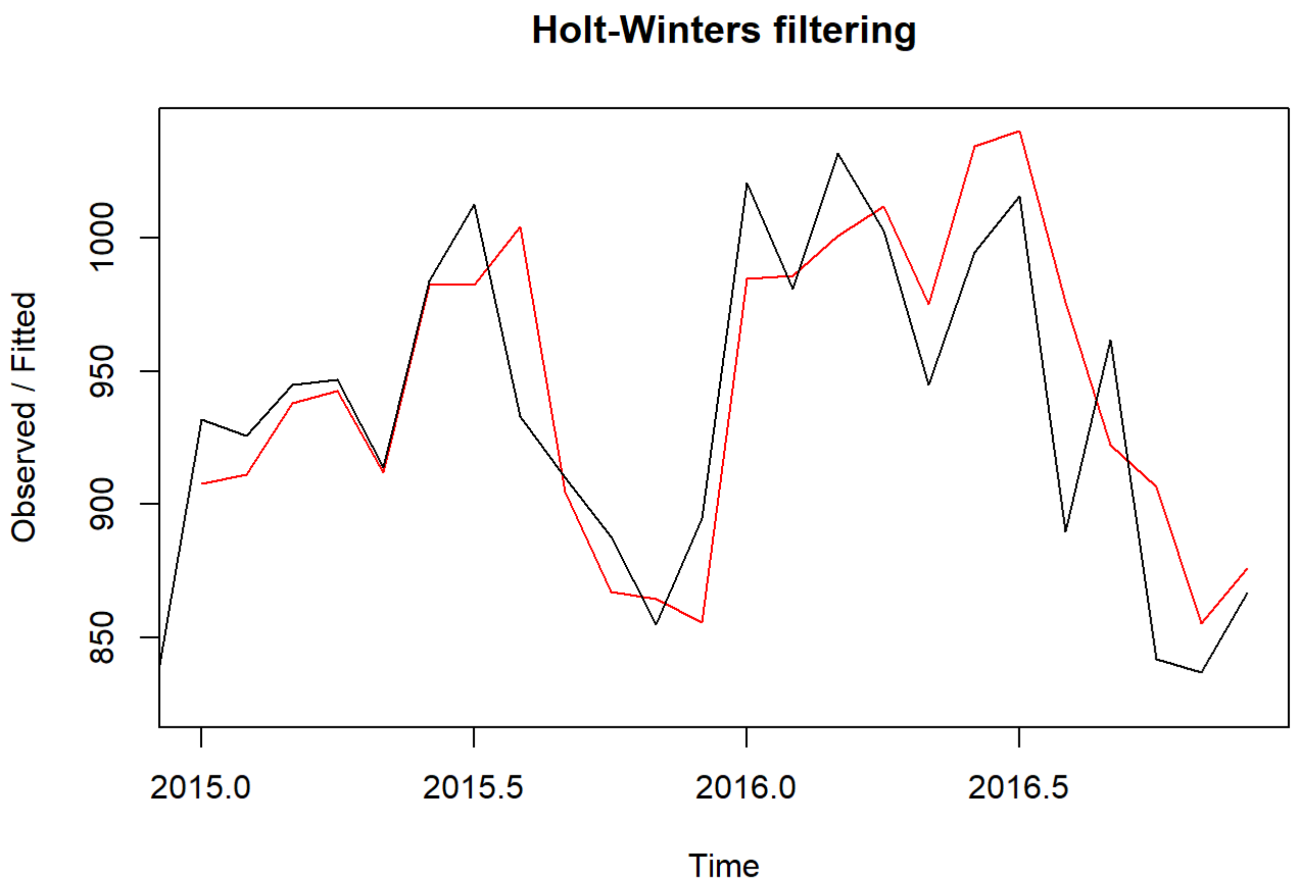

Decomposition of additive time series
observed
trend
seasonal
random
500
700
600
560
50
0
-100
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

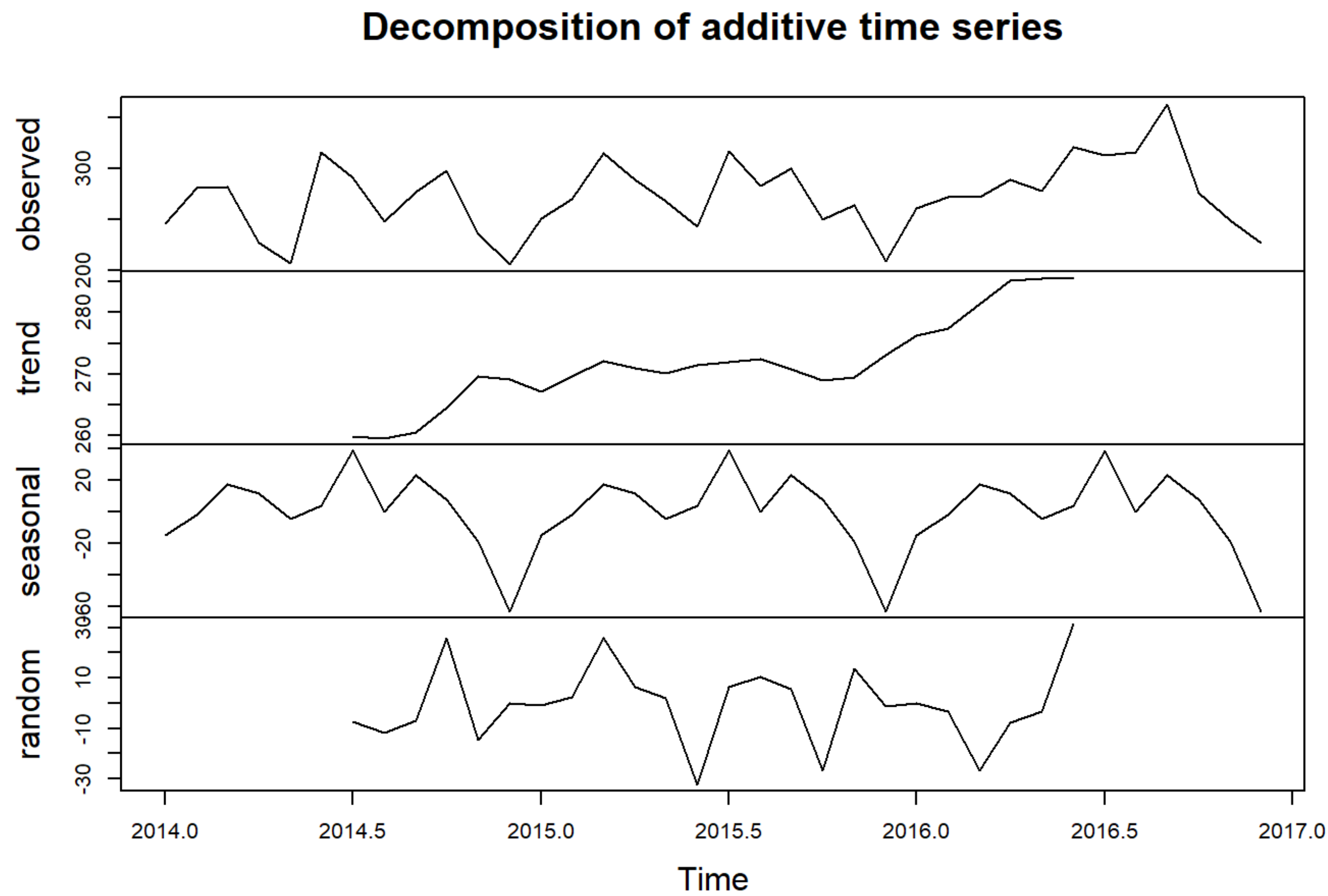

Holt-Winters filtering
Observed / Fitted
500
600
700
800
2015.0
2015.5
2016.0
2016.5
Time


Decomposition of additive time series
observed
trend
seasonal
random
850
950
890
920
950
-50
0
50
-30
0
20
40
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

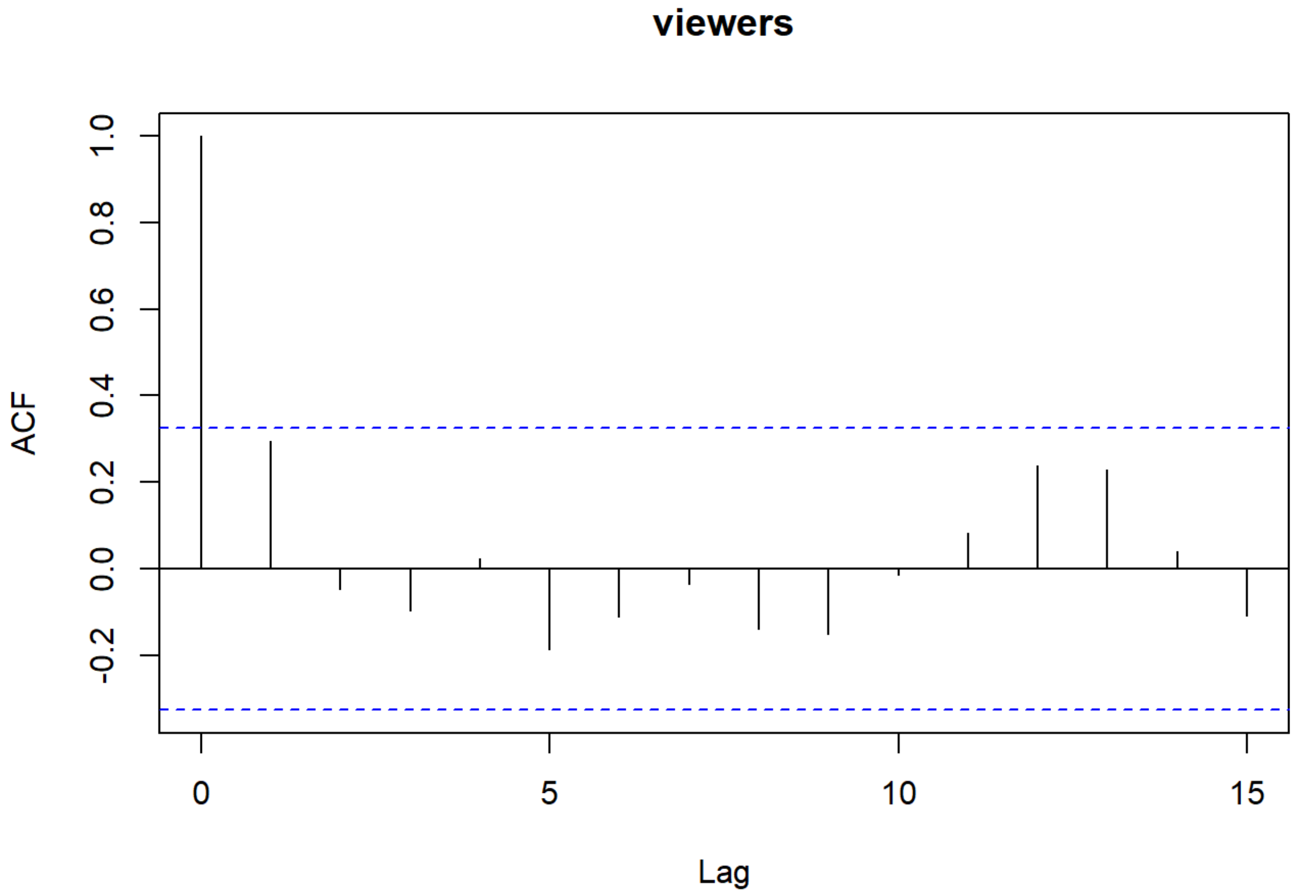

viewers
ACF
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
Lag


Series train_C[[i]]
Partial ACF
-0.2
0.0
0.2
0.4
2
4
6
8
10
12
14
Lag

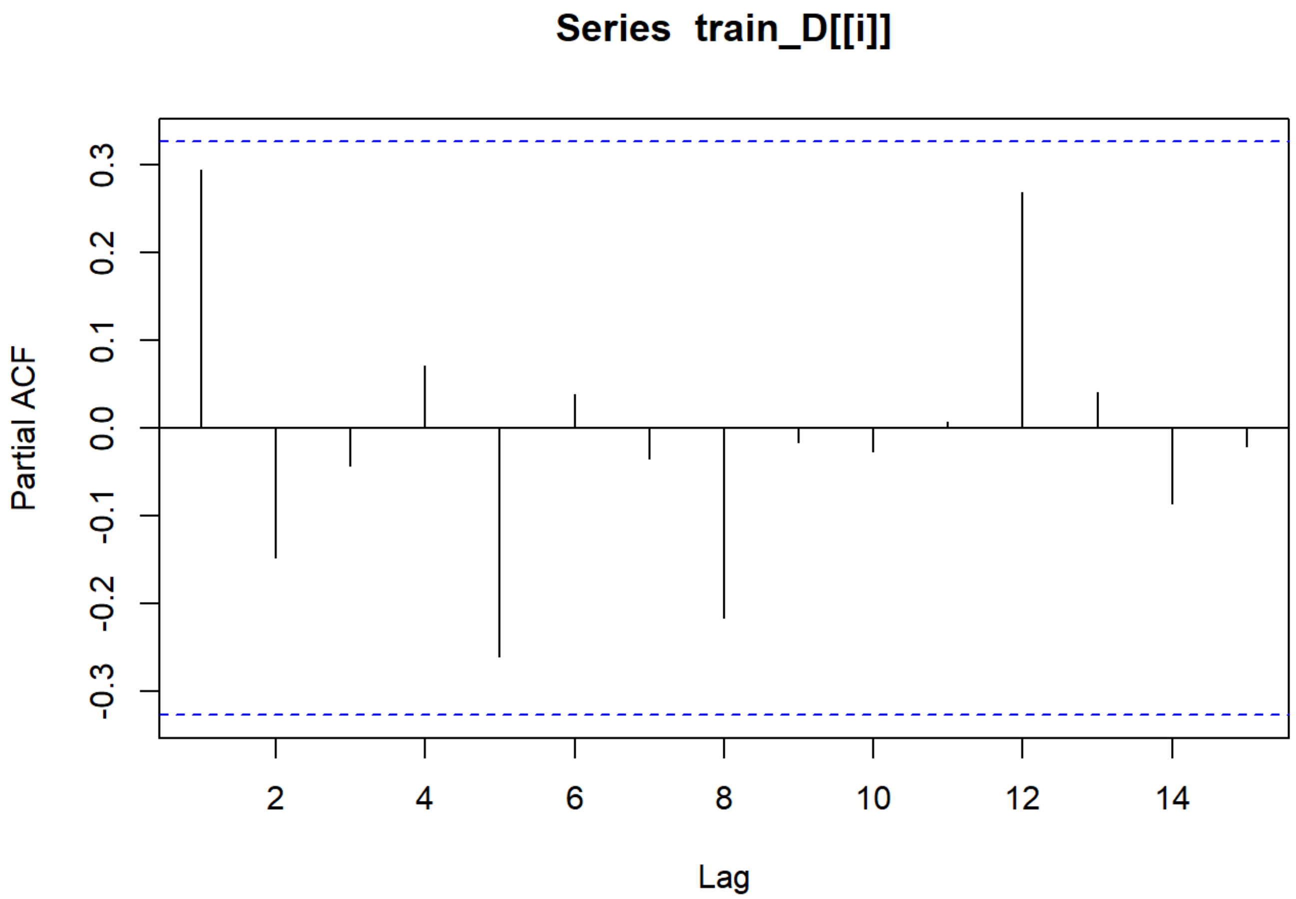

Holt-Winters filtering
Observed / Fitted
850
900
950
1000
2015.0
2015.5
2016.0
2016.5
Time



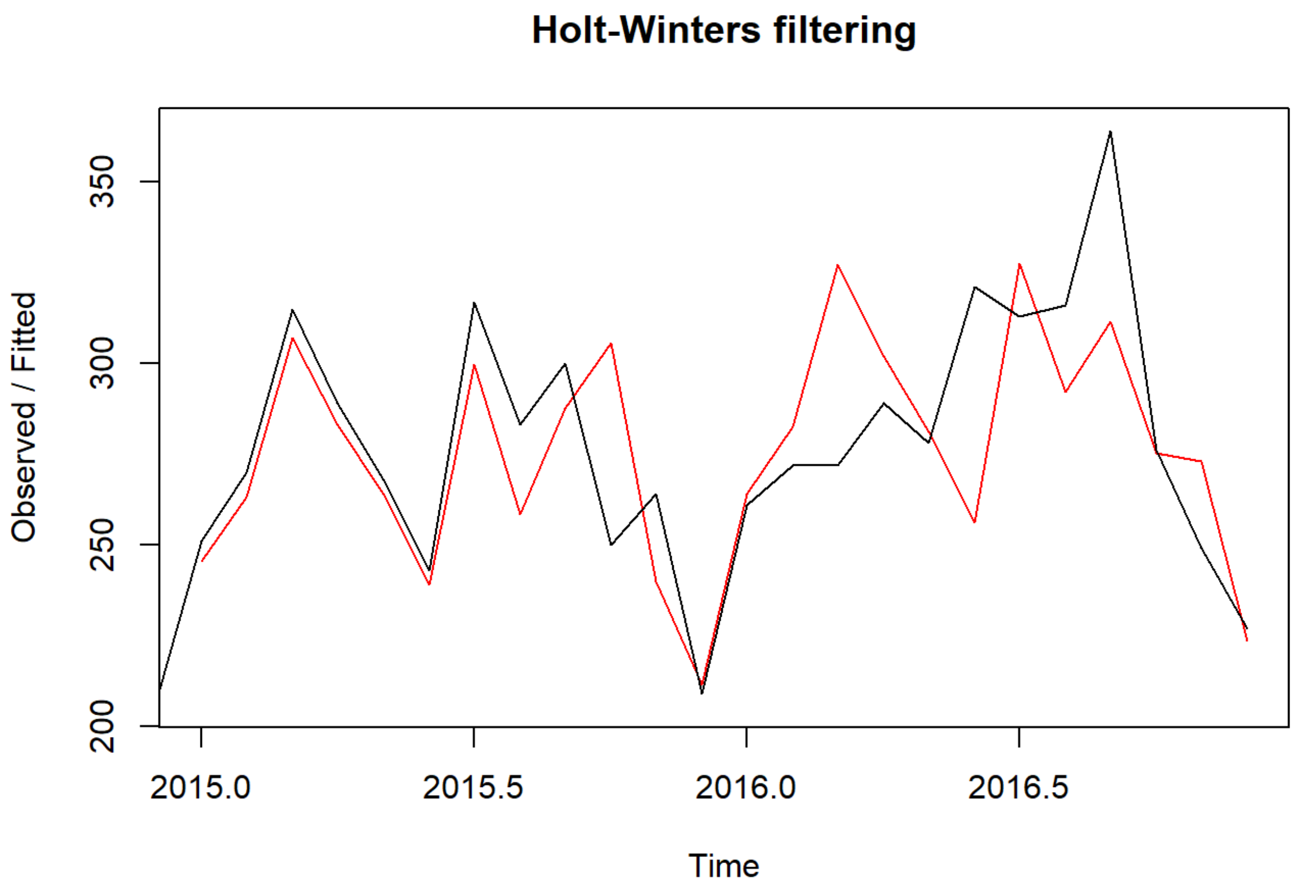
Decomposition of additive time series
observed
trend
seasonal
random
300
200
280
270
260
20
-20
-60
30
10
-10
-30
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

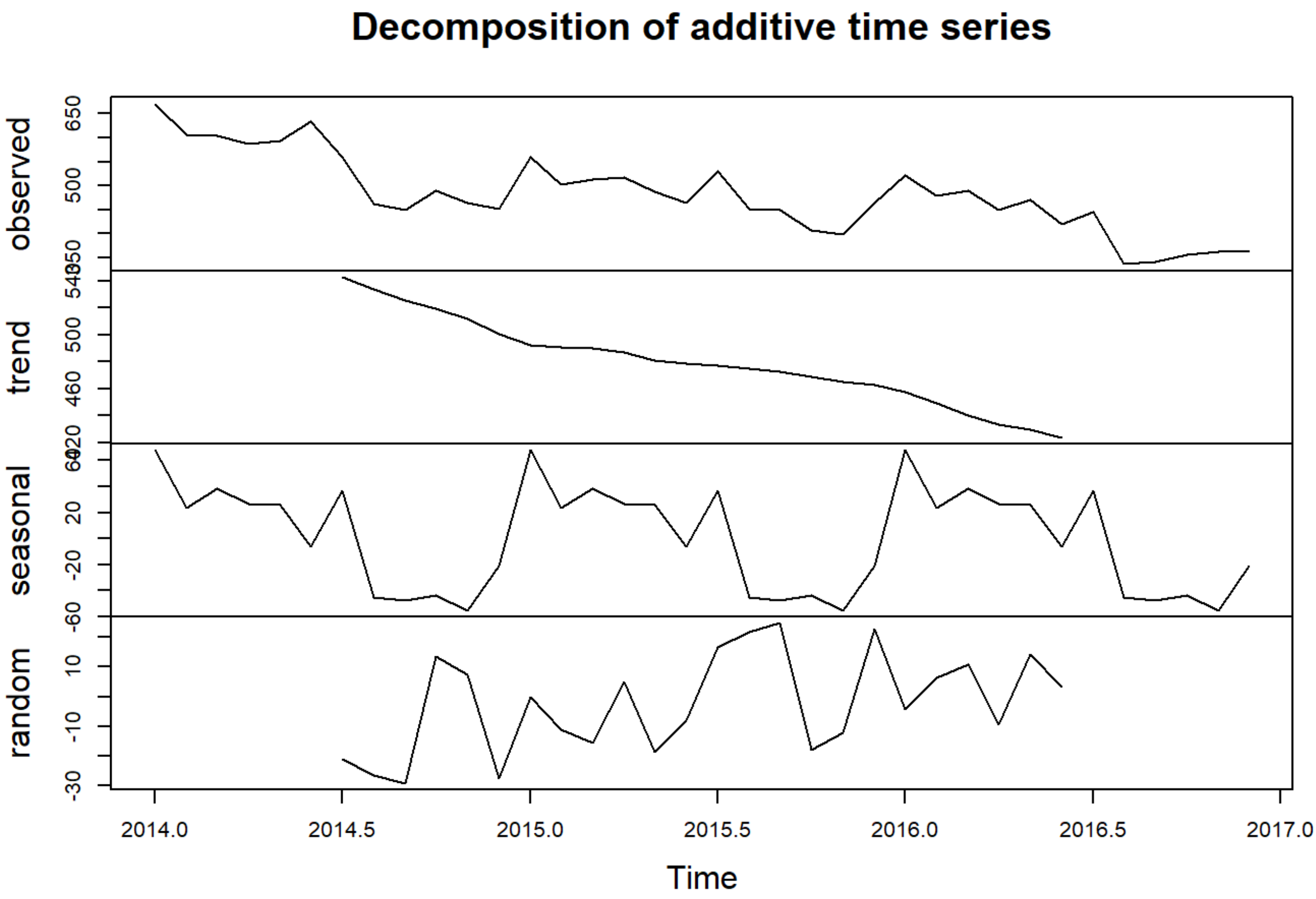
viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

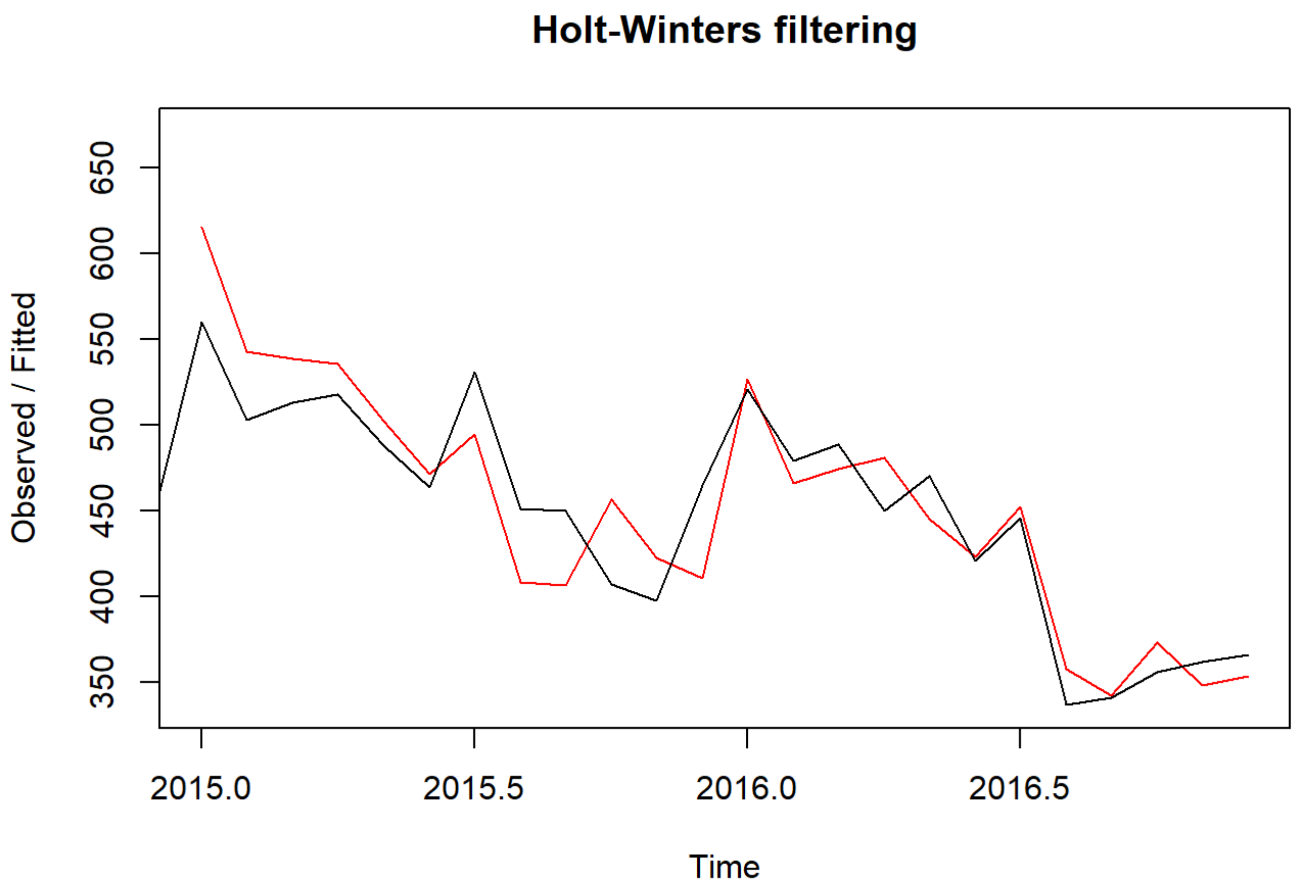


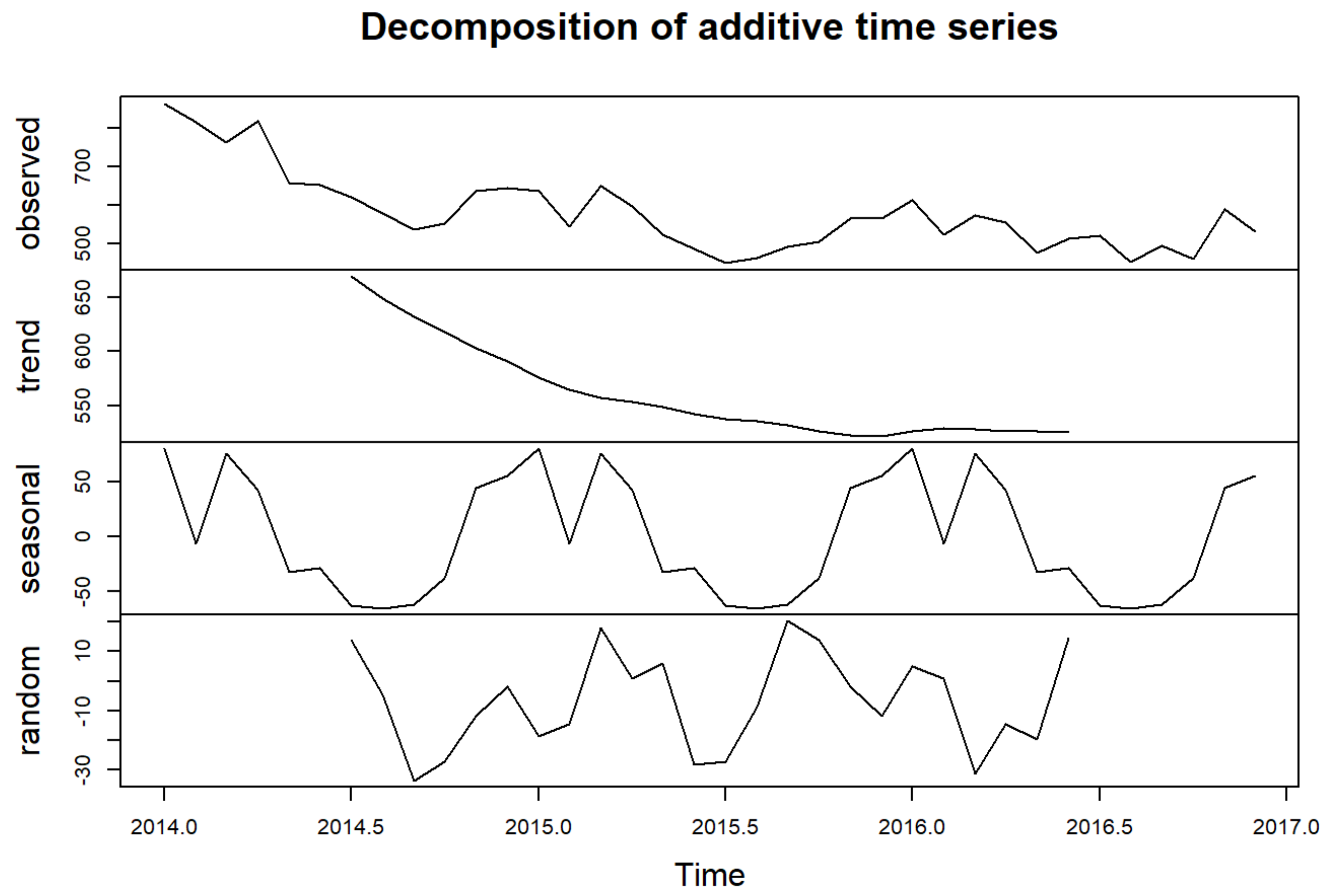
Series train_D[[i]]
Partial ACF
Lag
-0.3
-0.2
-0.1
0.0
0.1
0.2
0.3
2
4
6
8
10
12
14

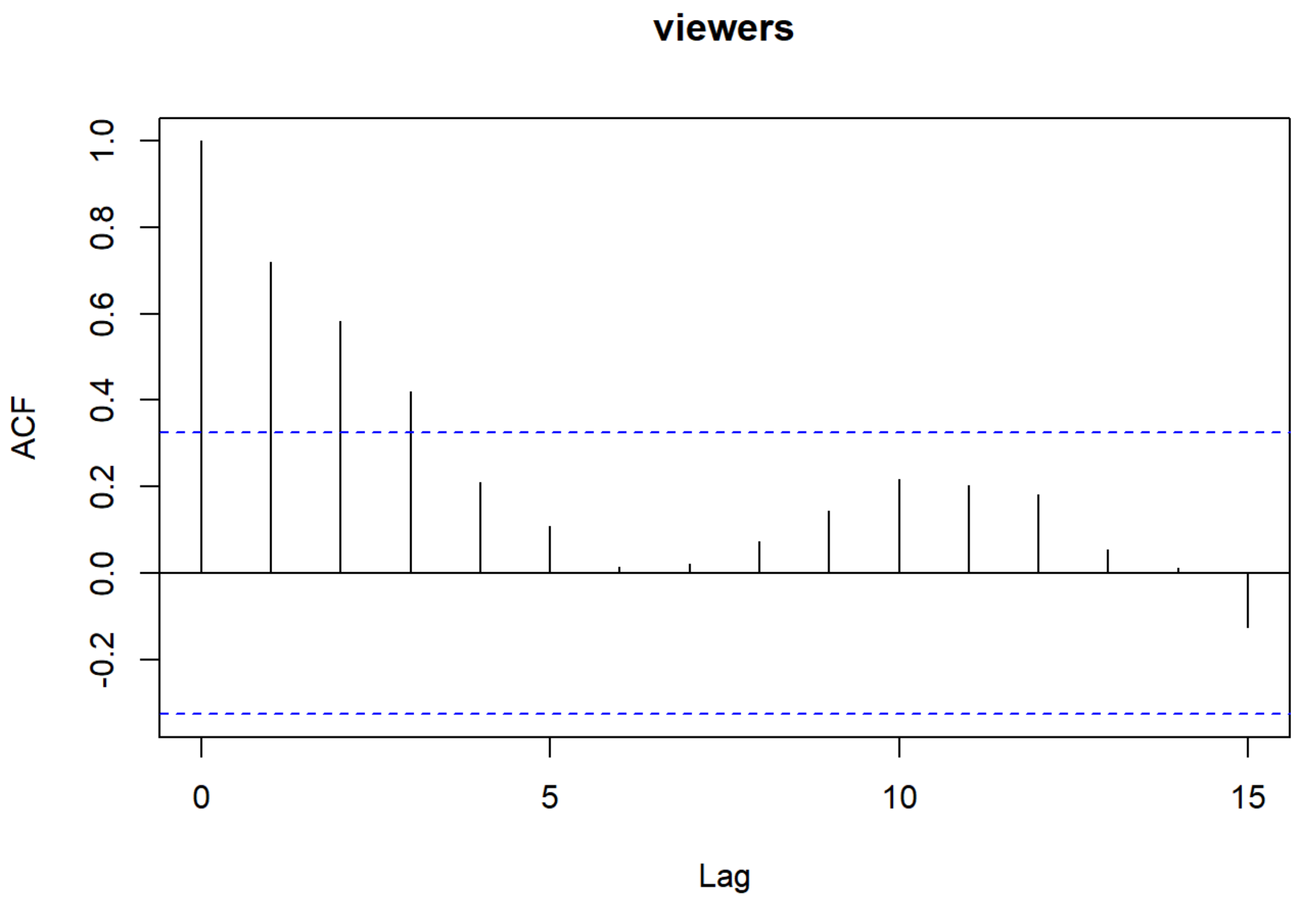



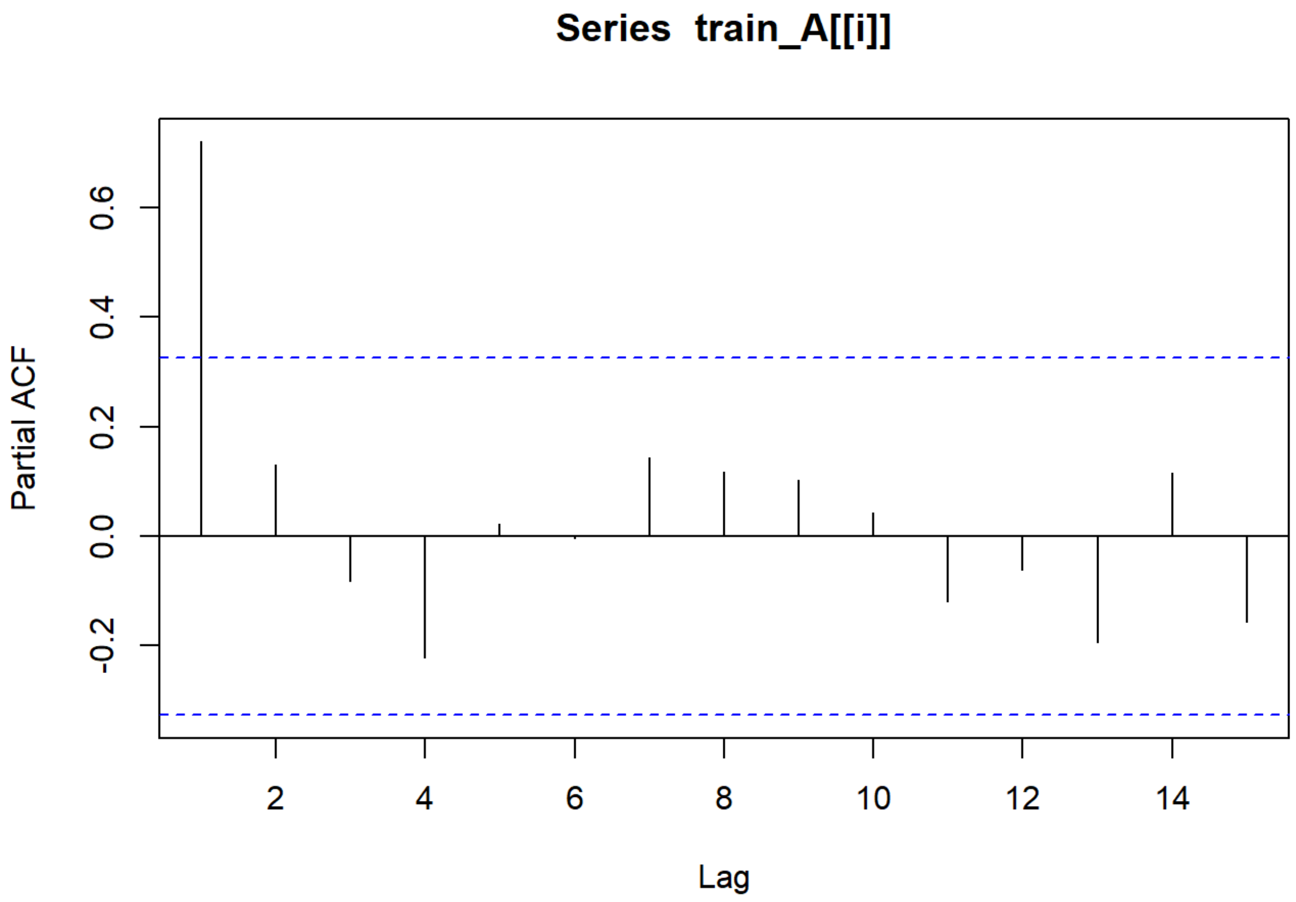
Holt-Winters filtering
Observed / Fitted
Time
200
250
300
350
2015.0
2015.5
2016.0
2016.5

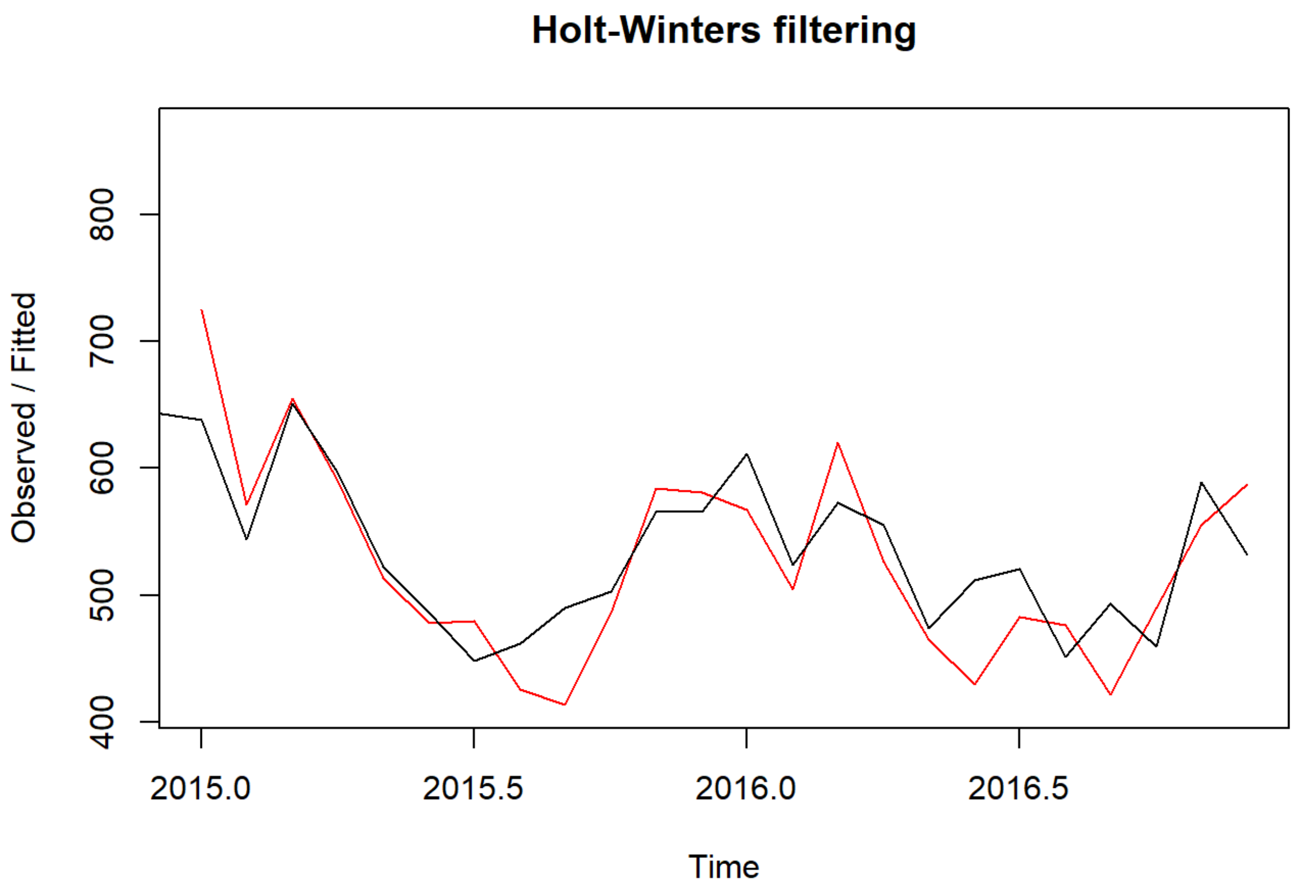

Decomposition of additive time series
observed
trend
seasonal
random
650
500
350
540
500
460
420
60
20
-20
-60
10
-10
-30
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

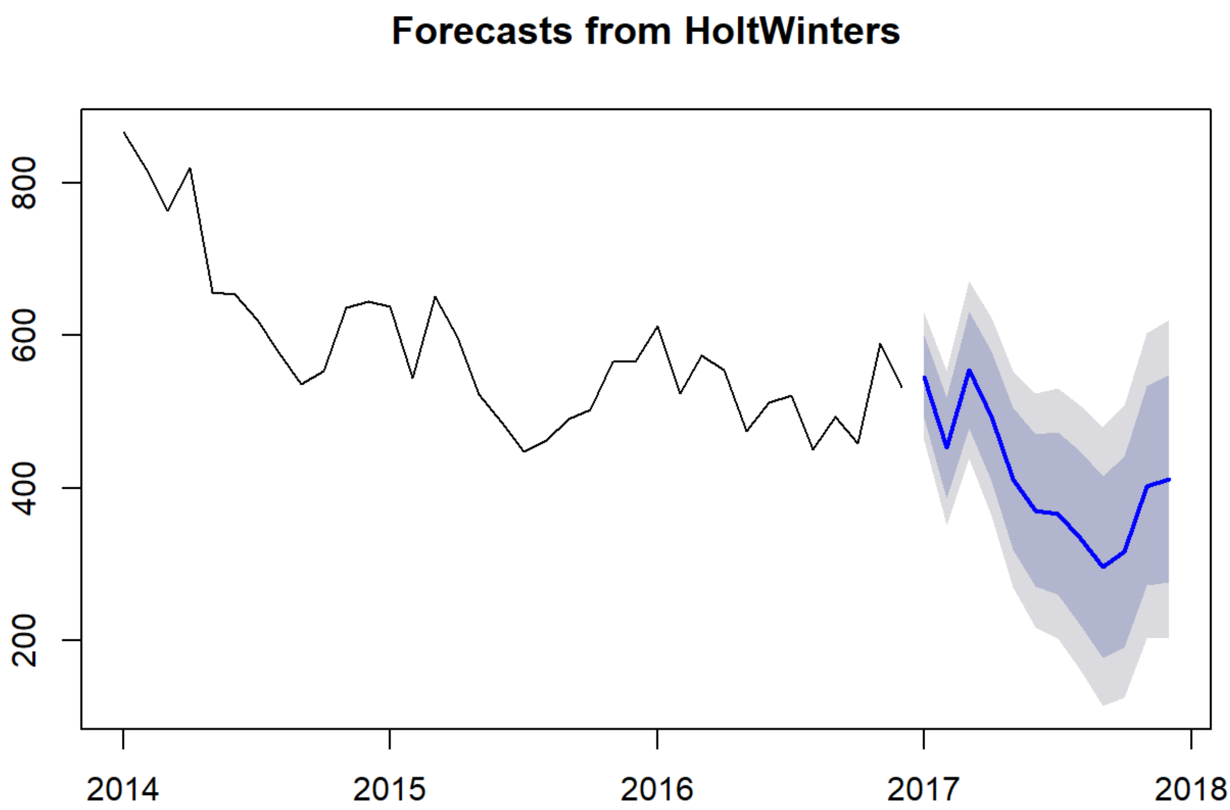

Holt-Winters filtering
Observed / Fitted
650
600
550
500
450
400
350
2015.0
2015.5
2016.0
2016.5
Time


Decomposition of additive time series
observed
500
700
trend
550
600
650
seasonal
-50
0
50
random
-30
-10
10
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

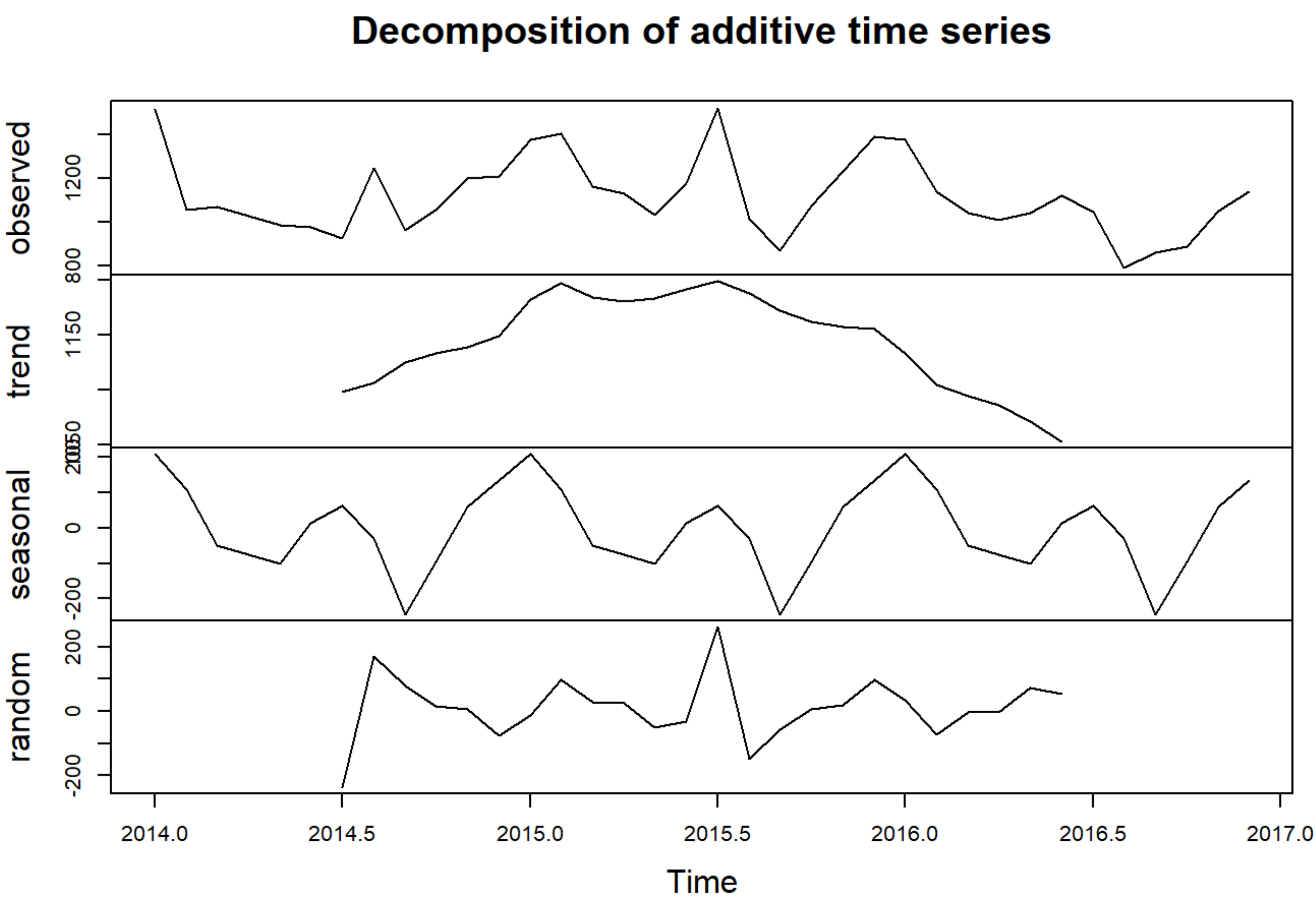

viewers
ACF
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
Lag


Series train_A[[i]]
Partial ACF
0.6
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag

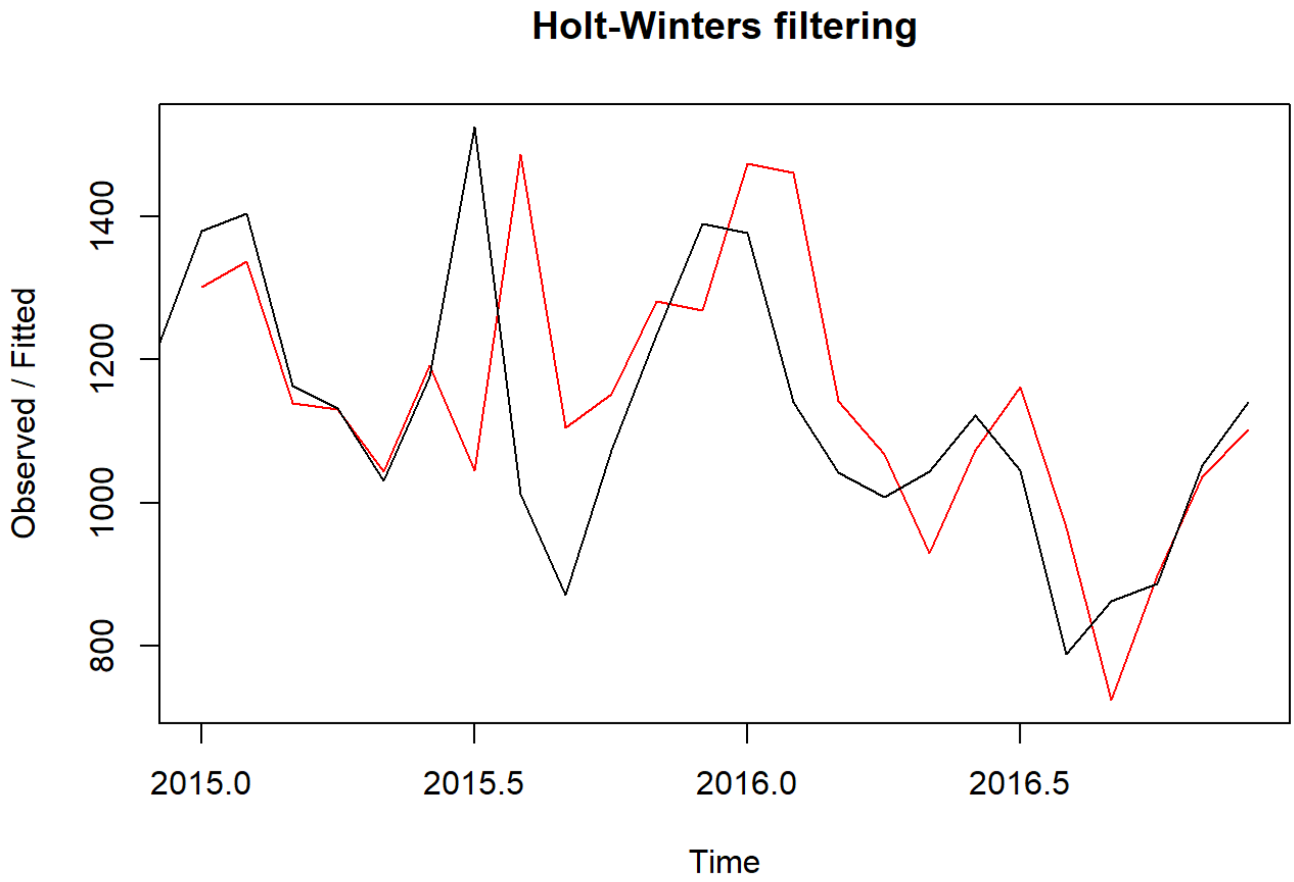

Holt-Winters filtering
Observed / Fitted
800
700
600
500
400
2015.0
2015.5
2016.0
2016.5
Time

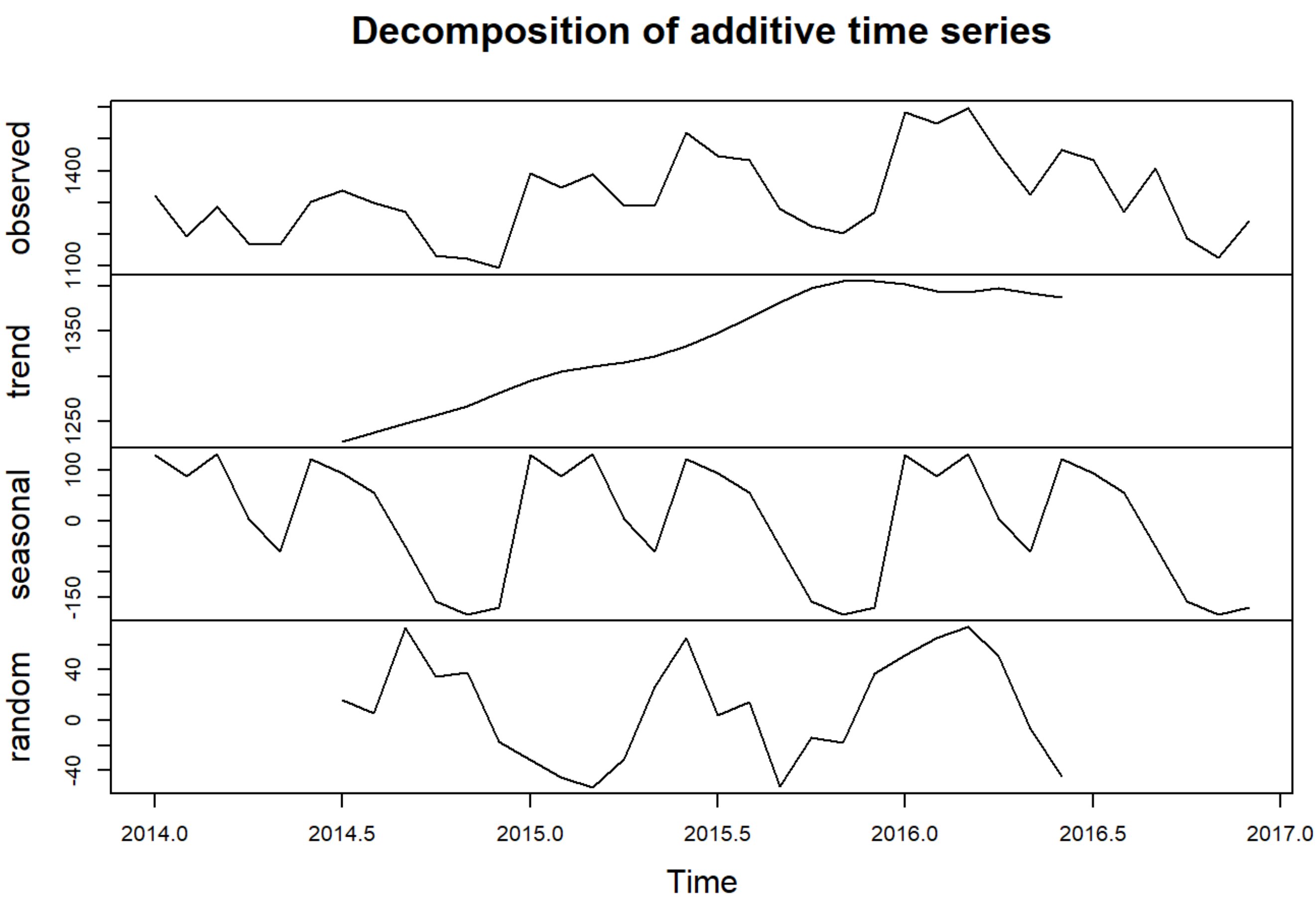


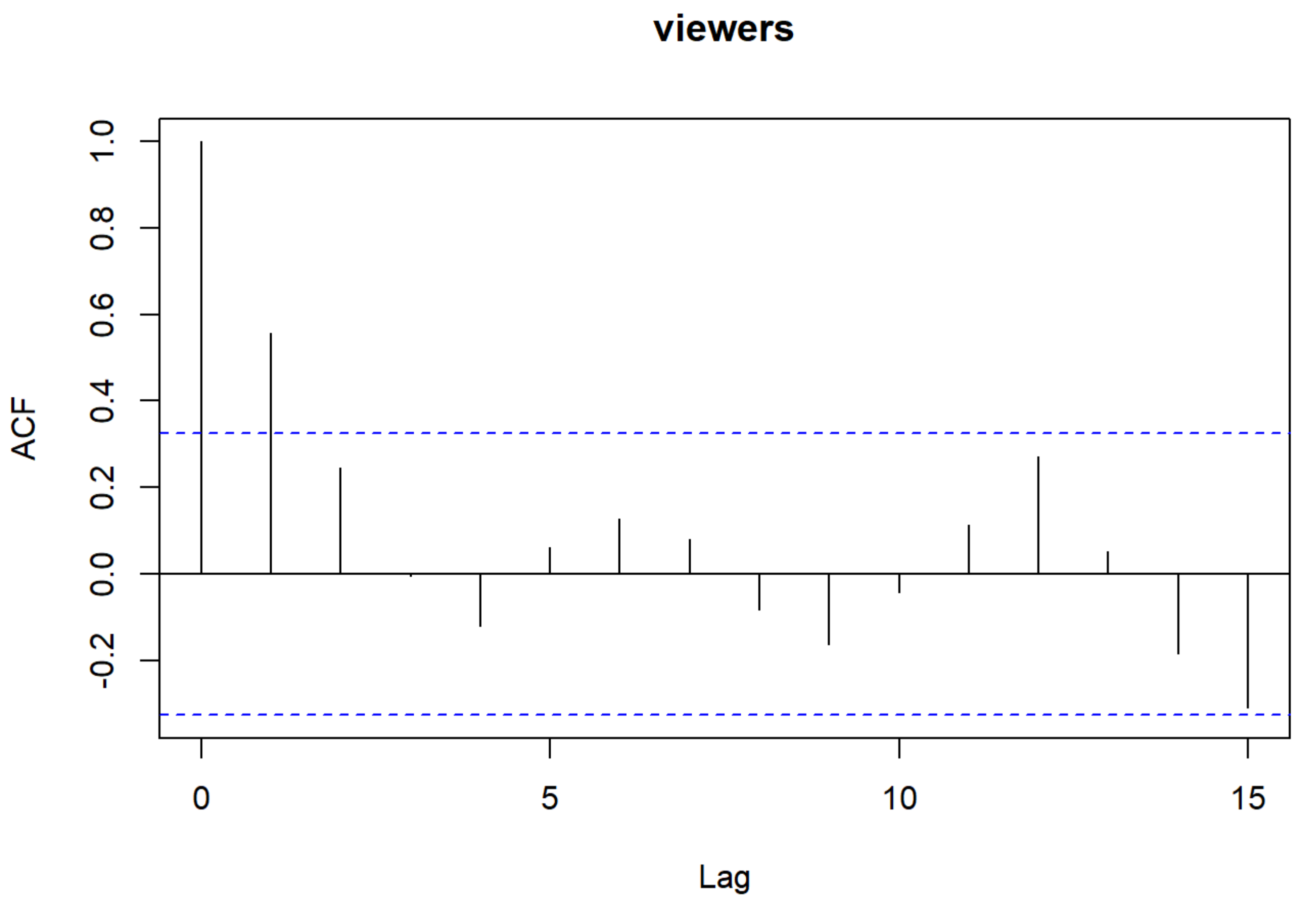
Forecasts from HoltWinters
800
600
400
200
2014
2015
2016
2017
2018

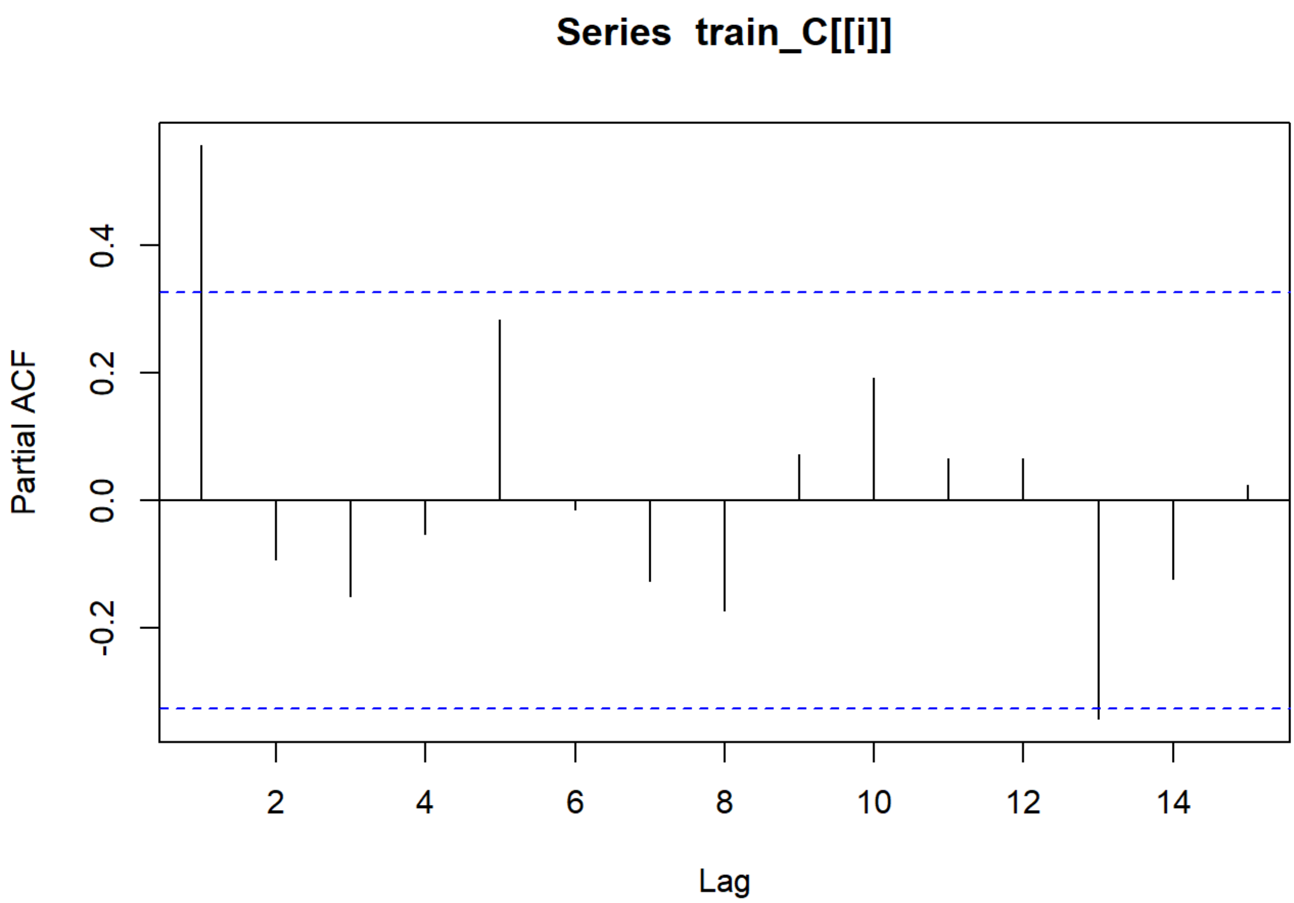



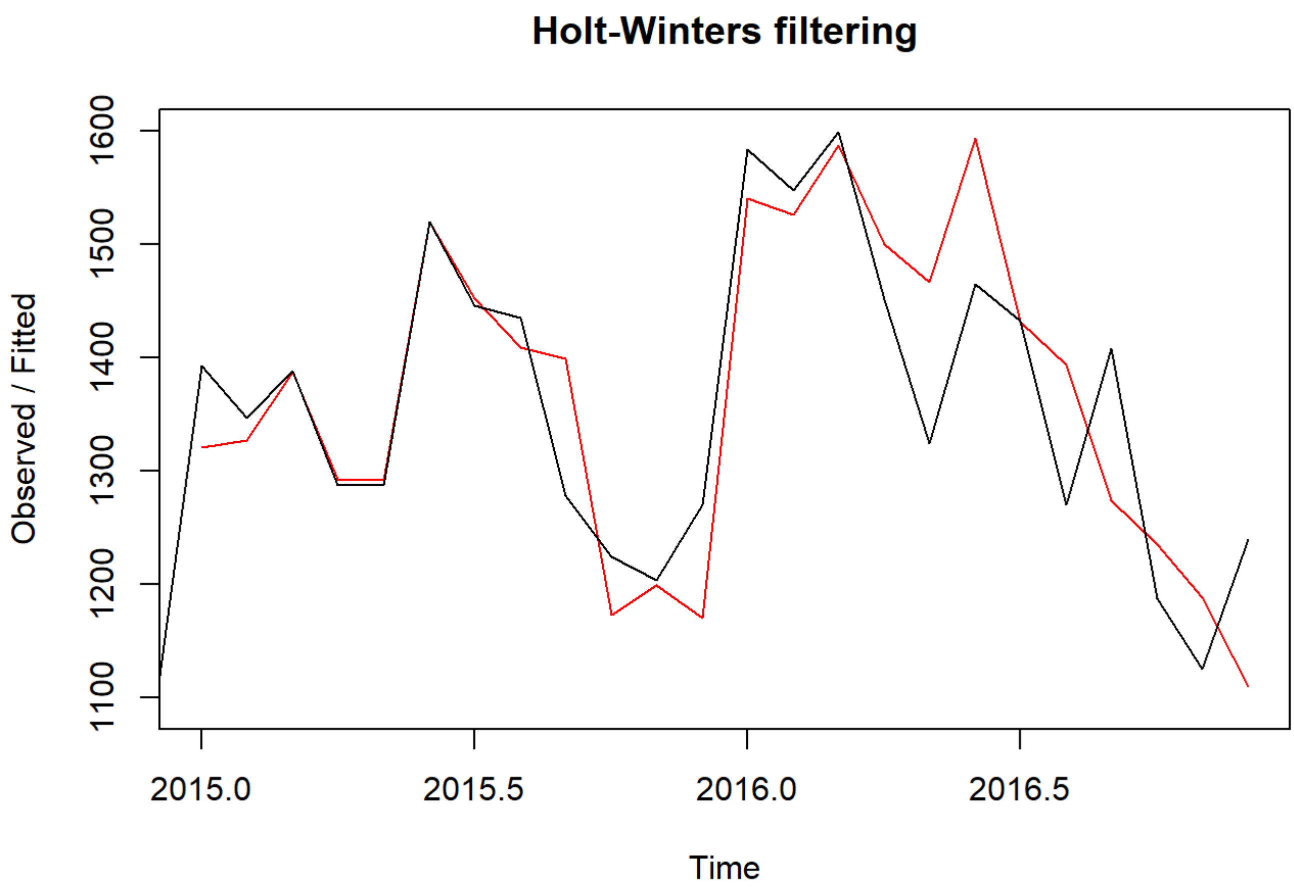
Decomposition of additive time series
observed
trend
seasonal
random
1200
800
1150
0
-200
200
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

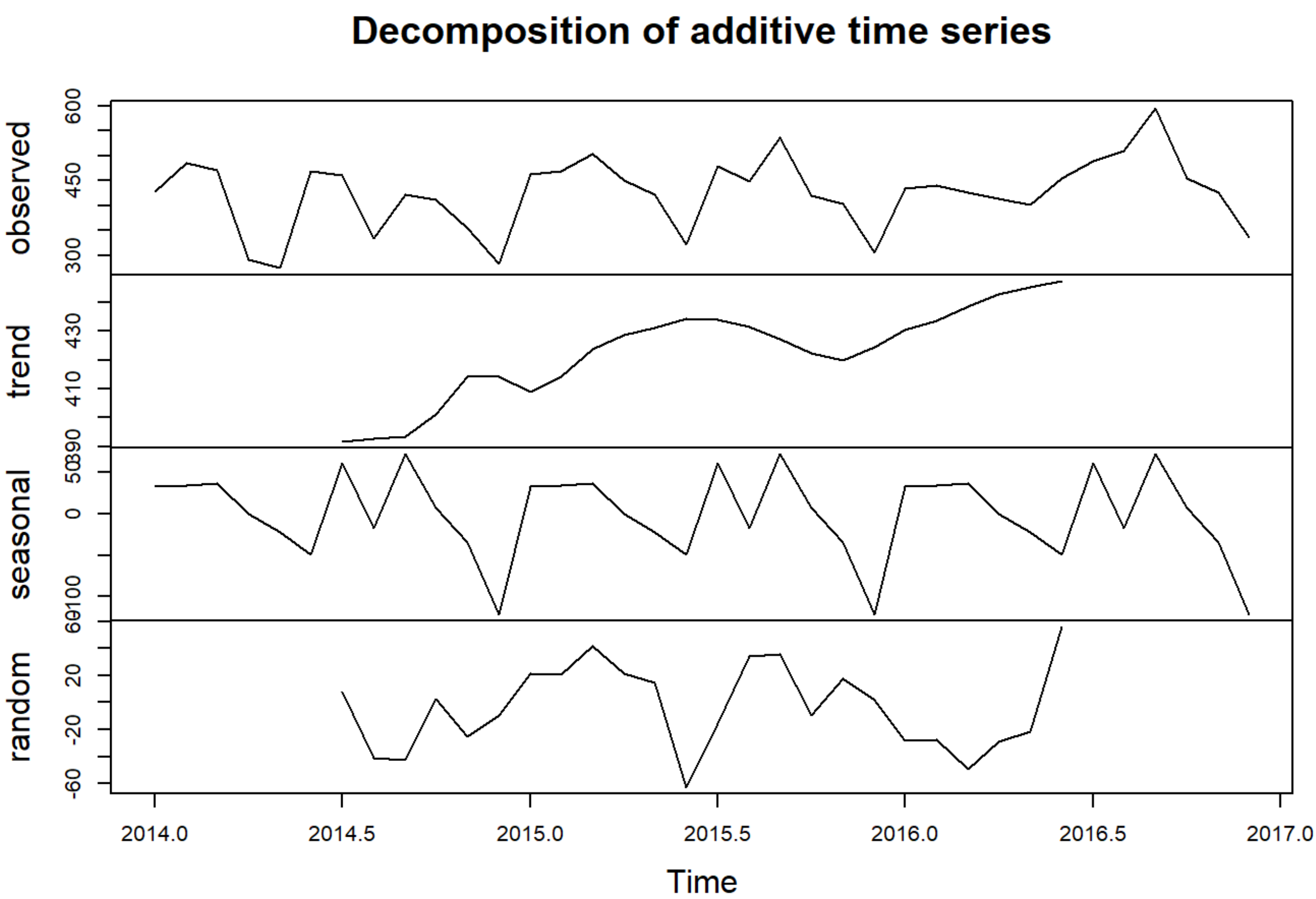

Holt-Winters filtering
Observed / Fitted
1400
1200
1000
800
2015.0
2015.5
2016.0
2016.5
Time

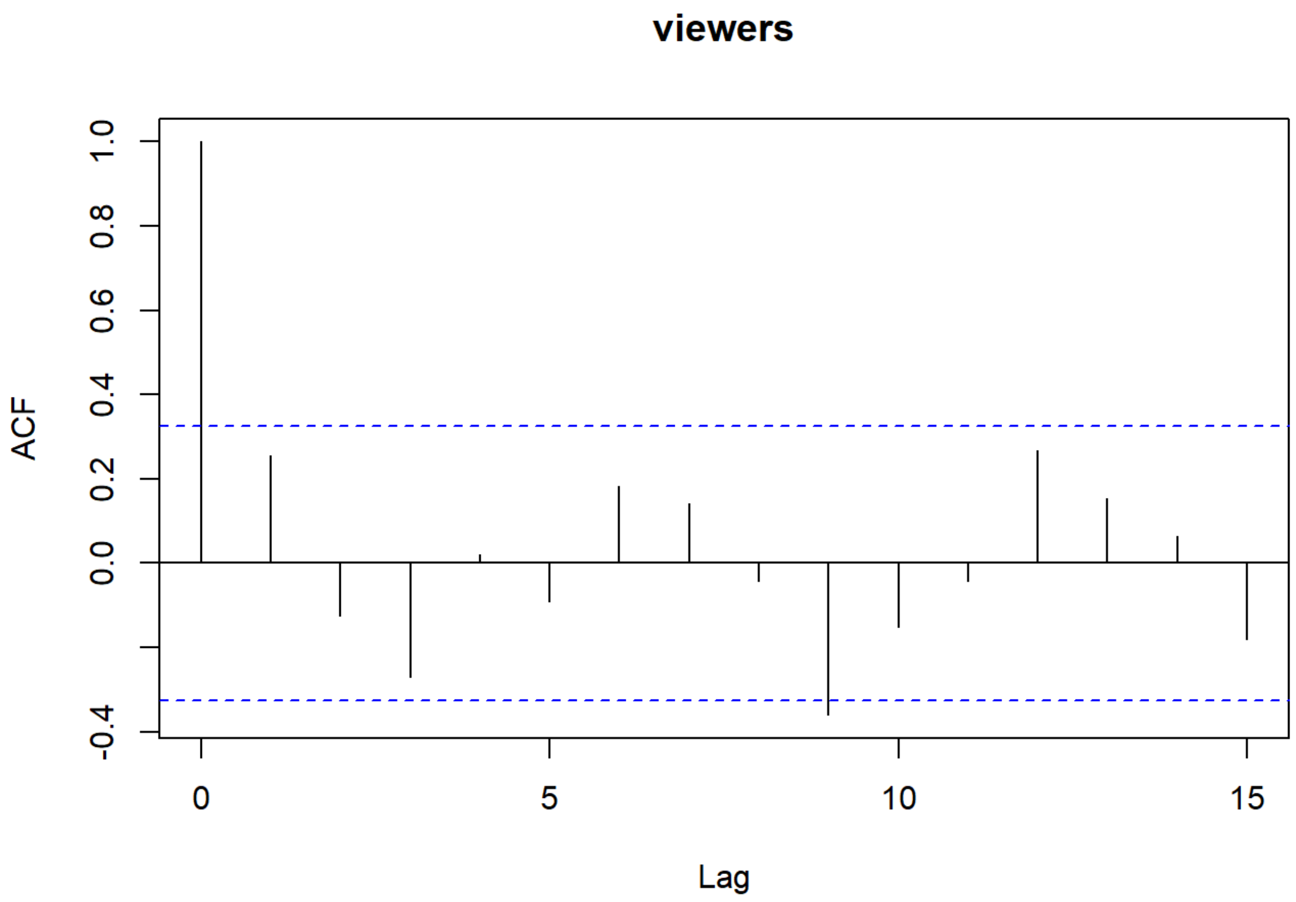

Decomposition of additive time series
observed
1100
1400
trend
1250
1350
seasonal
-150
0
100
random
-40
0
40
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

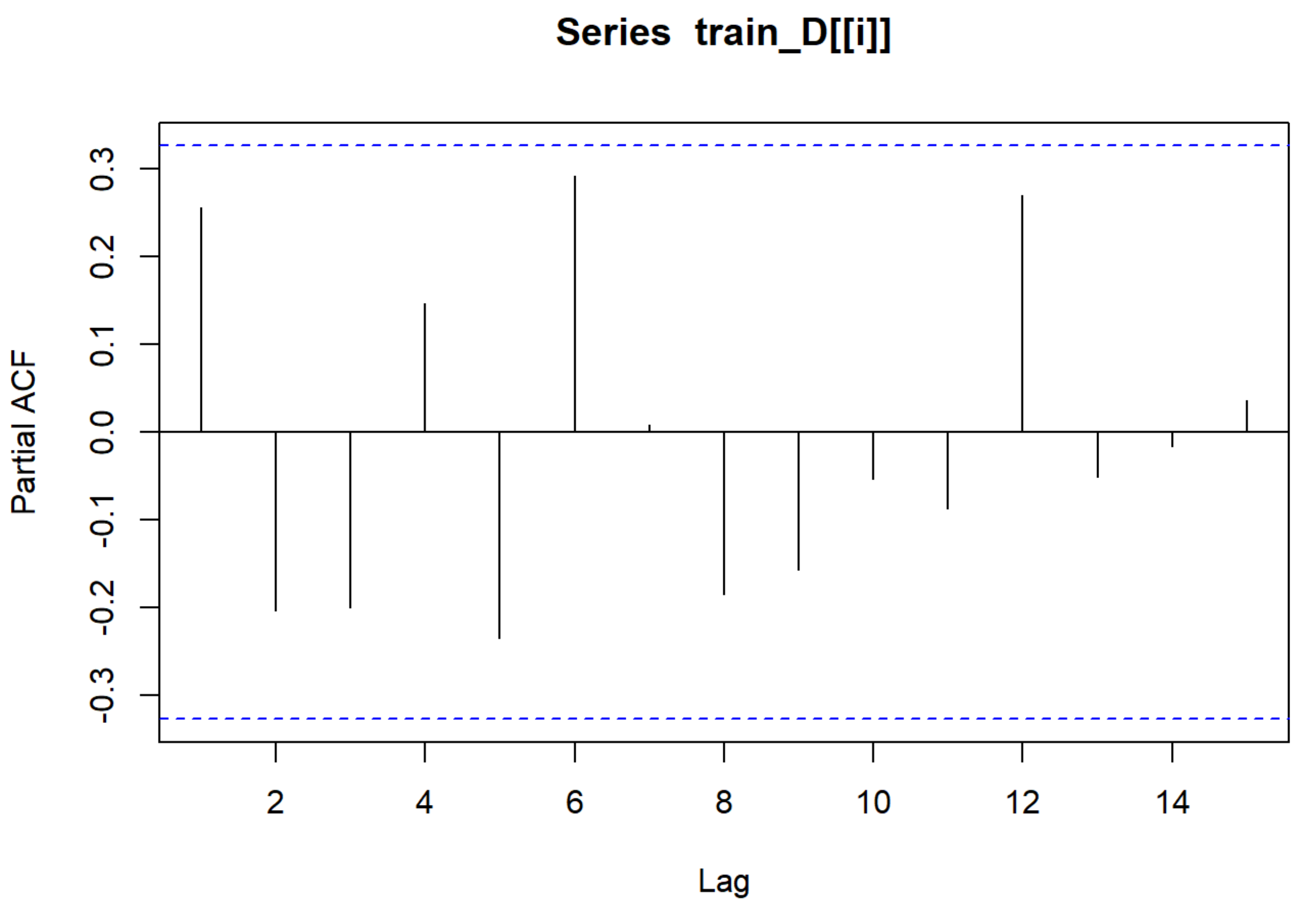

viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

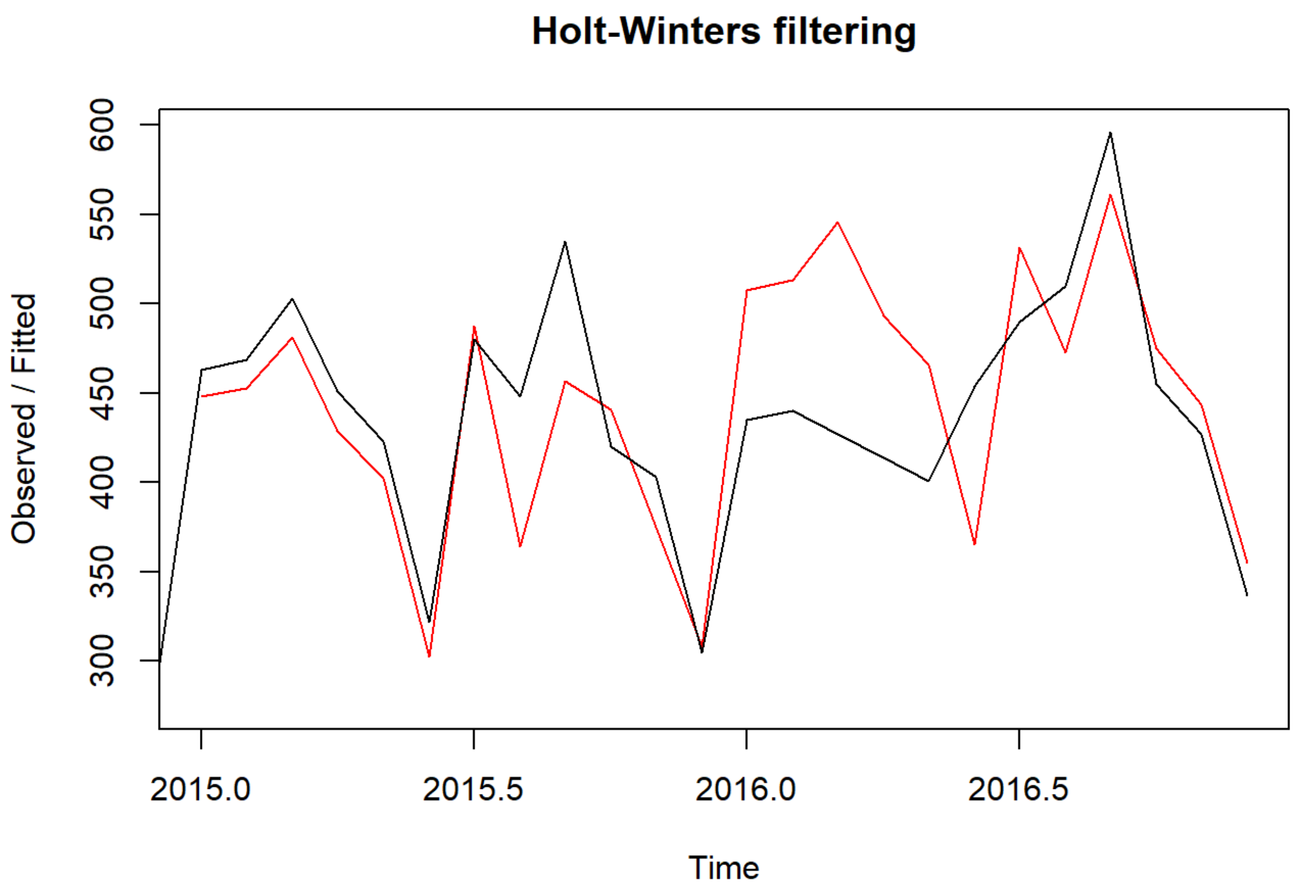

Series train_C[[i]]
Partial ACF
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag

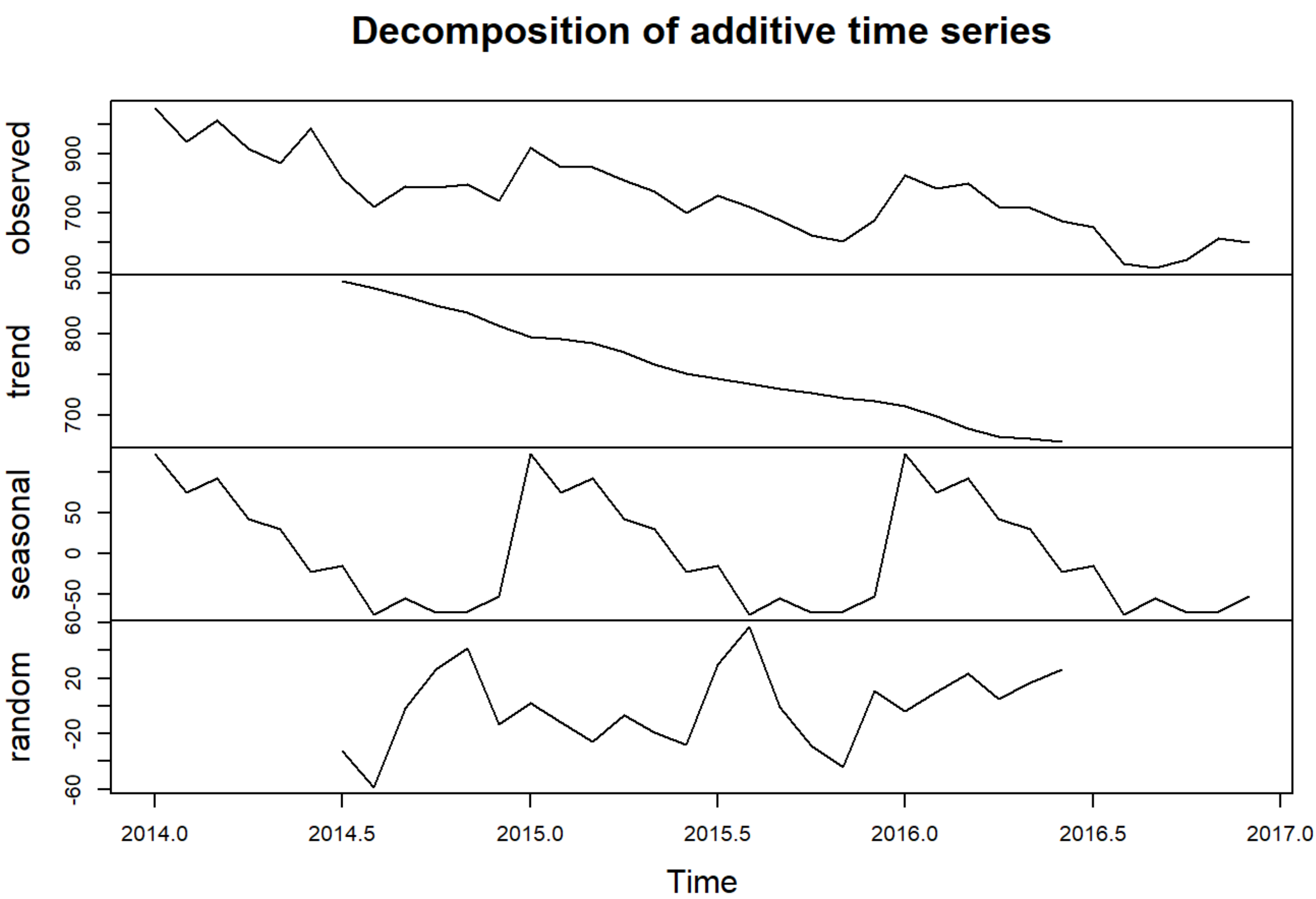

Holt-Winters filtering
Observed / Fitted
1100
1200
1300
1400
1500
1600
2015.0
2015.5
2016.0
2016.5
Time

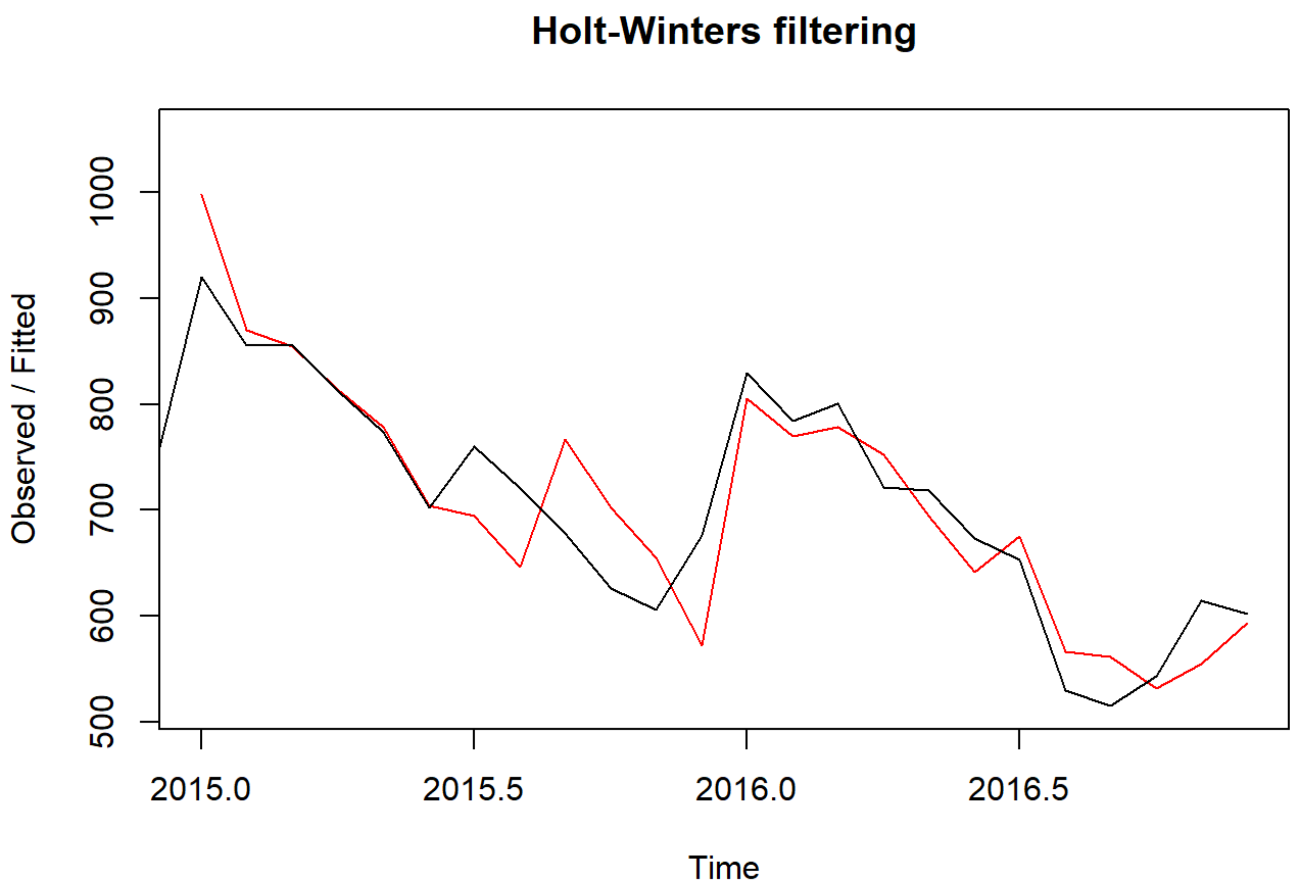

Decomposition of additive time series
observed
300
450
600
trend
390
410
430
seasonal
-100
0
50
random
-60
-20
20
60
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

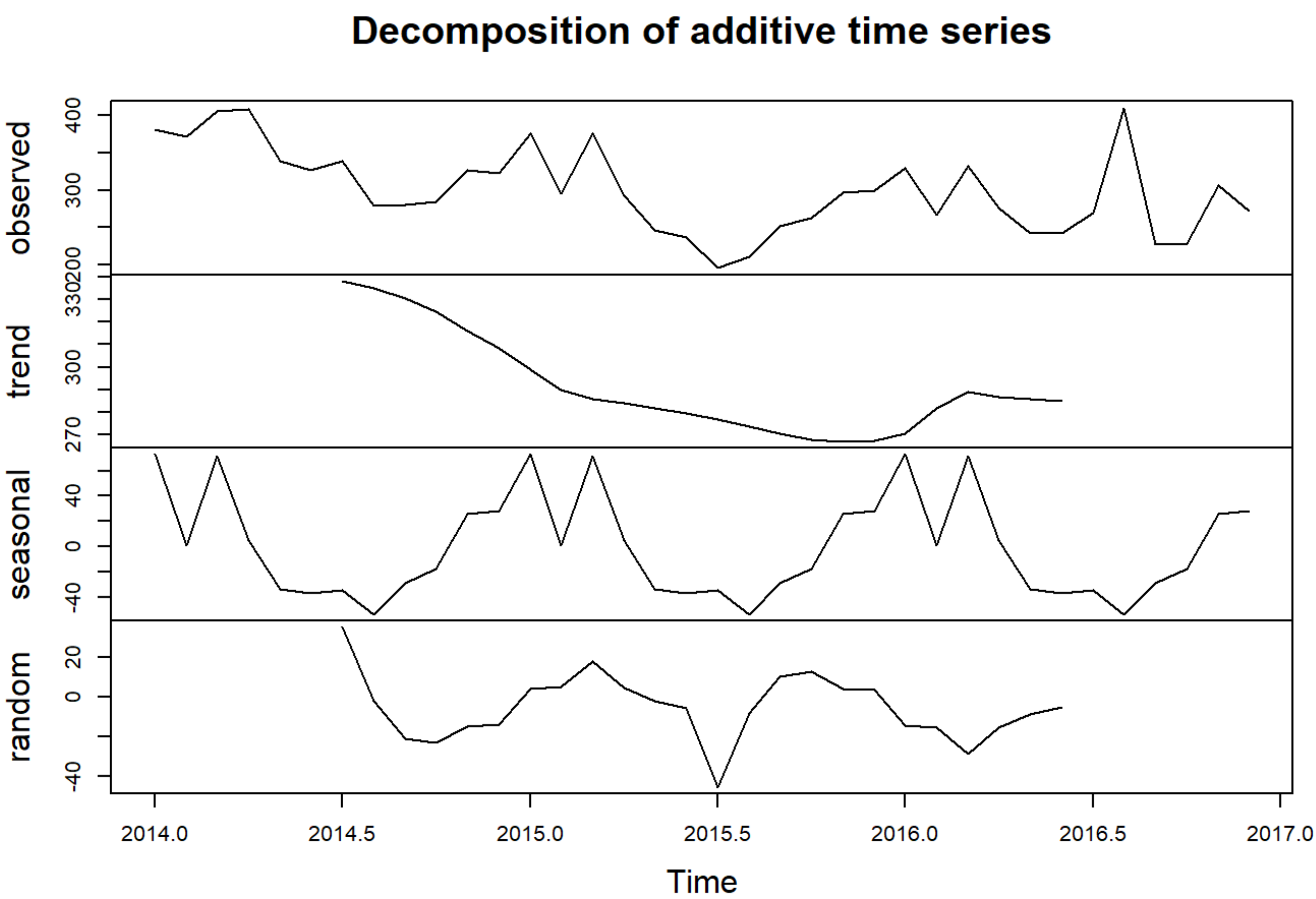

viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.4
0
5
10
15
Lag

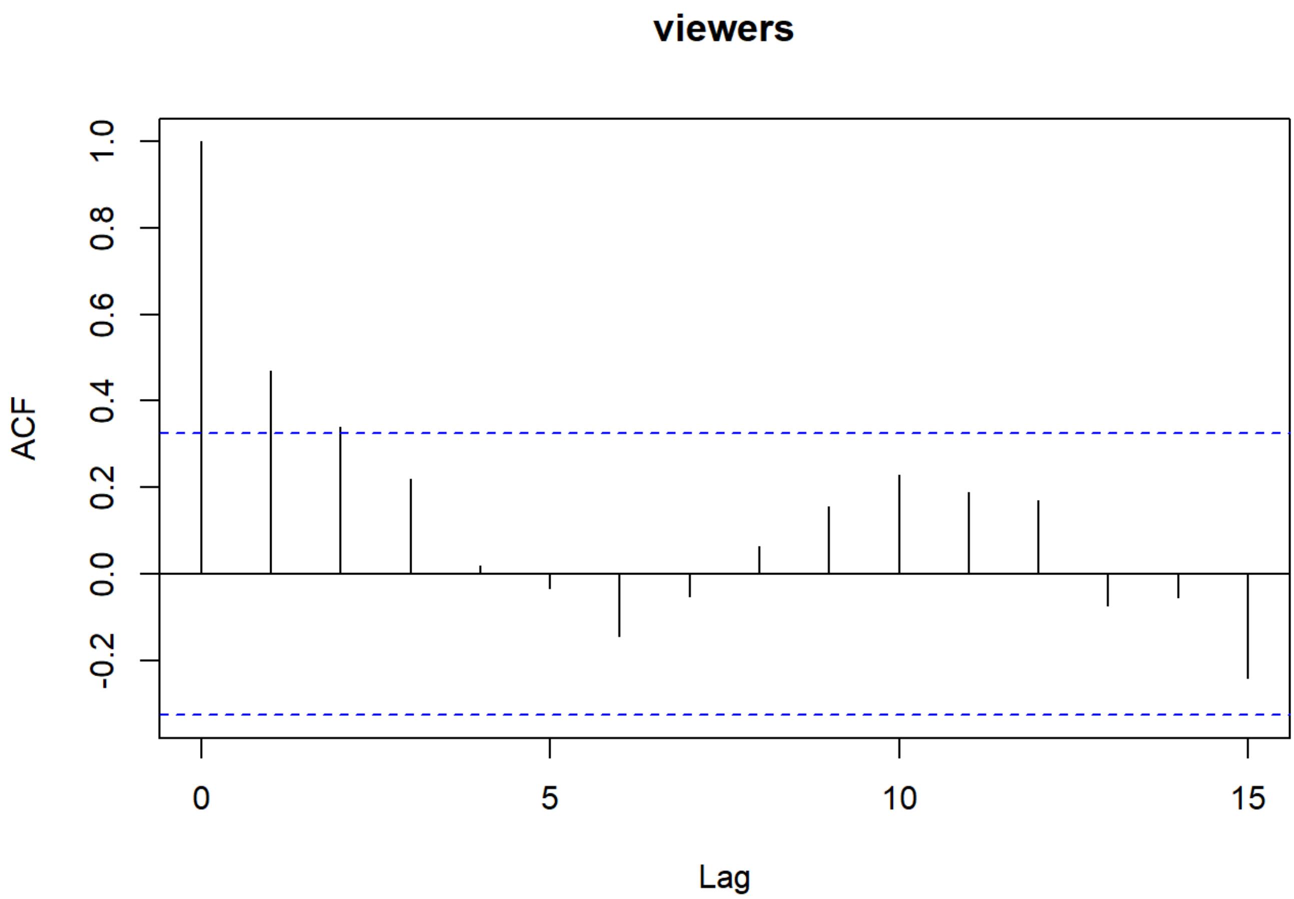

Series train_D[[i]]
Partial ACF
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
2
4
6
8
10
12
14
Lag

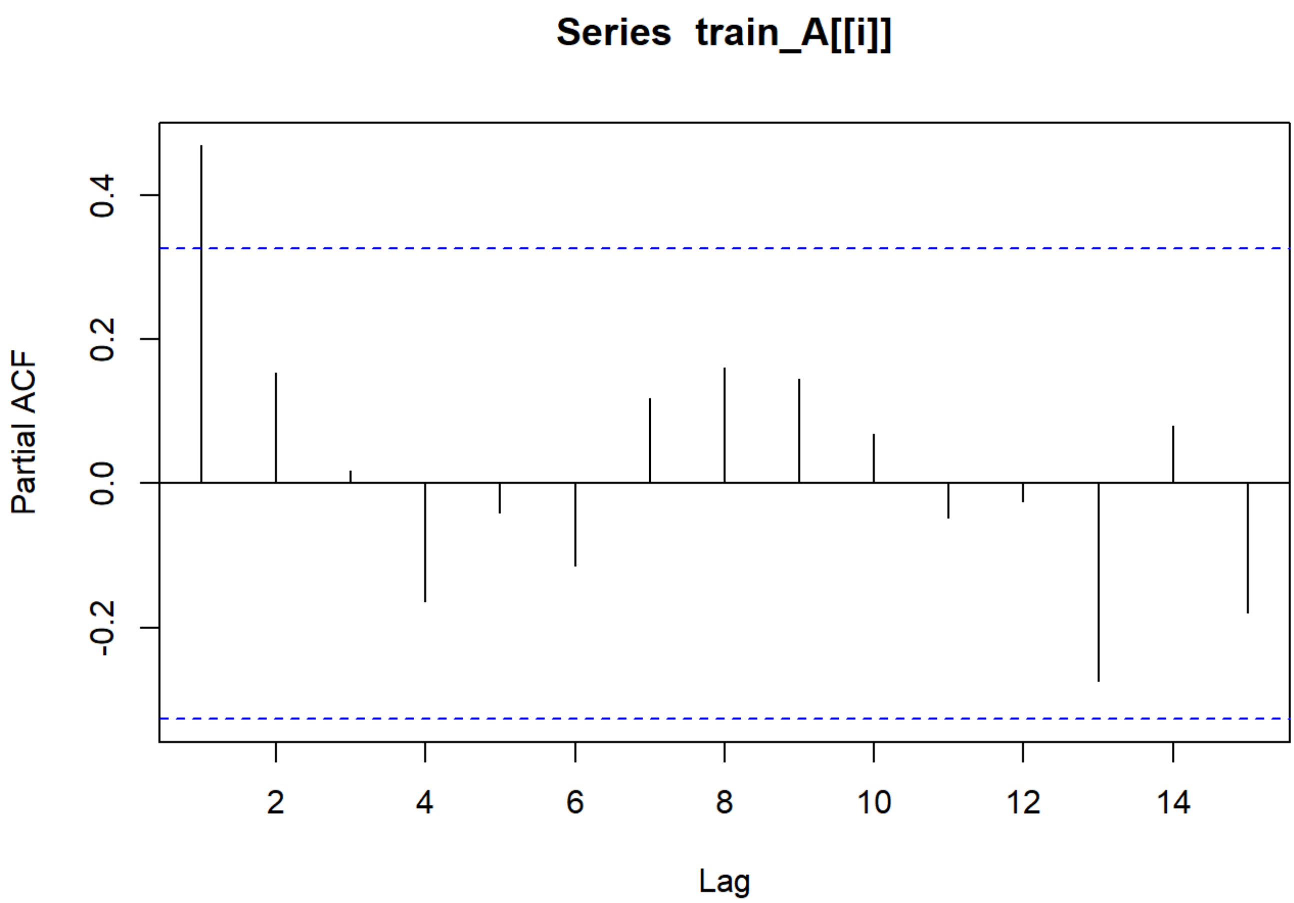

Holt-Winters filtering
Observed / Fitted
300
350
400
450
500
550
600
2015.0
2015.5
2016.0
2016.5
Time

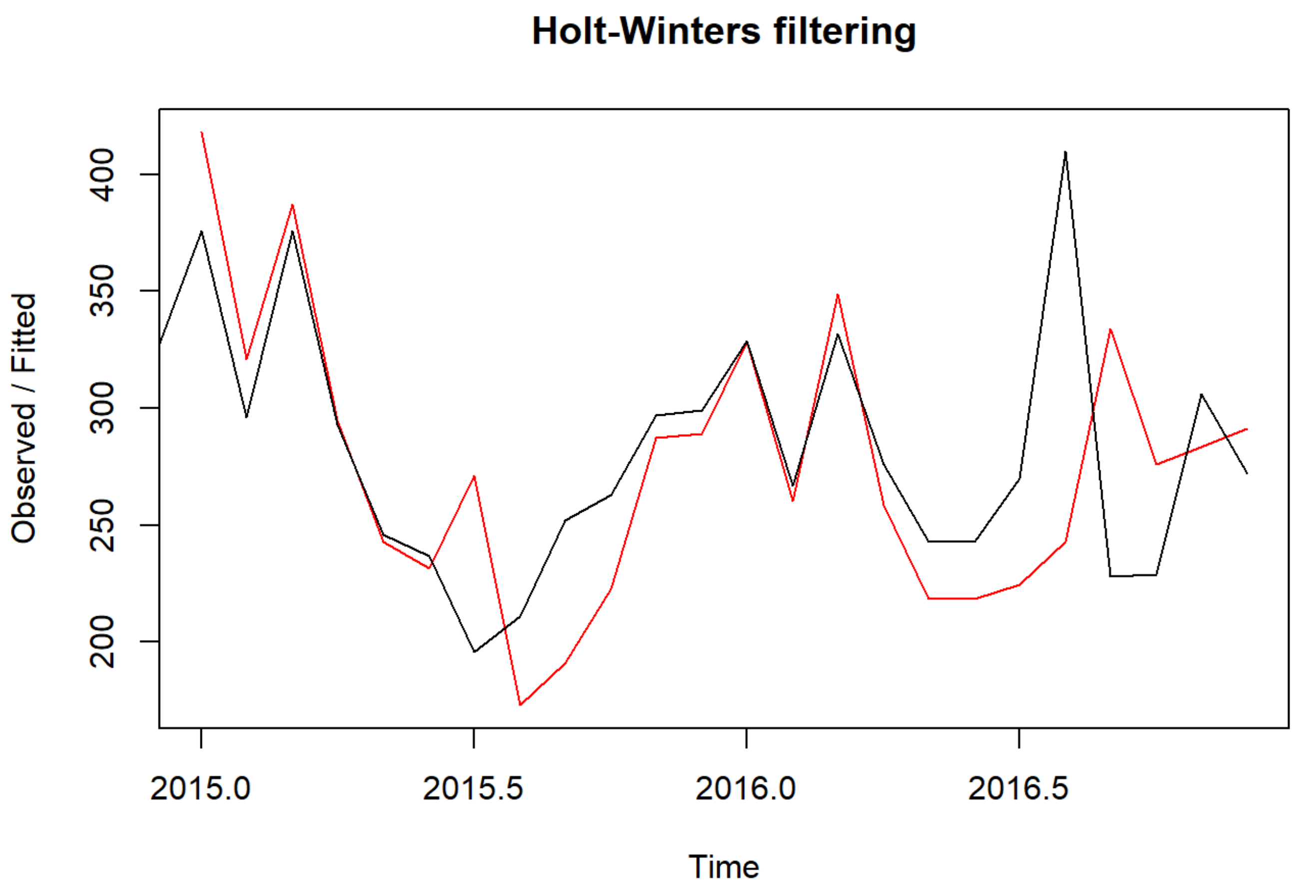

Decomposition of additive time series
observed
trend
seasonal
random
500
700
900
700
800
-50
0
50
-60
-20
20
60
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

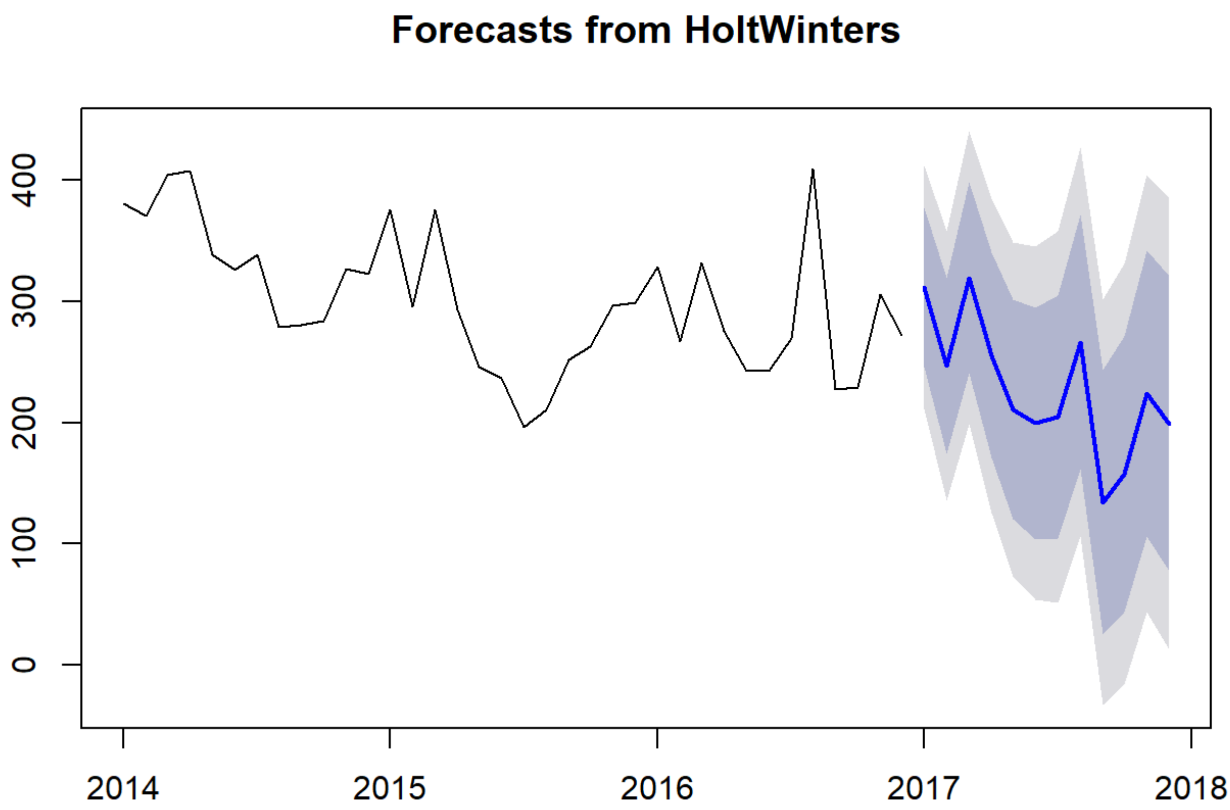

Holt-Winters filtering
Observed / Fitted
1000
900
800
700
600
500
2015.0
2015.5
2016.0
2016.5
Time

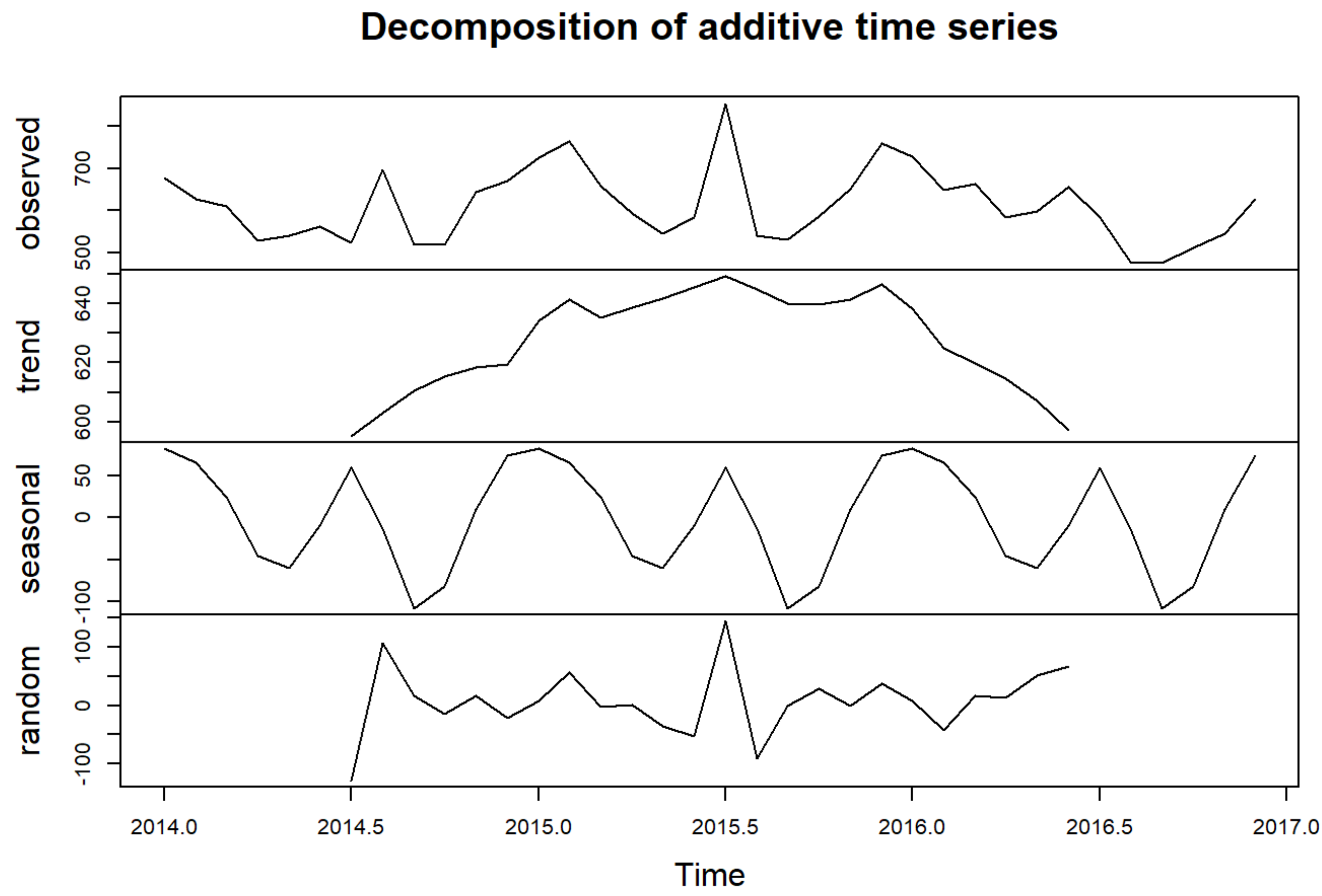

Decomposition of additive time series
observed
trend
seasonal
random
400
300
200
330
300
270
40
0
-40
20
0
-40
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

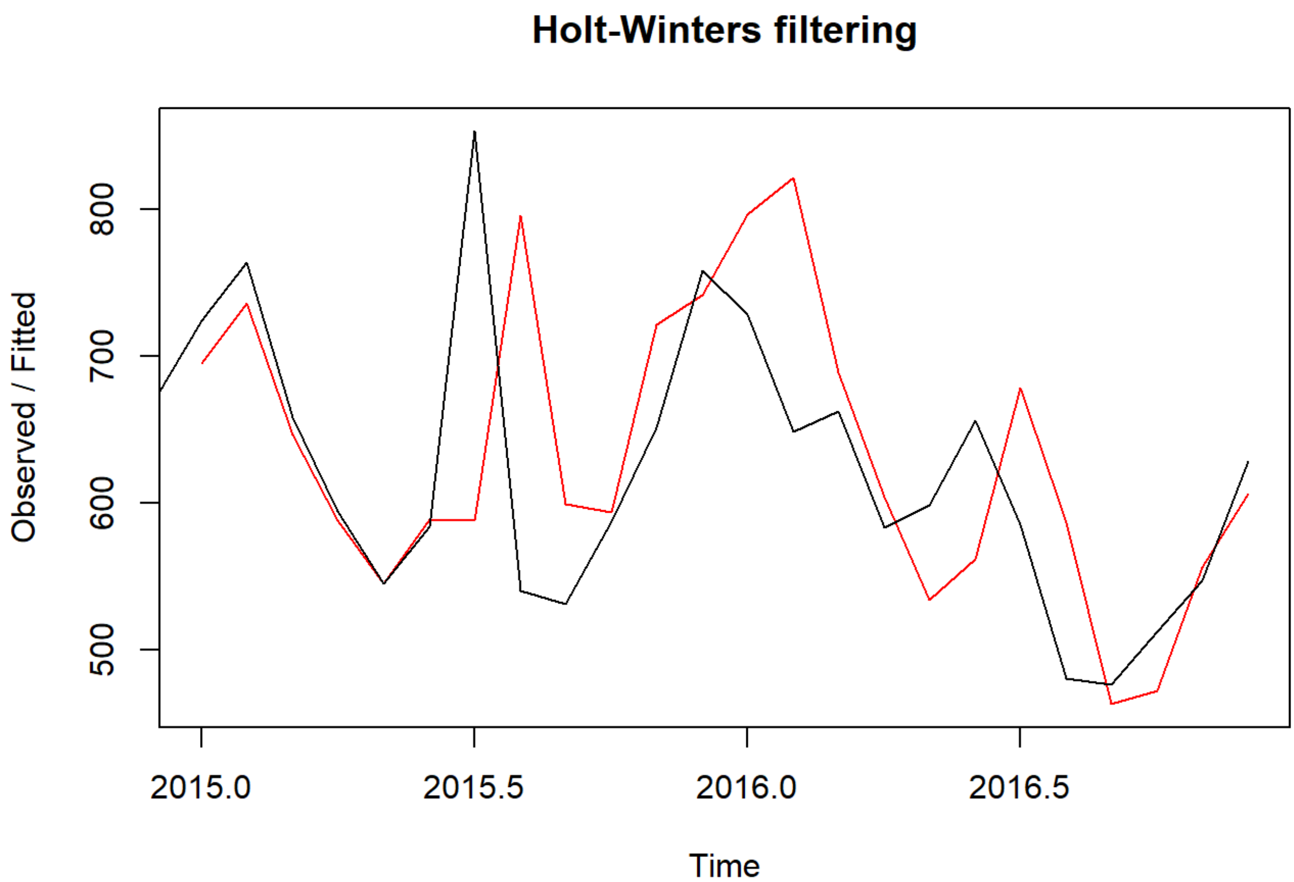

viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

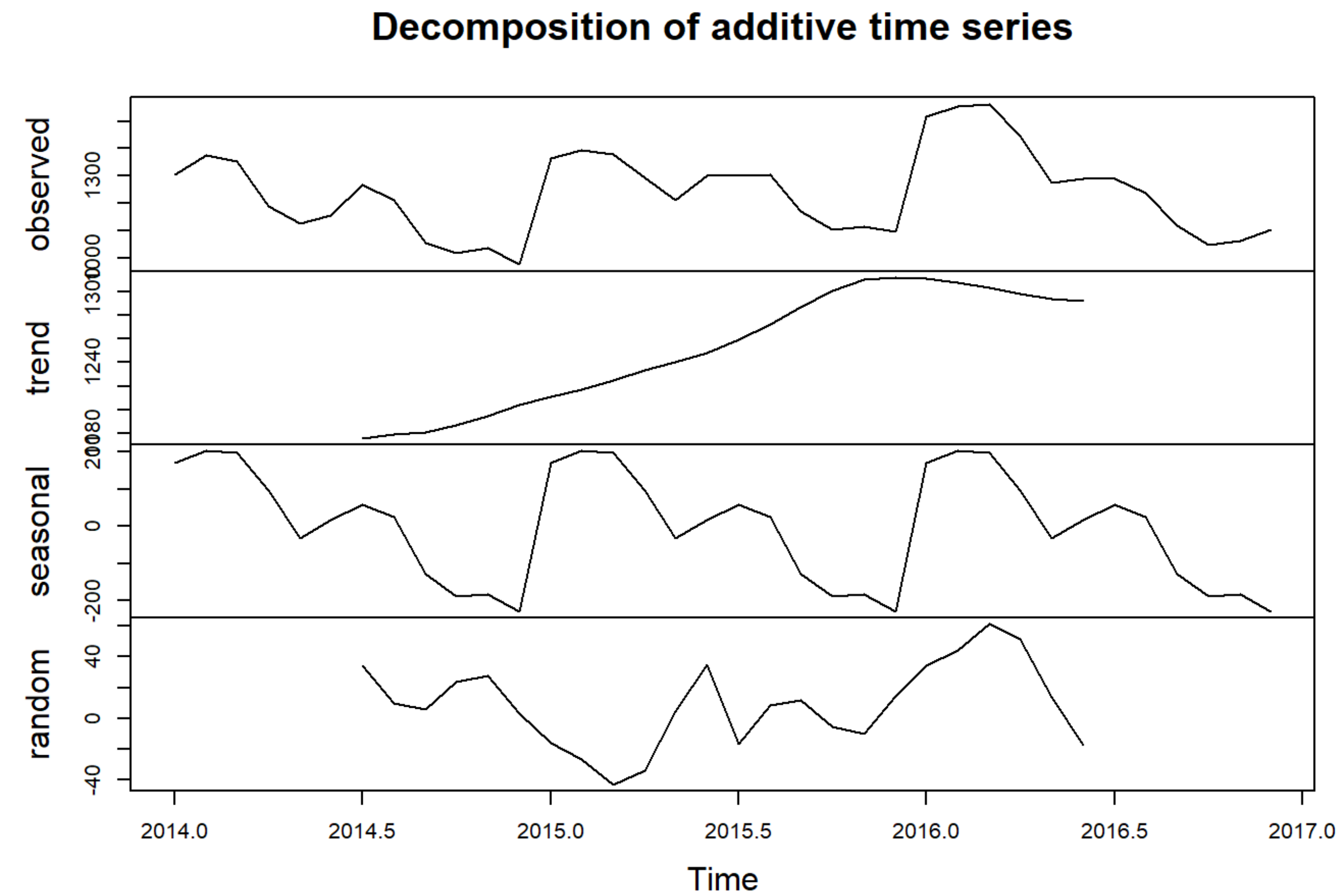

Series train_A[[i]]
Partial ACF
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag


Holt-Winters filtering
Observed / Fitted
400
350
300
250
200
2015.0
2015.5
2016.0
2016.5
Time

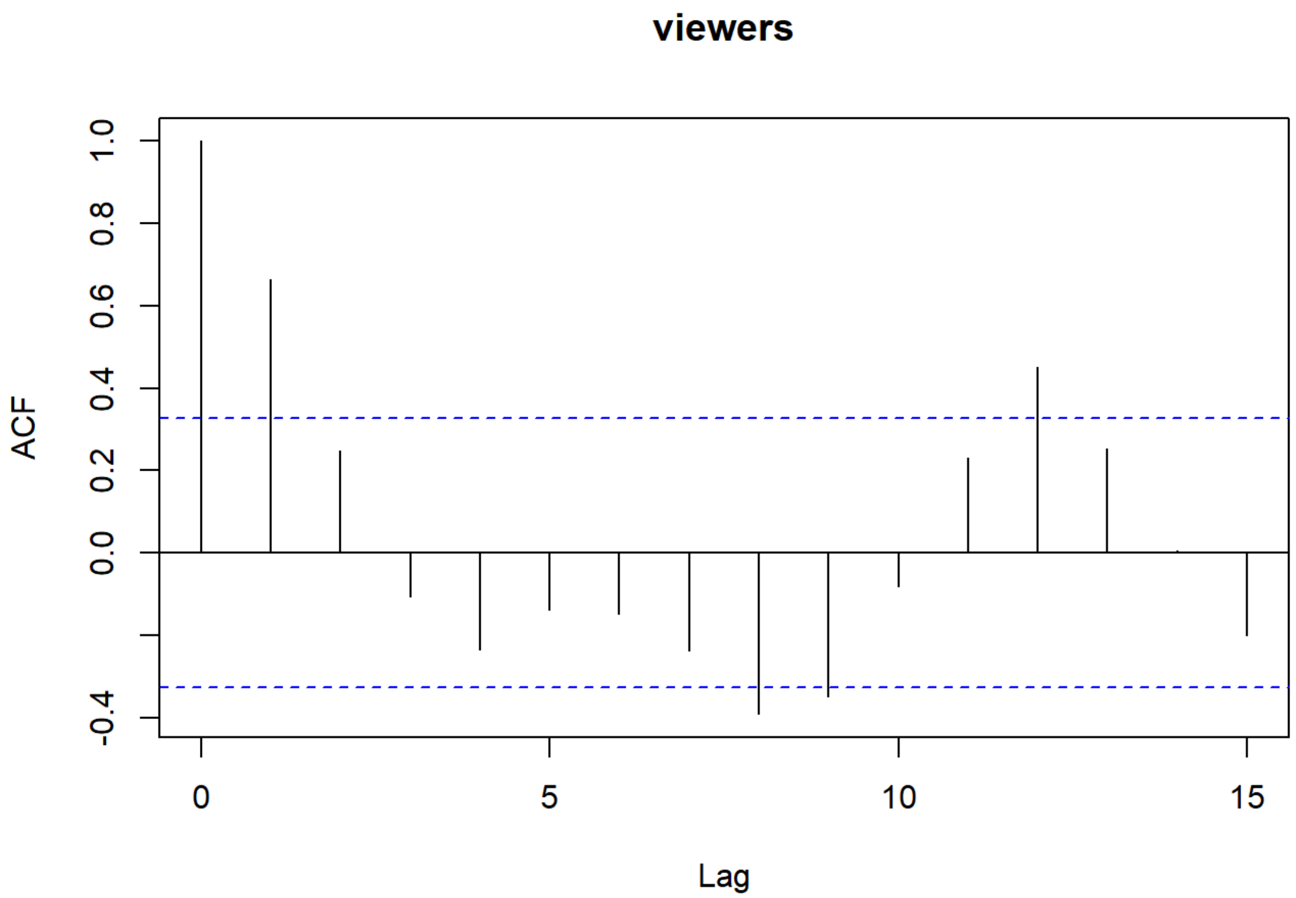

Forecasts from HoltWinters
400
300
200
100
0
2014
2015
2016
2017
2018


Decomposition of additive time series
observed
trend
seasonal
random
Time
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0

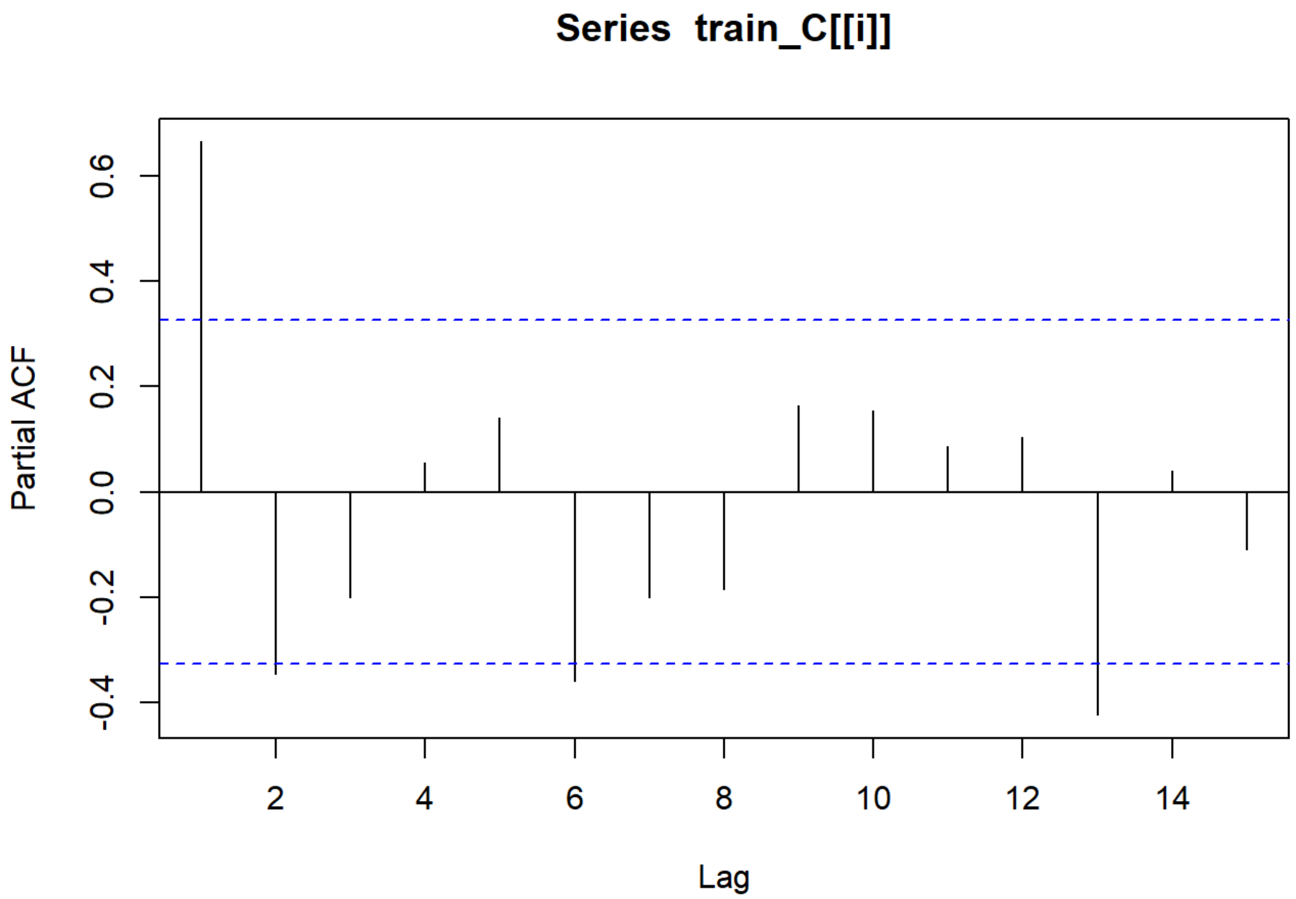

Holt-Winters filtering
Observed / Fitted
Time
500
600
700
800
2015.0
2015.5
2016.0
2016.5

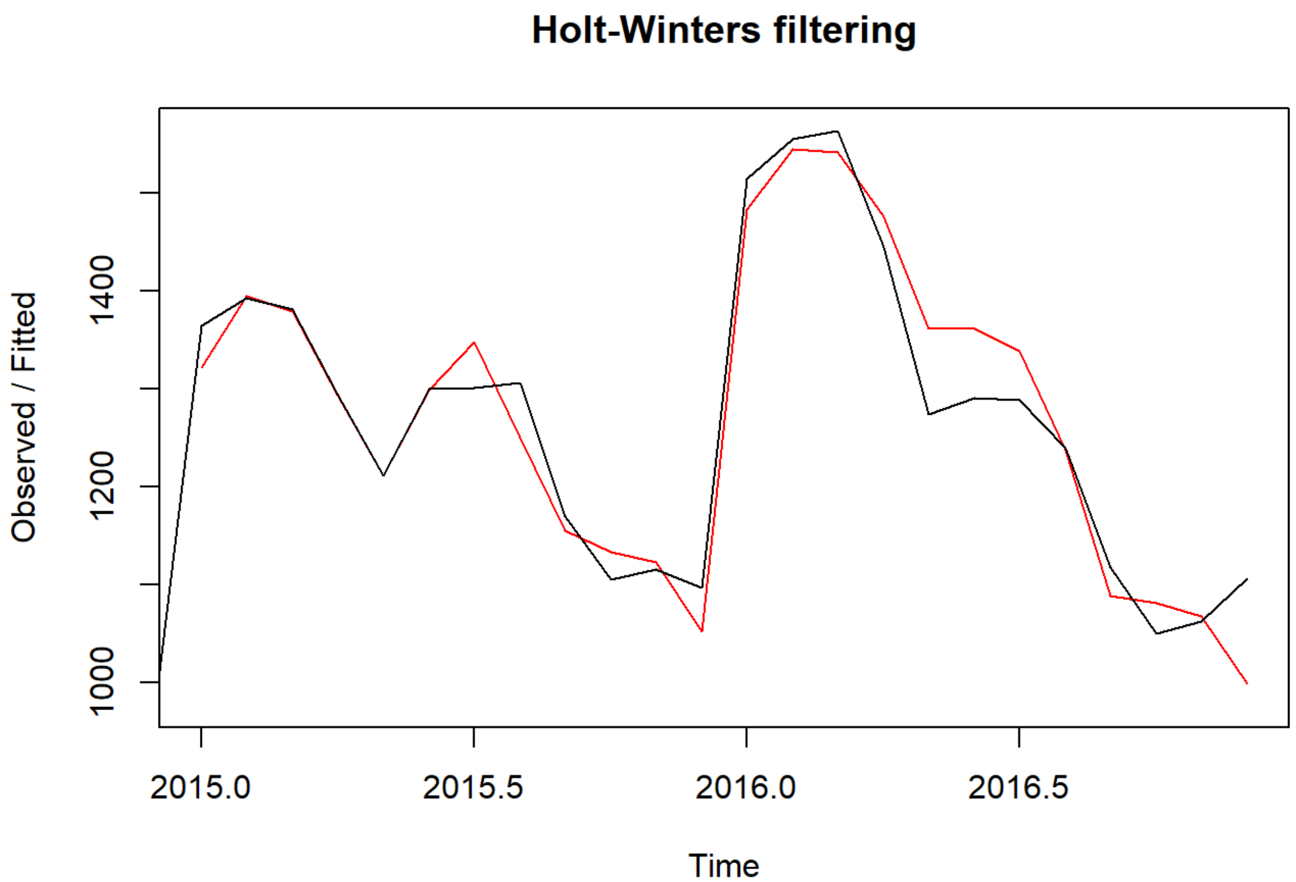


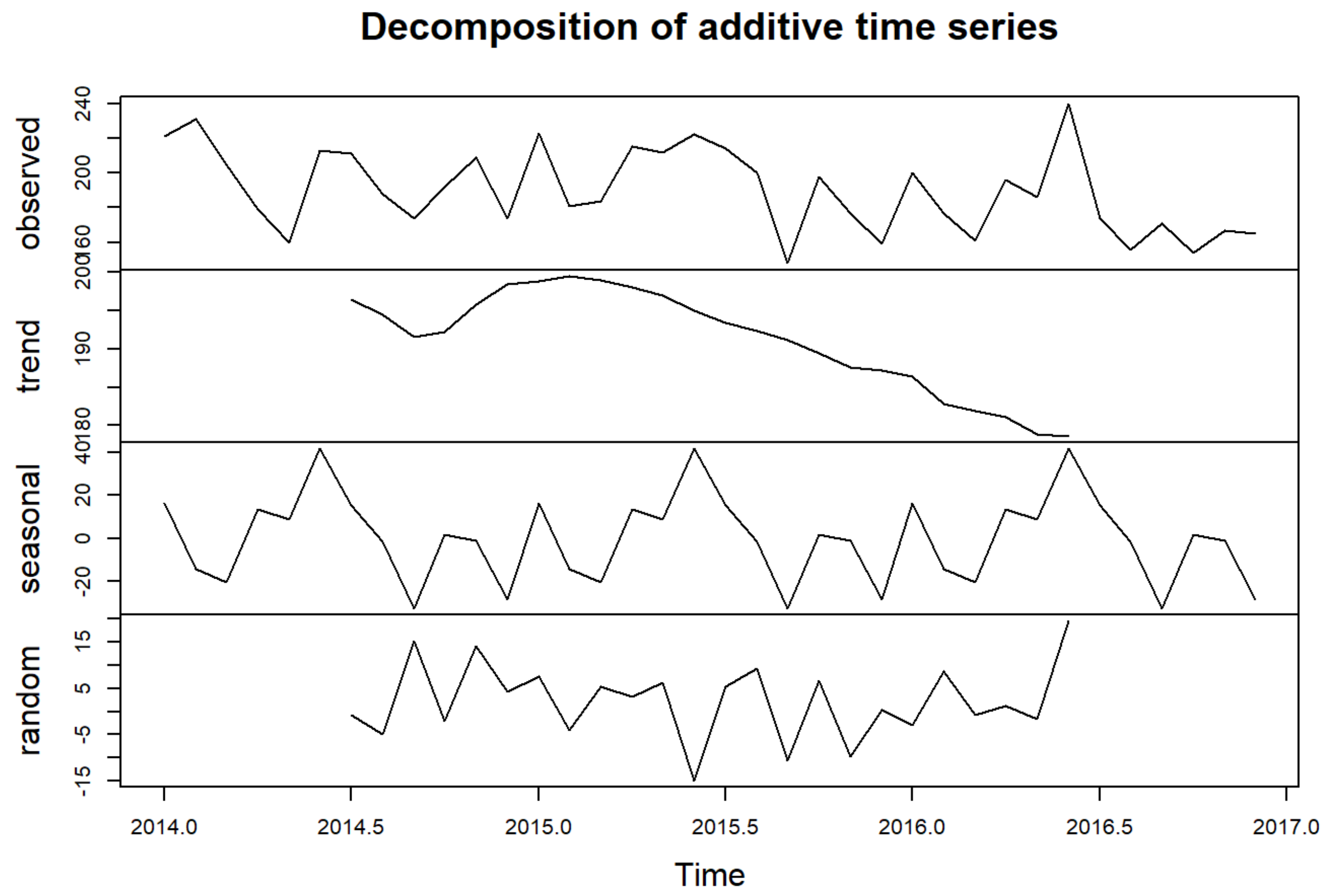
Decomposition of additive time series
observed
trend
seasonal
random
1300
1000
1300
1240
1180
200
0
-200
40
0
-40
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

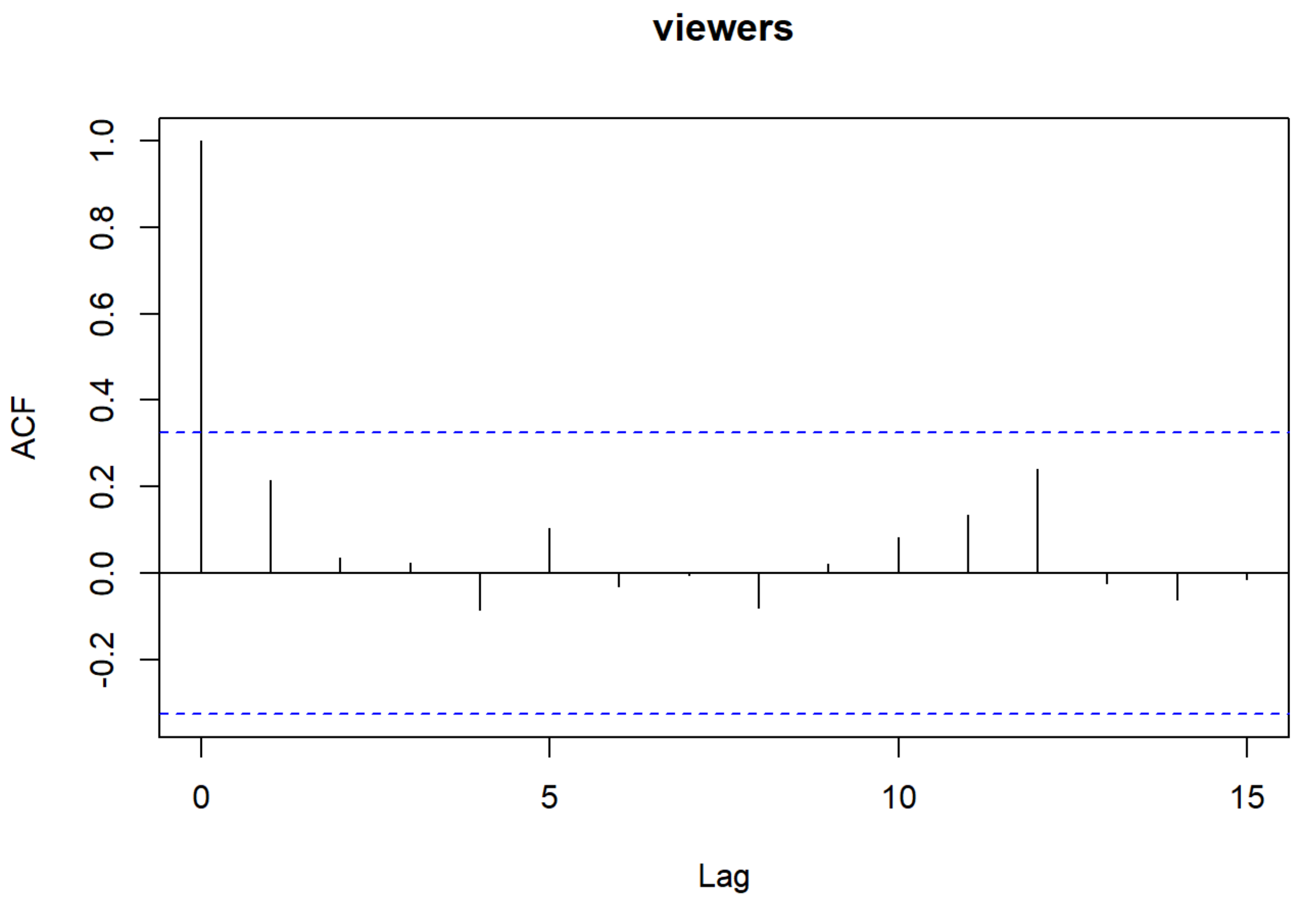



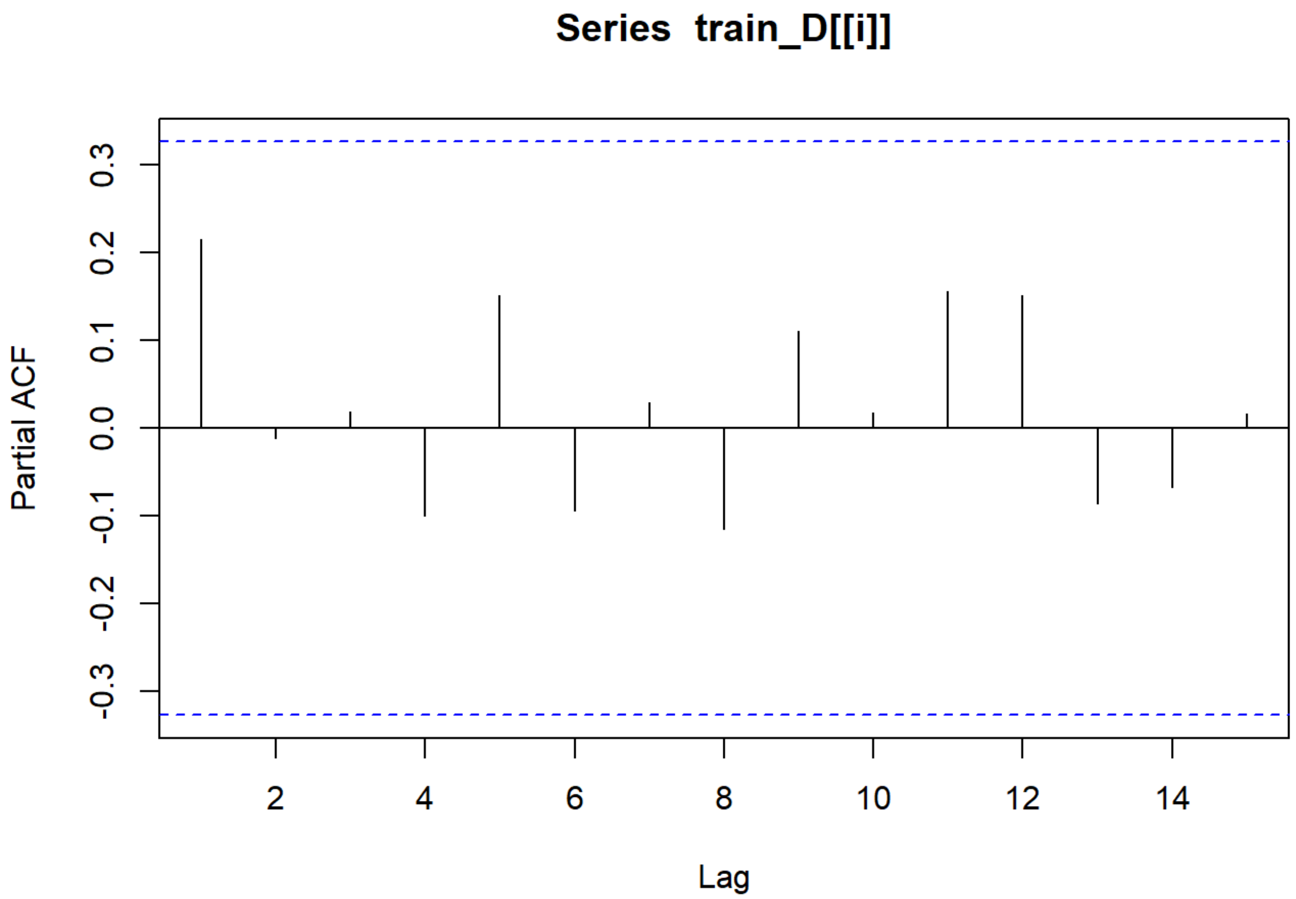
viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.4
0
5
10
15
Lag

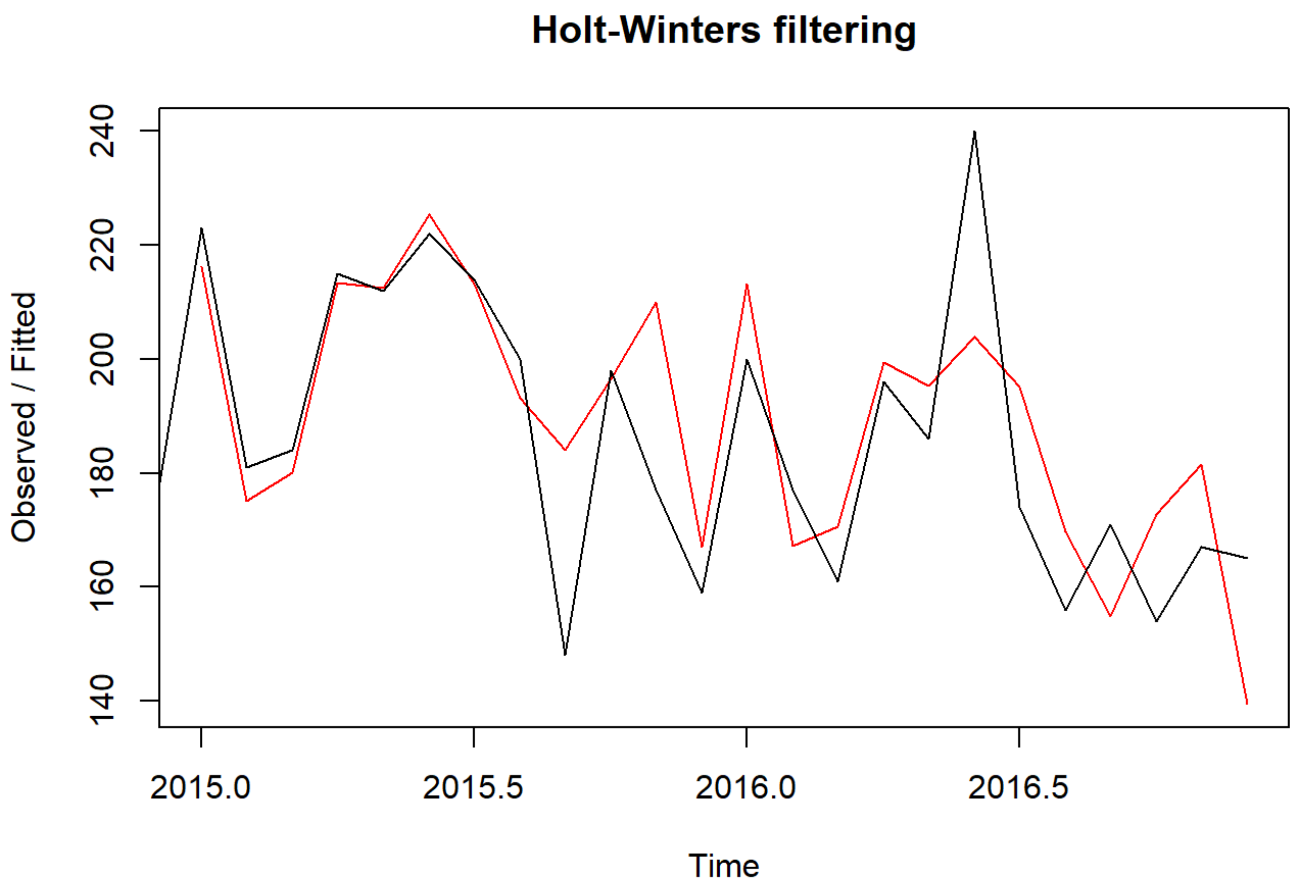

Series train_C[[i]]
Partial ACF
0.6
0.4
0.2
0.0
-0.2
-0.4
2
4
6
8
10
12
14
Lag

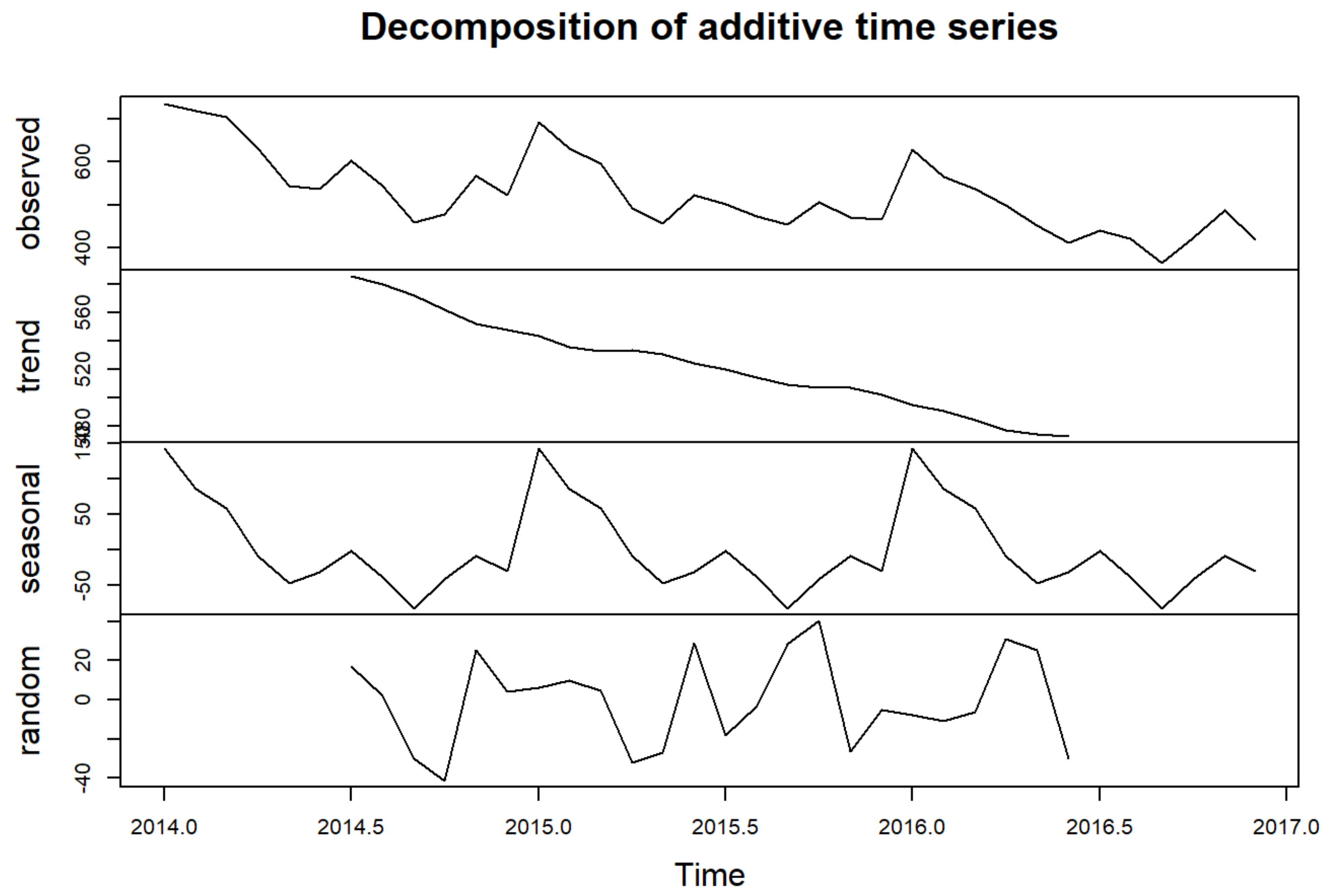

Holt-Winters filtering
Observed / Fitted
1400
1200
1000
2015.0
2015.5
2016.0
2016.5
Time

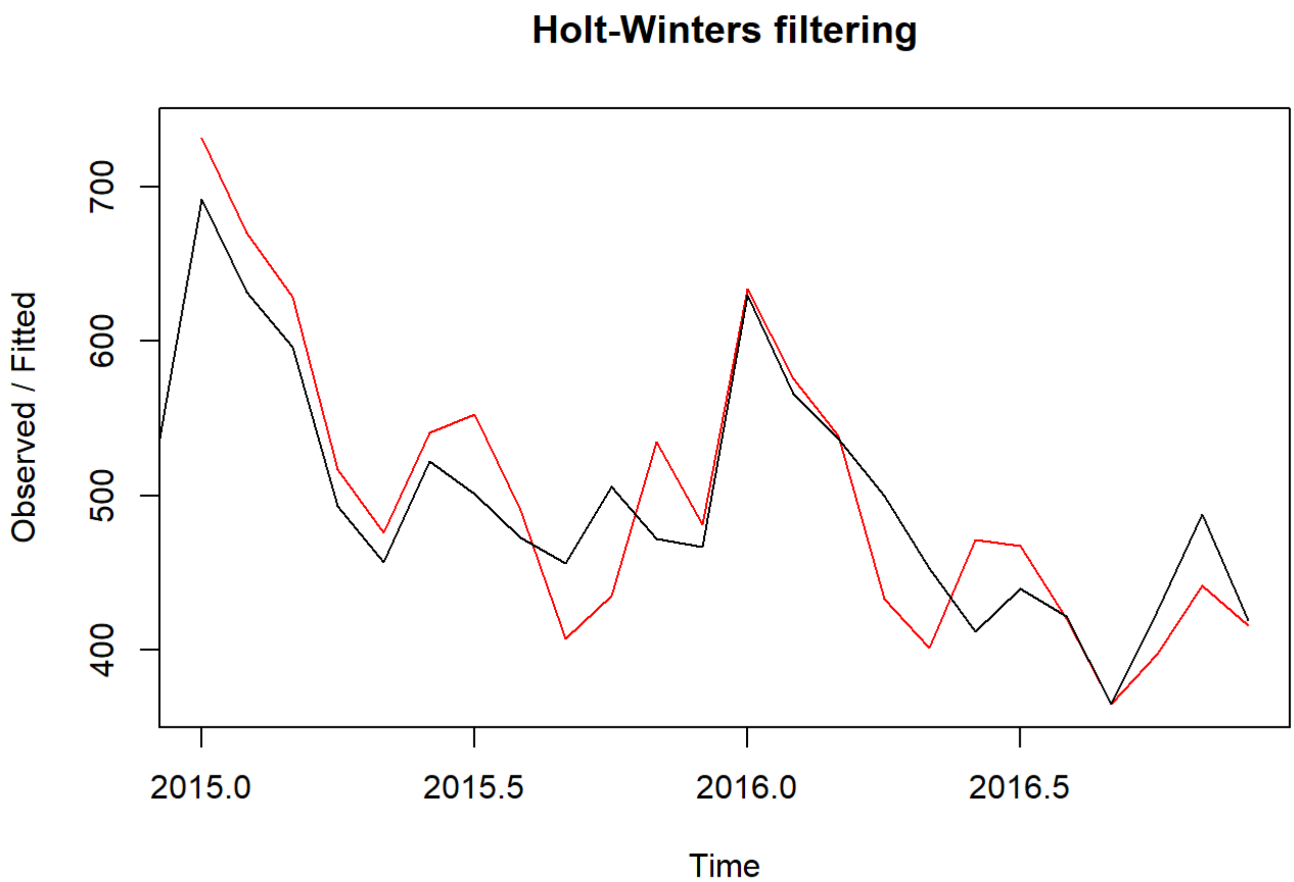

Decomposition of additive time series
observed
trend
seasonal
random
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

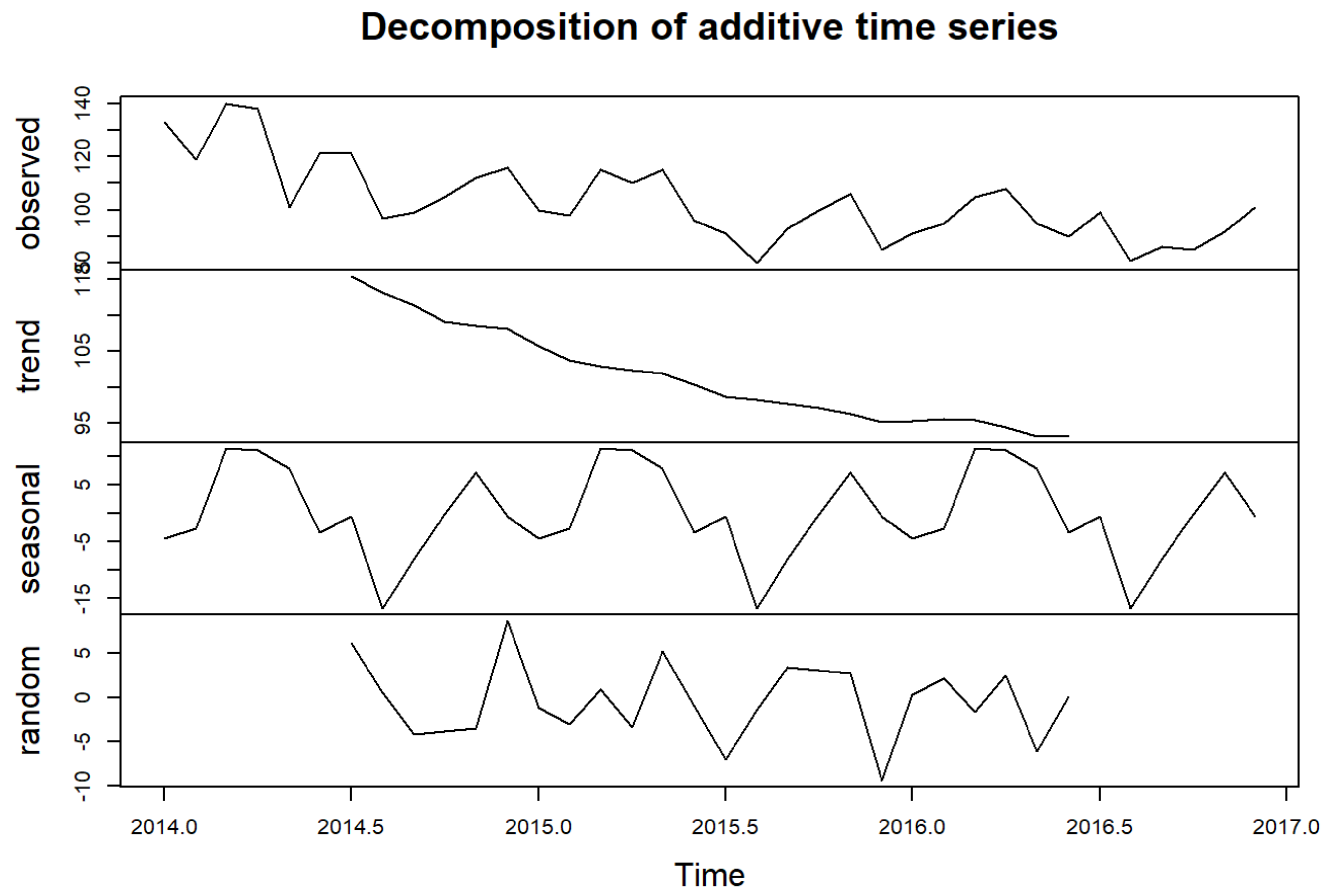

viewers
ACF
Lag
0
5
10
15

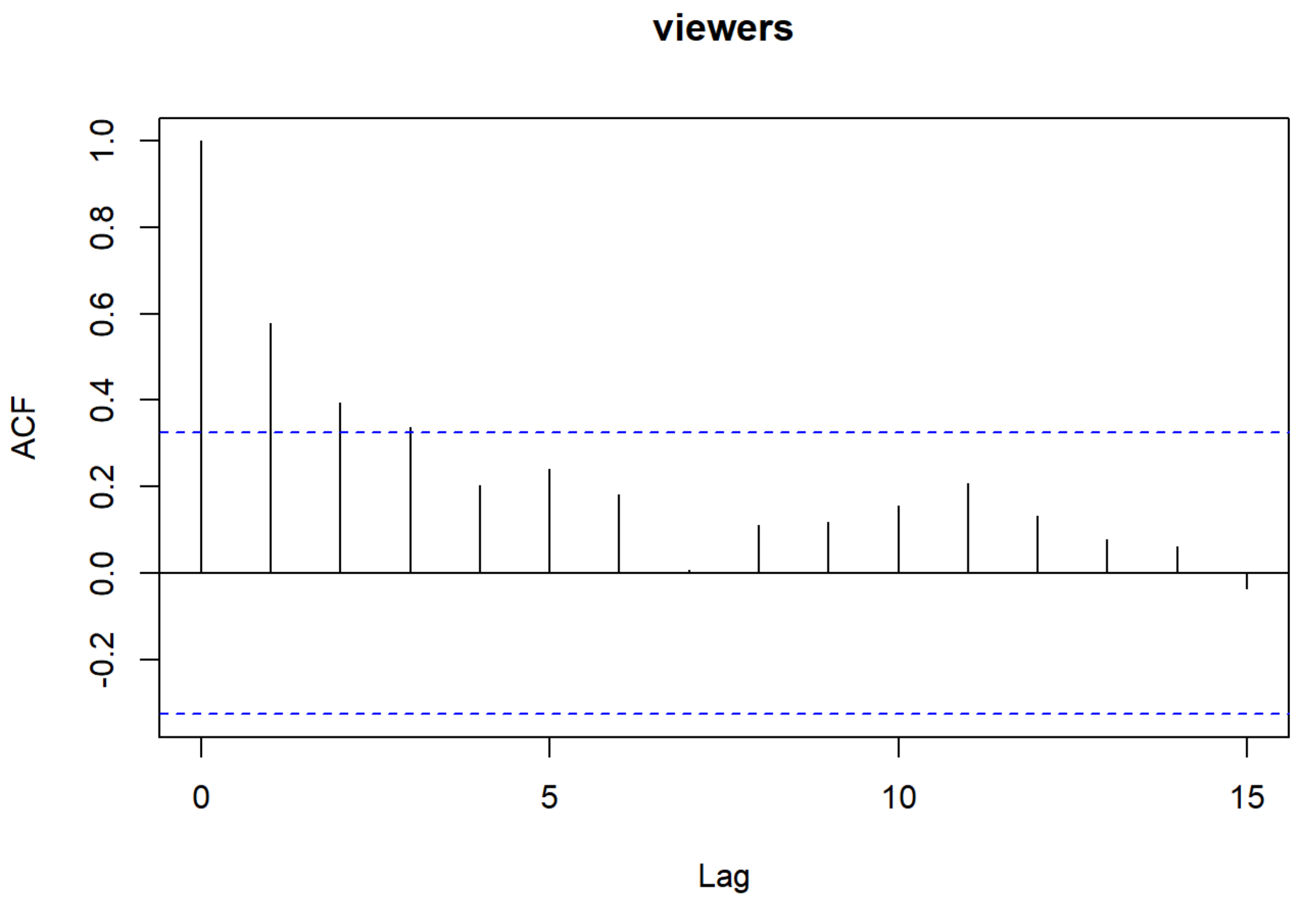

Series train_D[[i]]
Partial ACF
Lag
-0.3
-0.2
-0.1
0.0
0.1
0.2
0.3
2
4
6
8
10
12
14

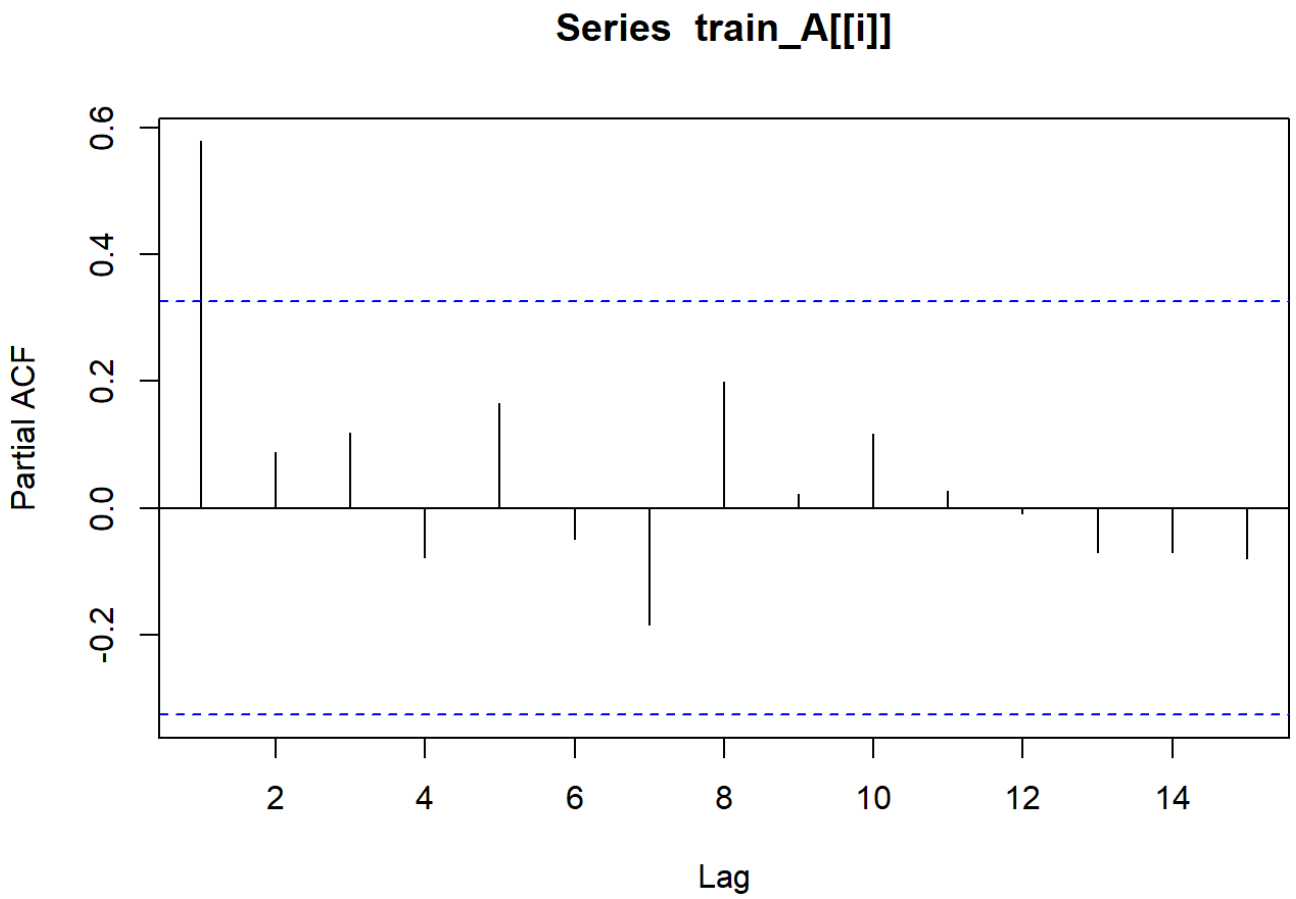

Holt-Winters filtering
Observed / Fitted
Time
140
160
180
200
220
240
2015.0
2015.5
2016.0
2016.5

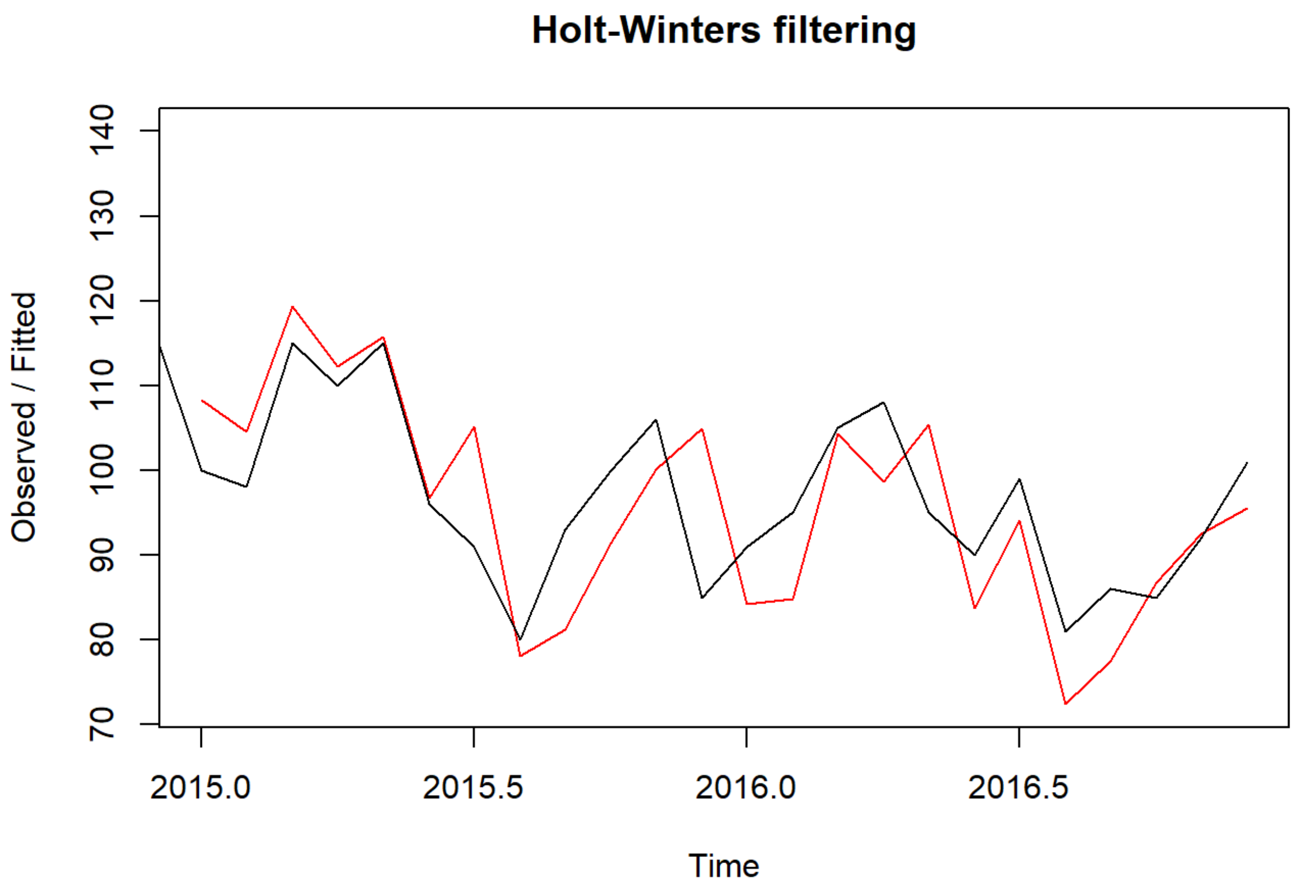

Decomposition of additive time series
observed
trend
seasonal
random
Time

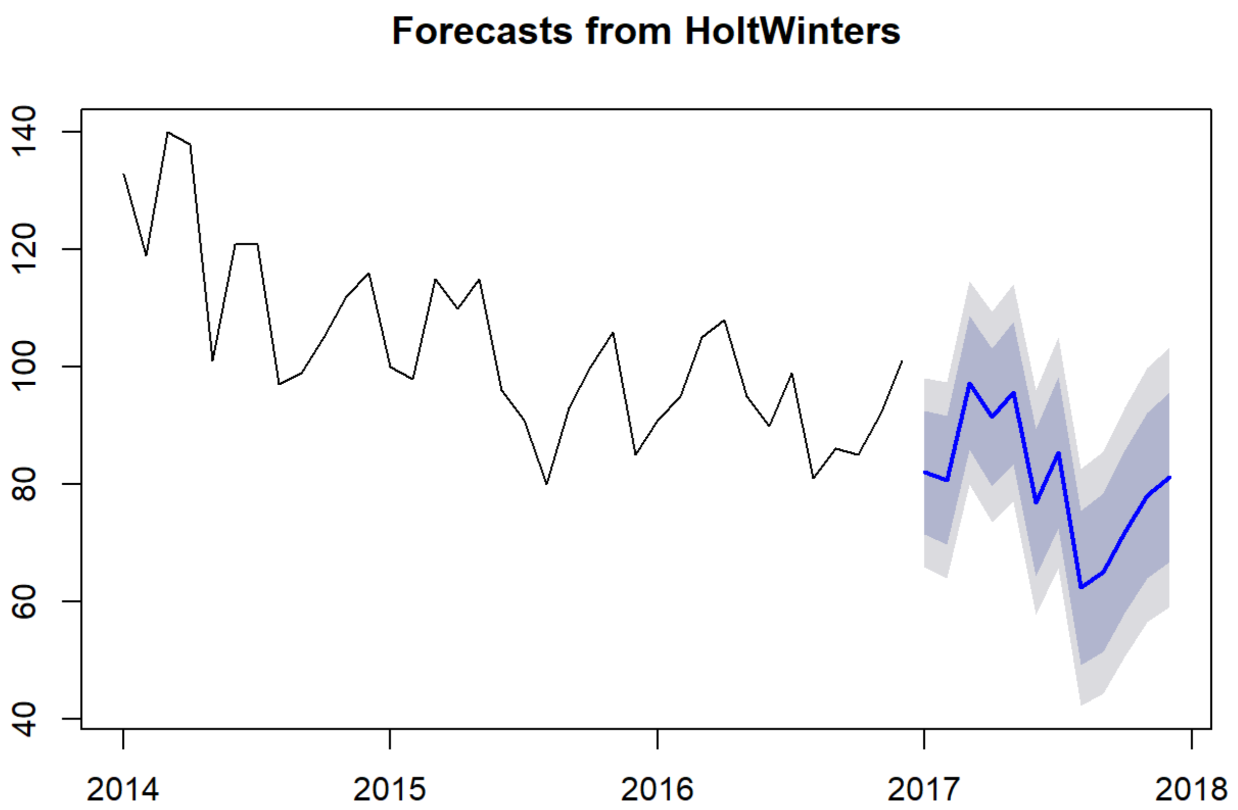

Holt-Winters filtering
Observed / Fitted
Time

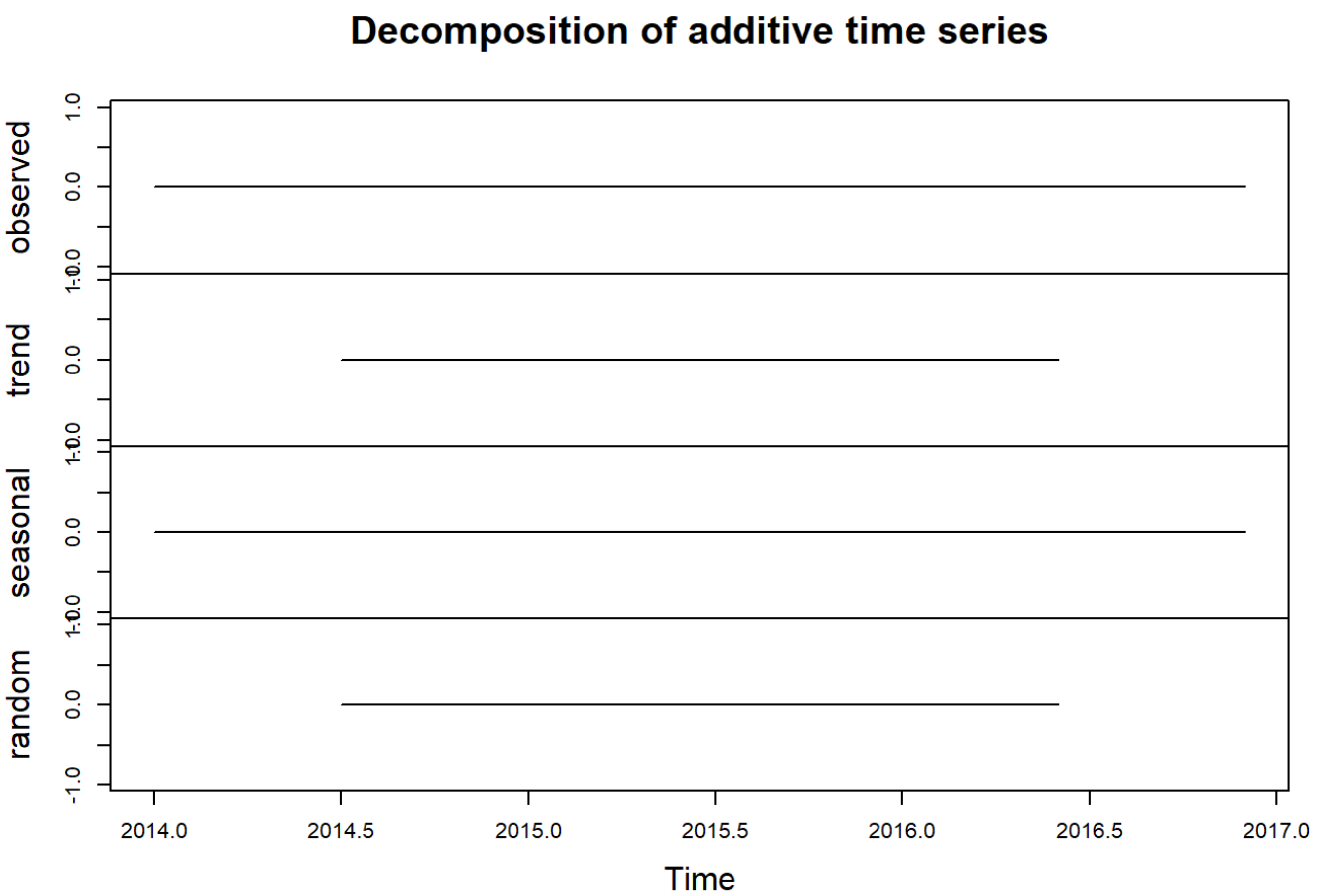

Decomposition of additive time series
observed
trend
seasonal
random
Time
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0

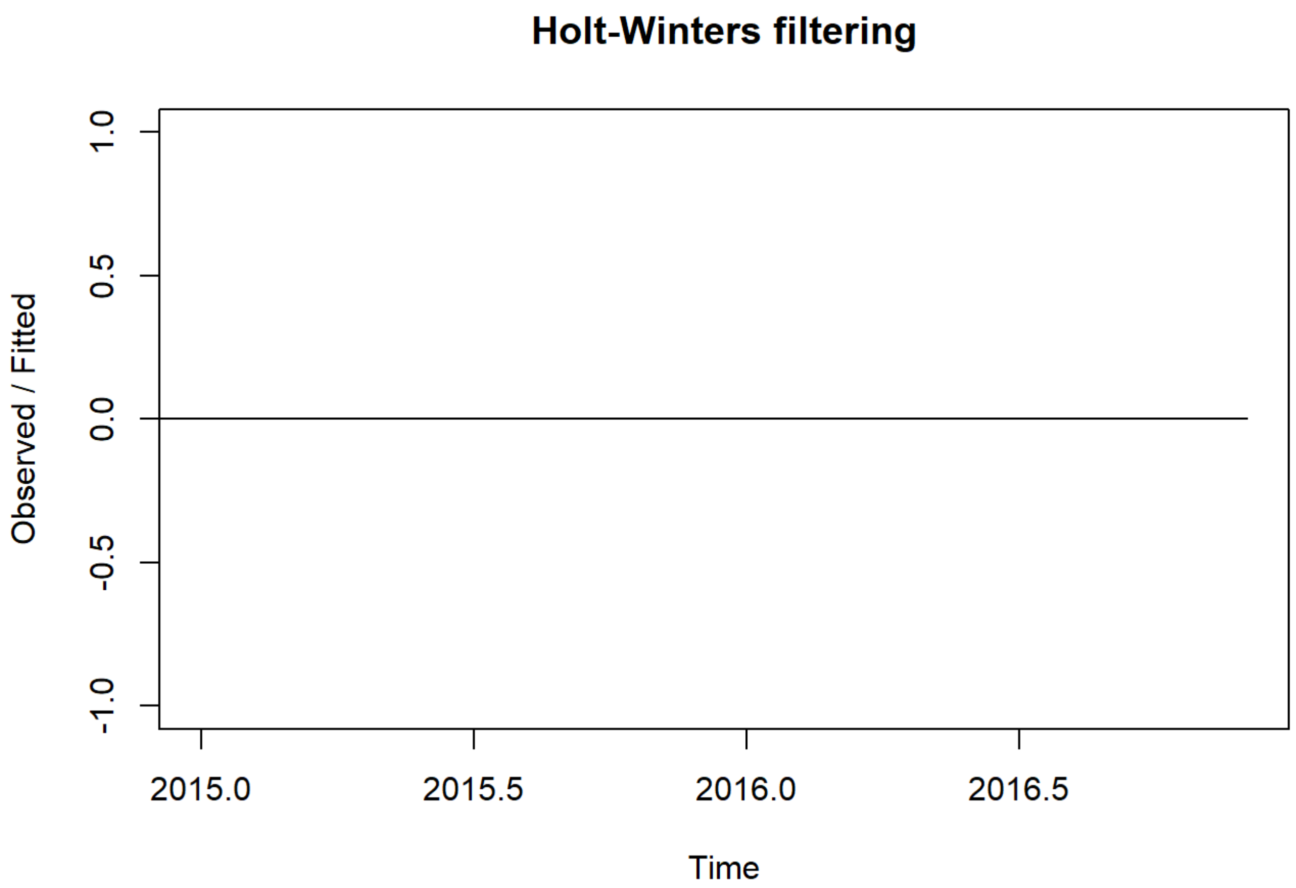

viewers
ACF
Lag
0
5
10
15

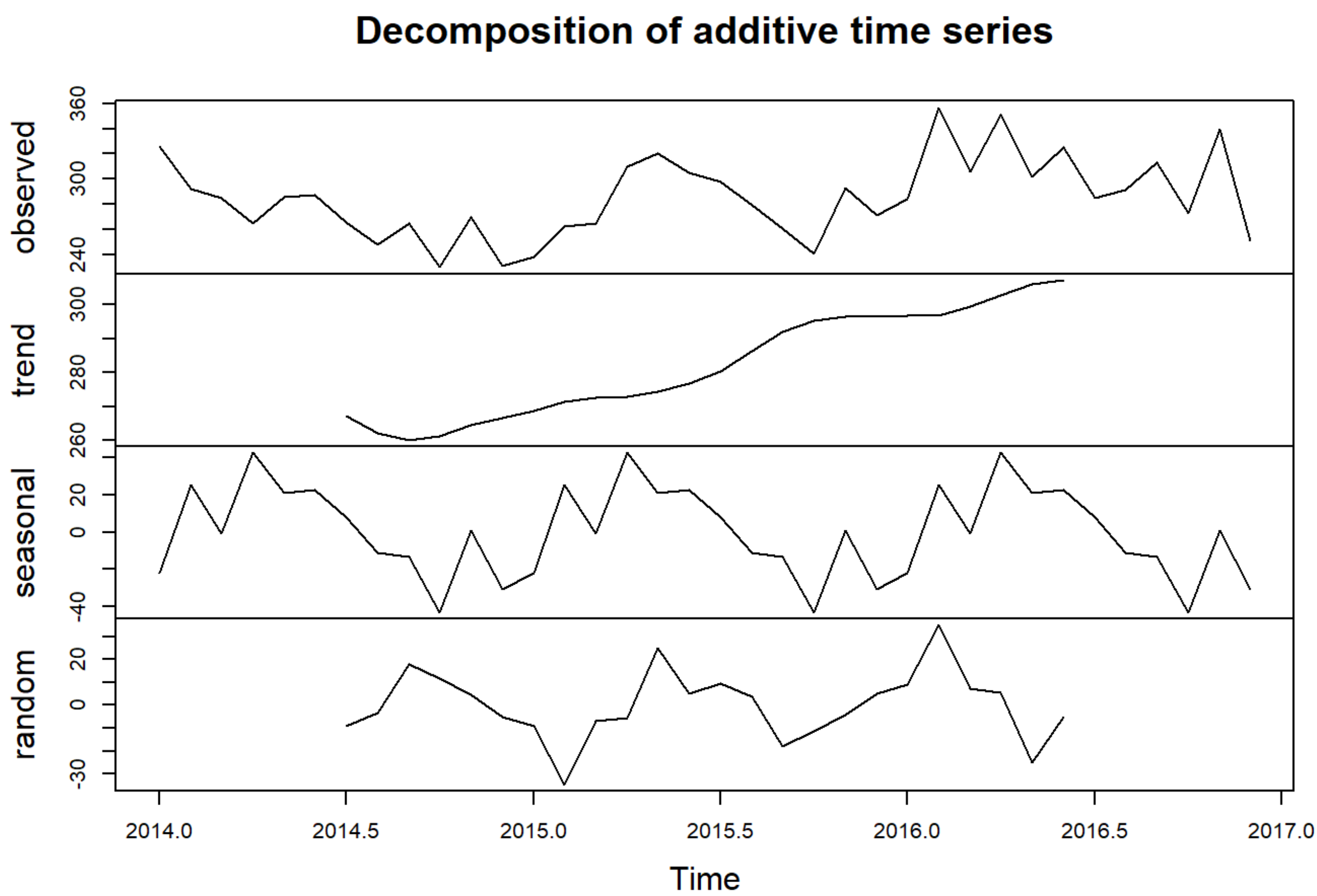

Series train_A[[i]]
Partial ACF
-0.2
0.0
0.2
0.4
0.6
2
4
6
8
10
12
14
Lag

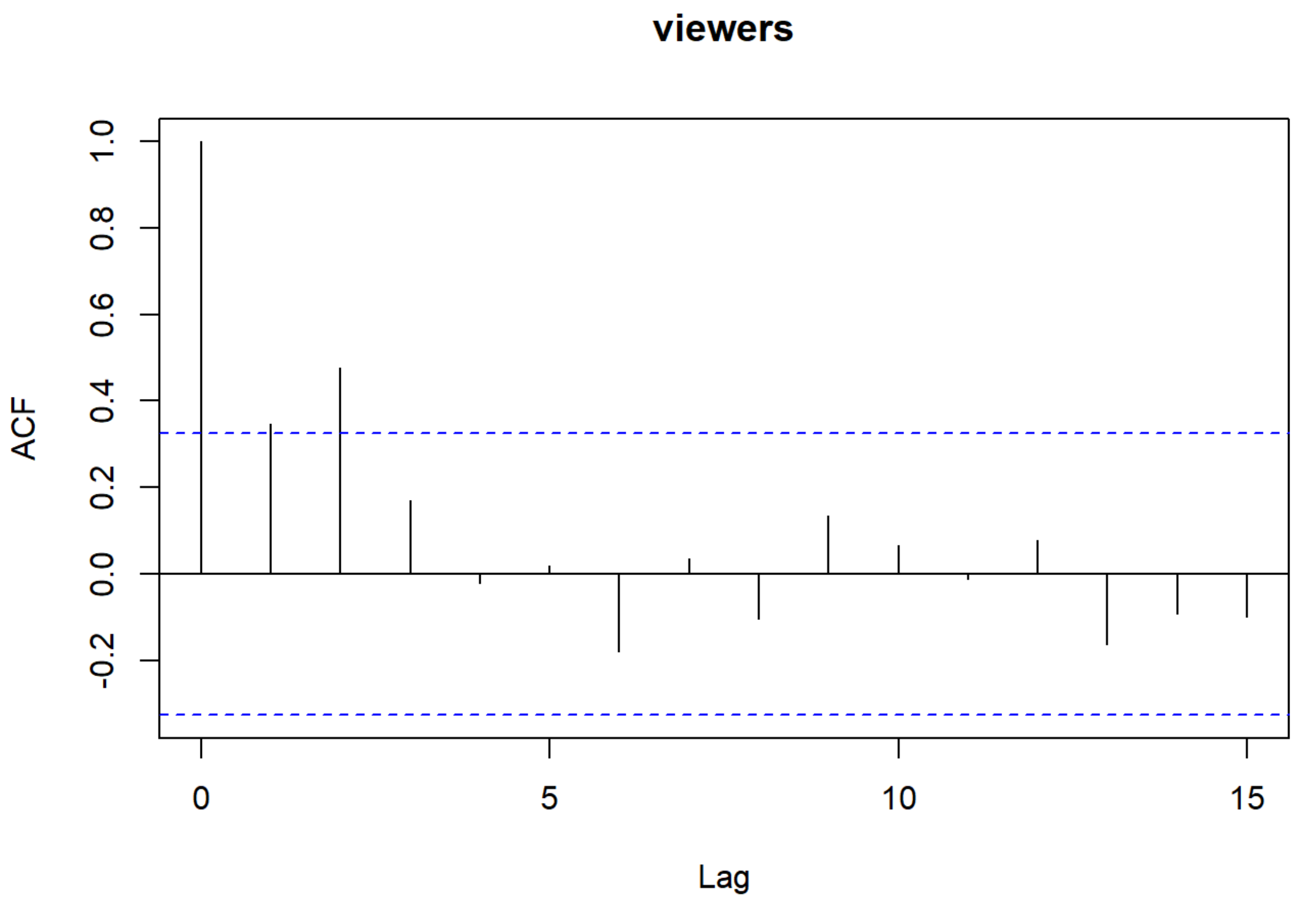

Holt-Winters filtering
Observed / Fitted
70
80
90
100
110
120
130
140
2015.0
2015.5
2016.0
2016.5
Time

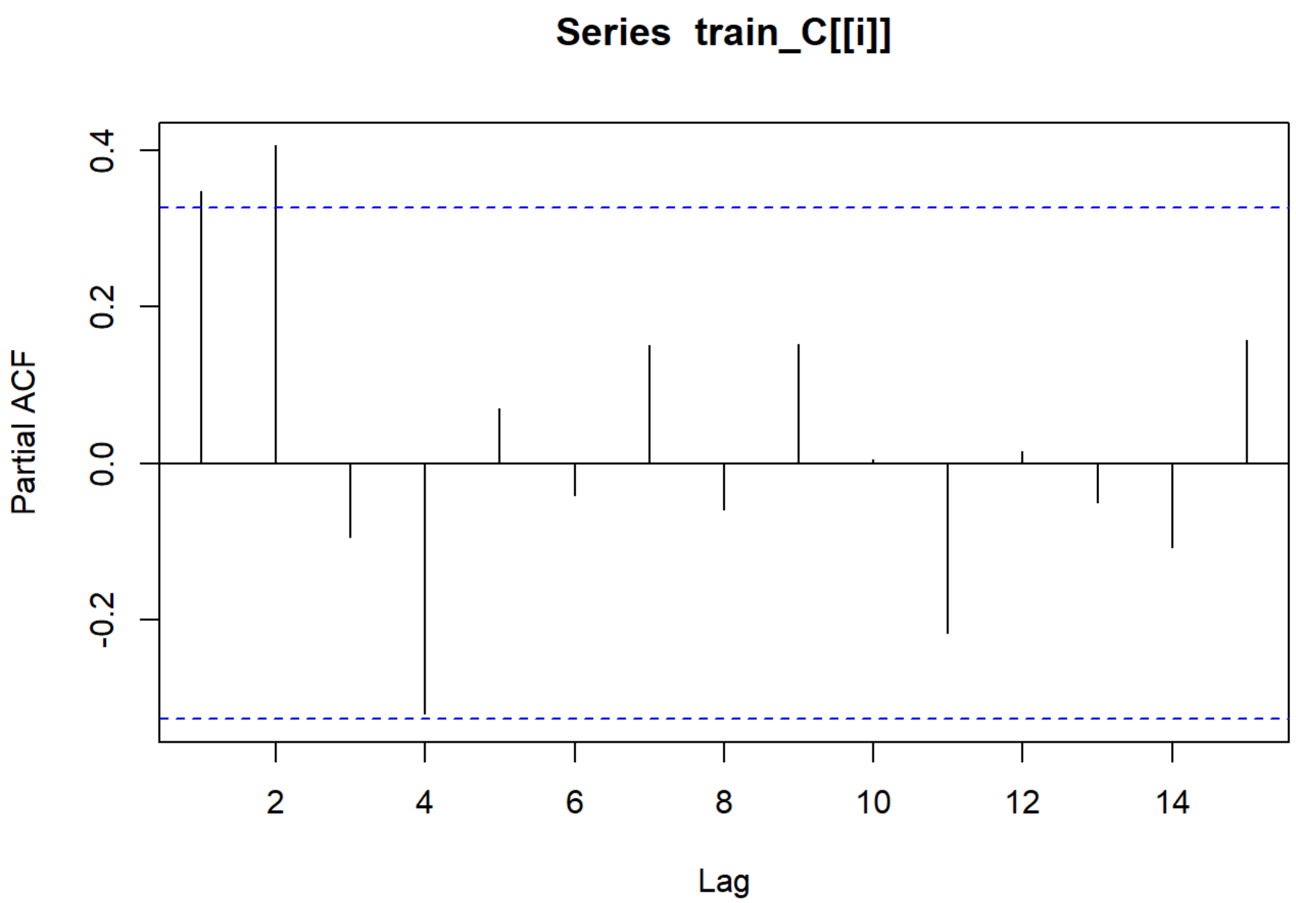

Forecasts from HoltWinters
140
120
100
80
60
40
2014
2015
2016
2017
2018

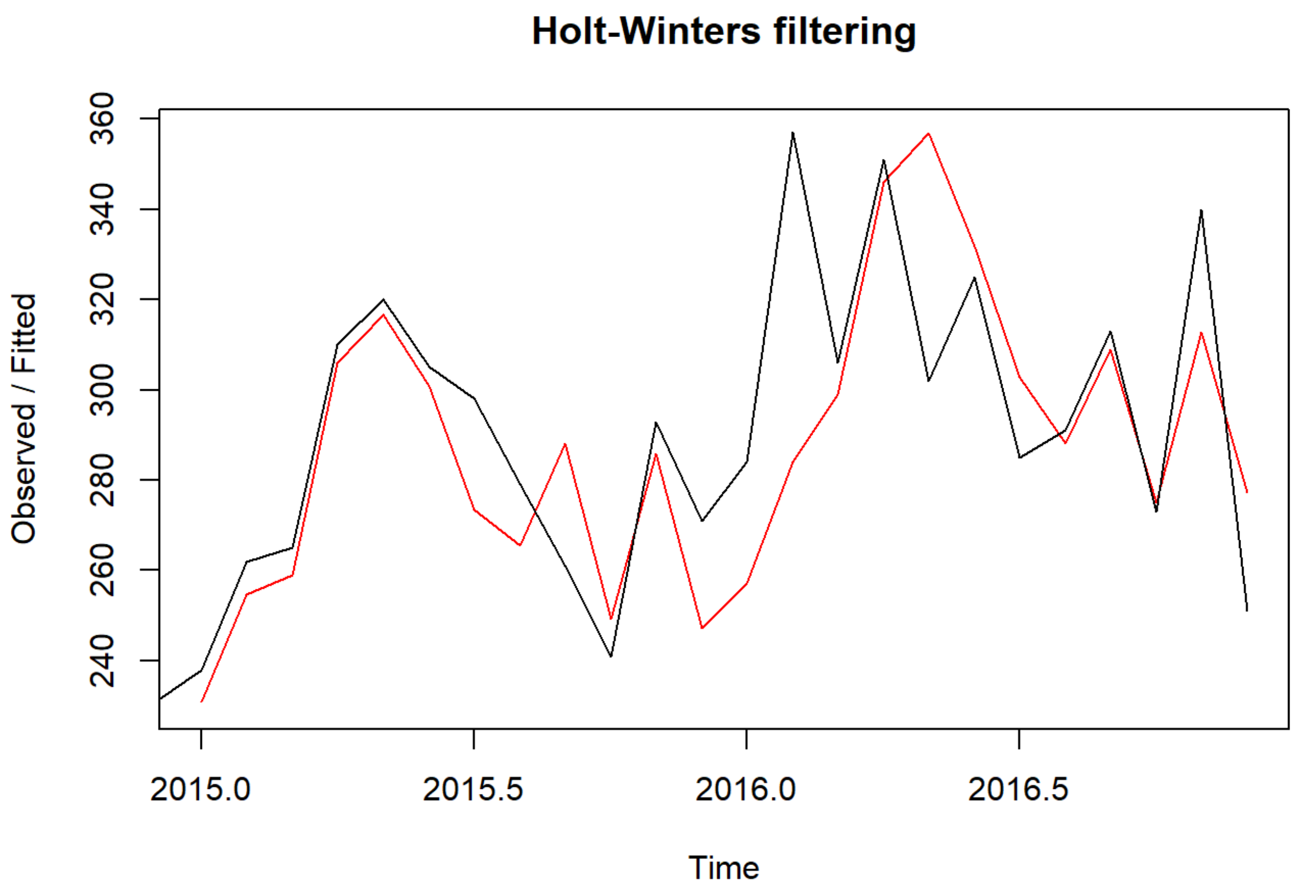

Decomposition of additive time series
observed
trend
seasonal
random
1.0
0.0
-1.0
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time


Holt-Winters filtering
Observed / Fitted
1.0
0.5
0.0
-0.5
-1.0
2015.0
2015.5
2016.0
2016.5
Time

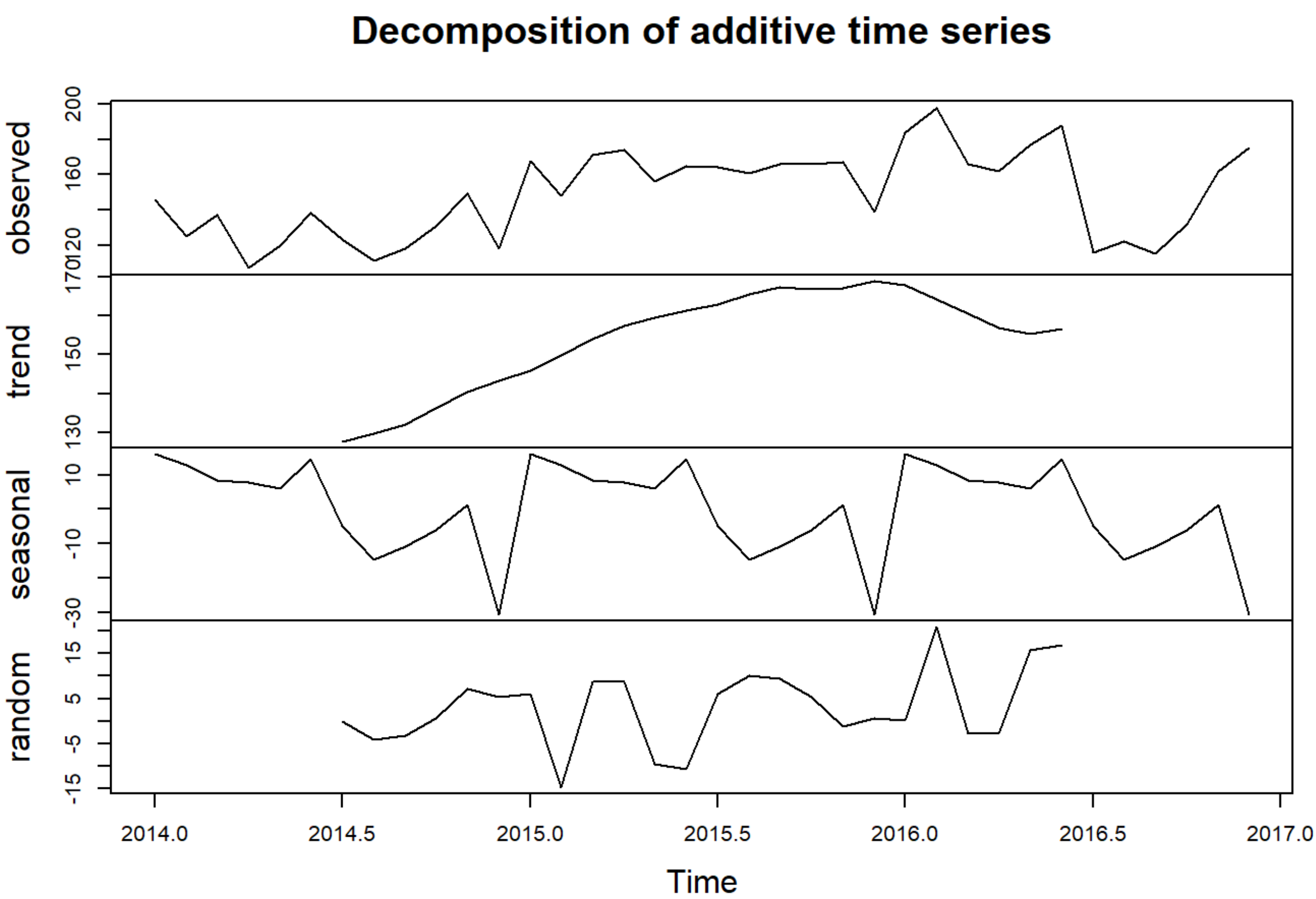

Decomposition of additive time series
observed
trend
seasonal
random
360
300
240
300
280
260
20
0
-40
20
0
-30
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time


viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag


Series train_C[[i]]
Partial ACF
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag

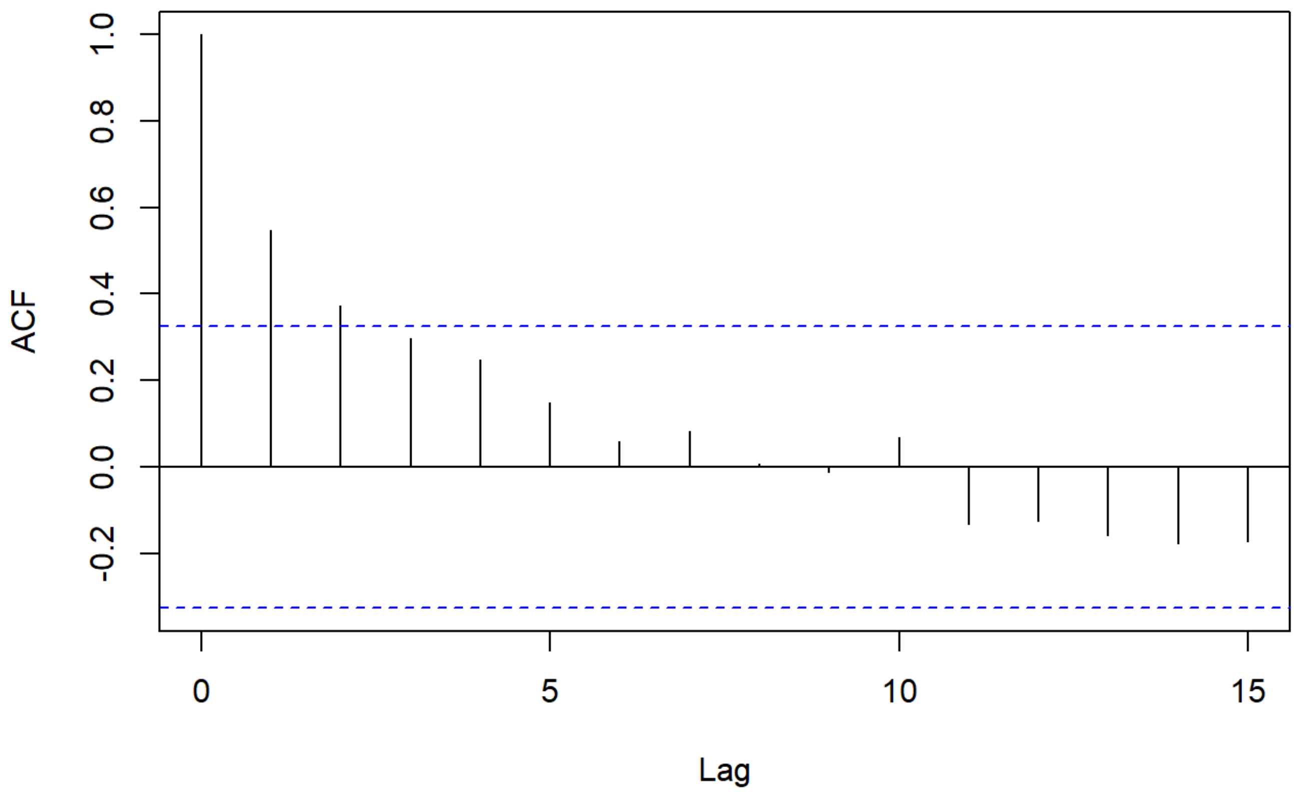


Holt-Winters filtering
Observed / Fitted
240
260
280
300
320
340
360
2015.0
2015.5
2016.0
2016.5
Time

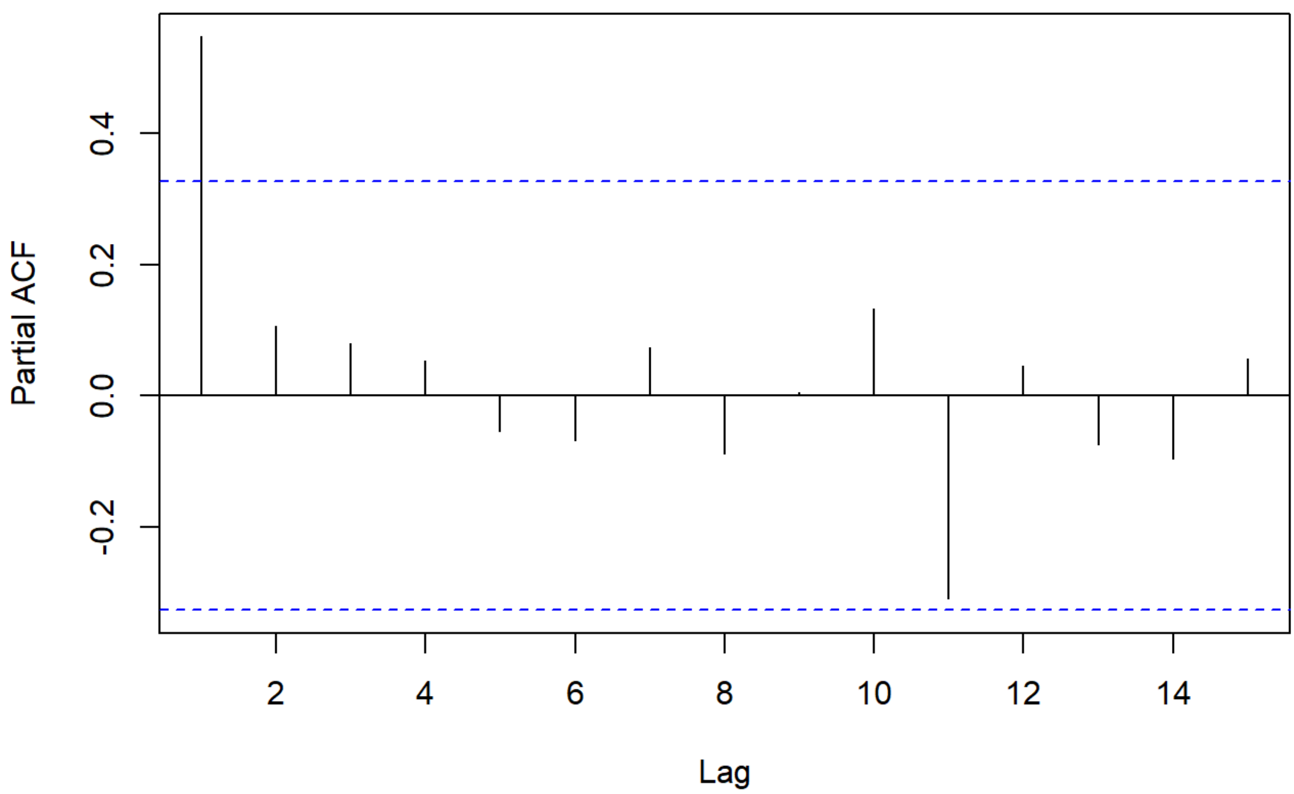



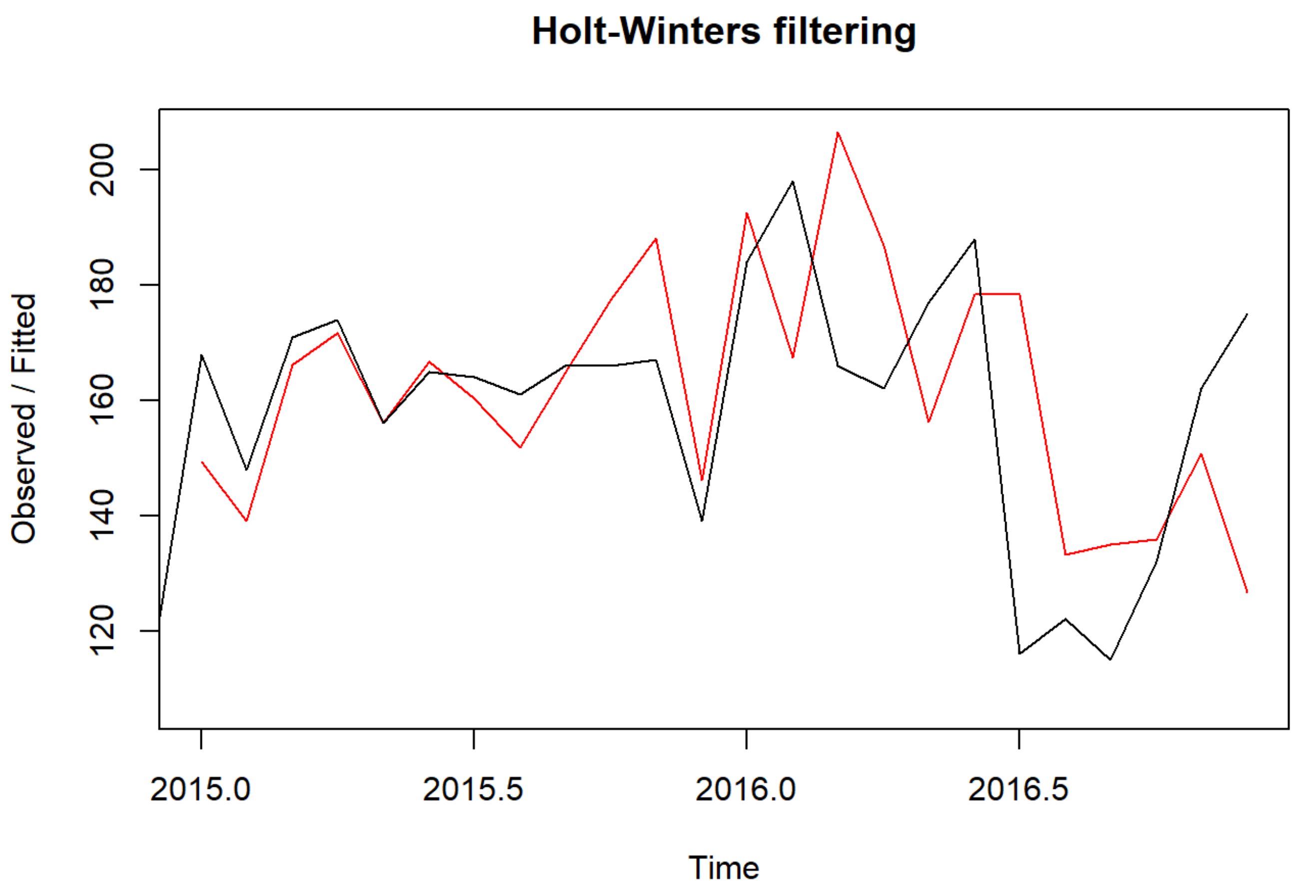
Decomposition of additive time series
observed
trend
seasonal
random
120
160
200
130
150
170
-30
-10
10
-15
-5
5
15
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

**viewers**

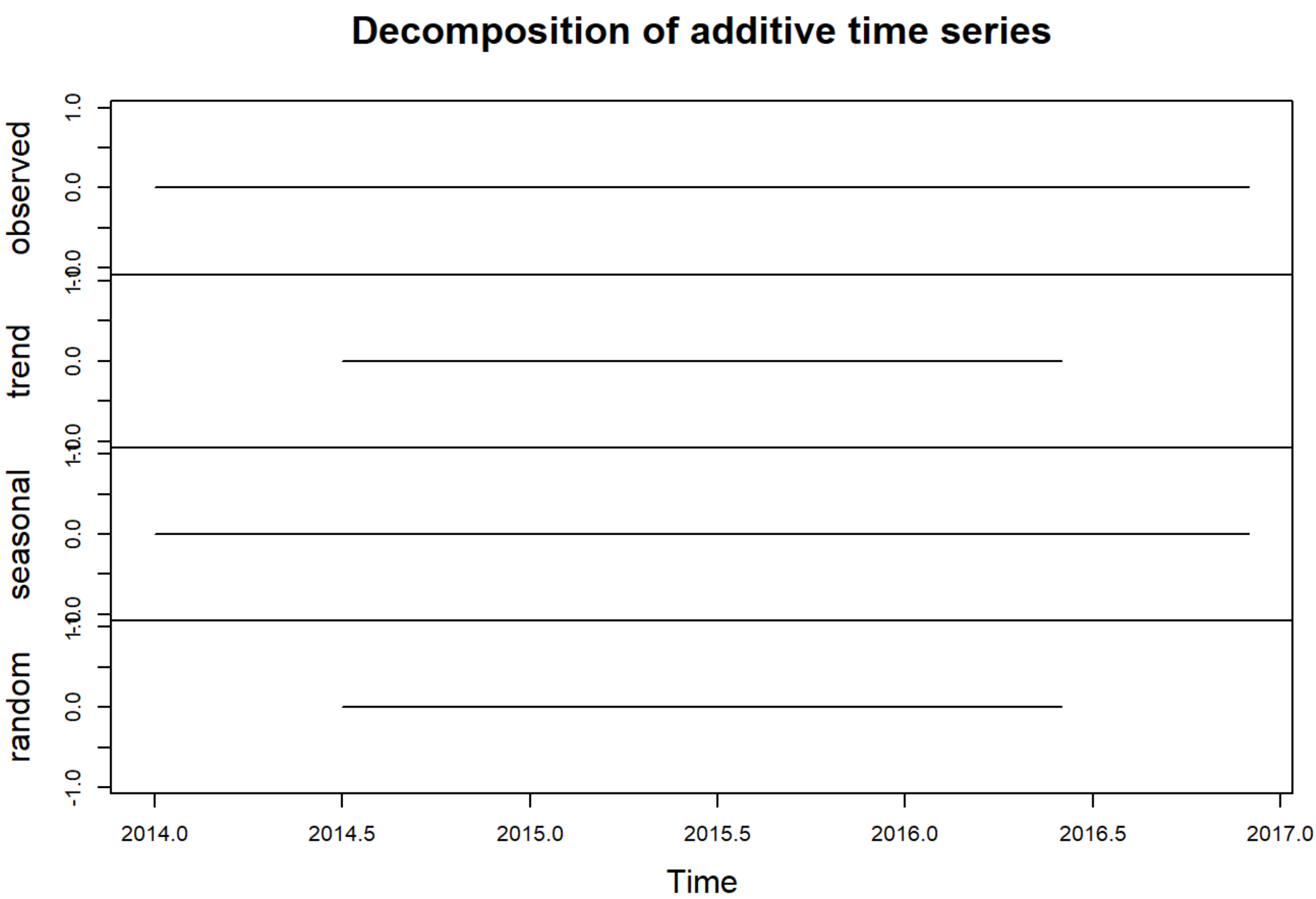



**Series train_D[[i]]**

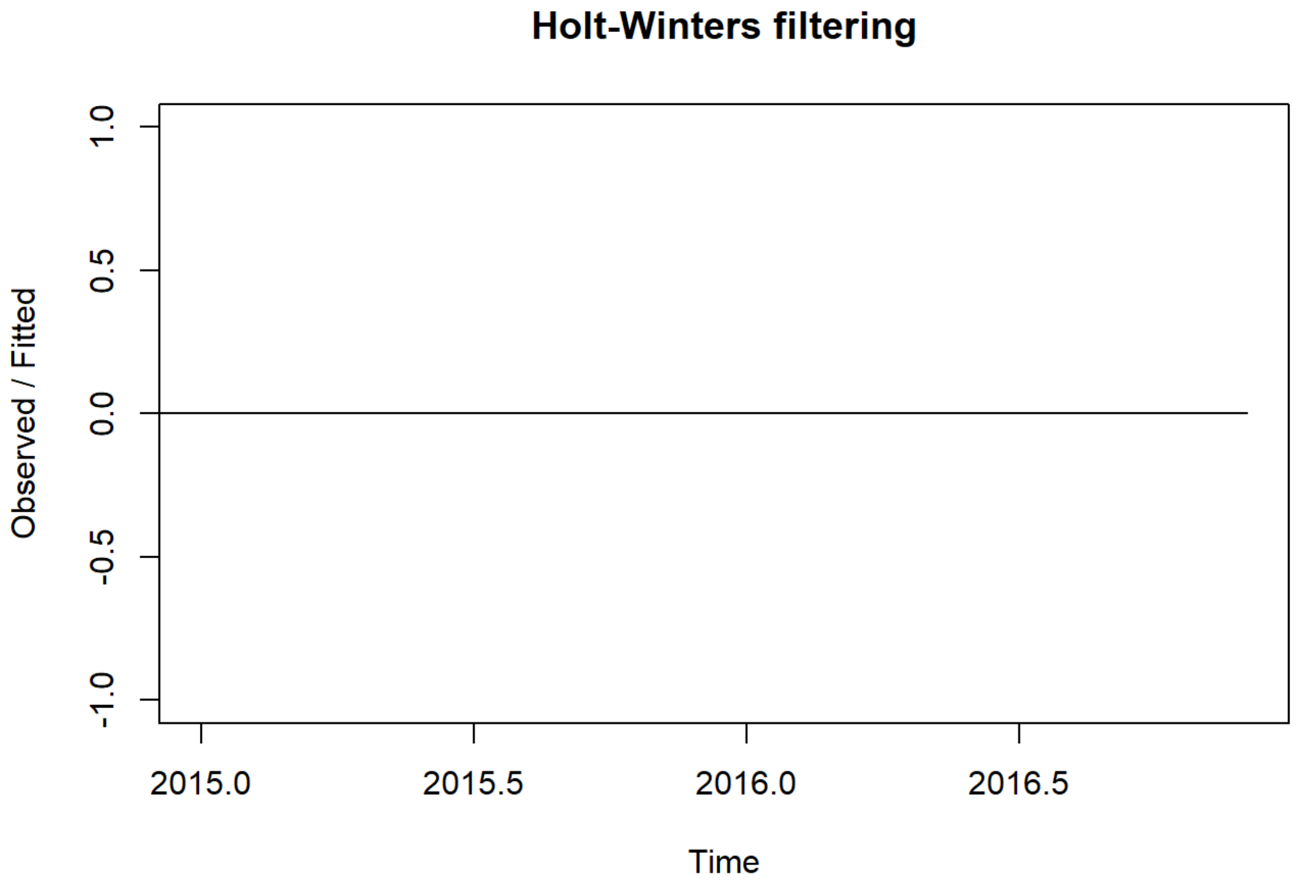




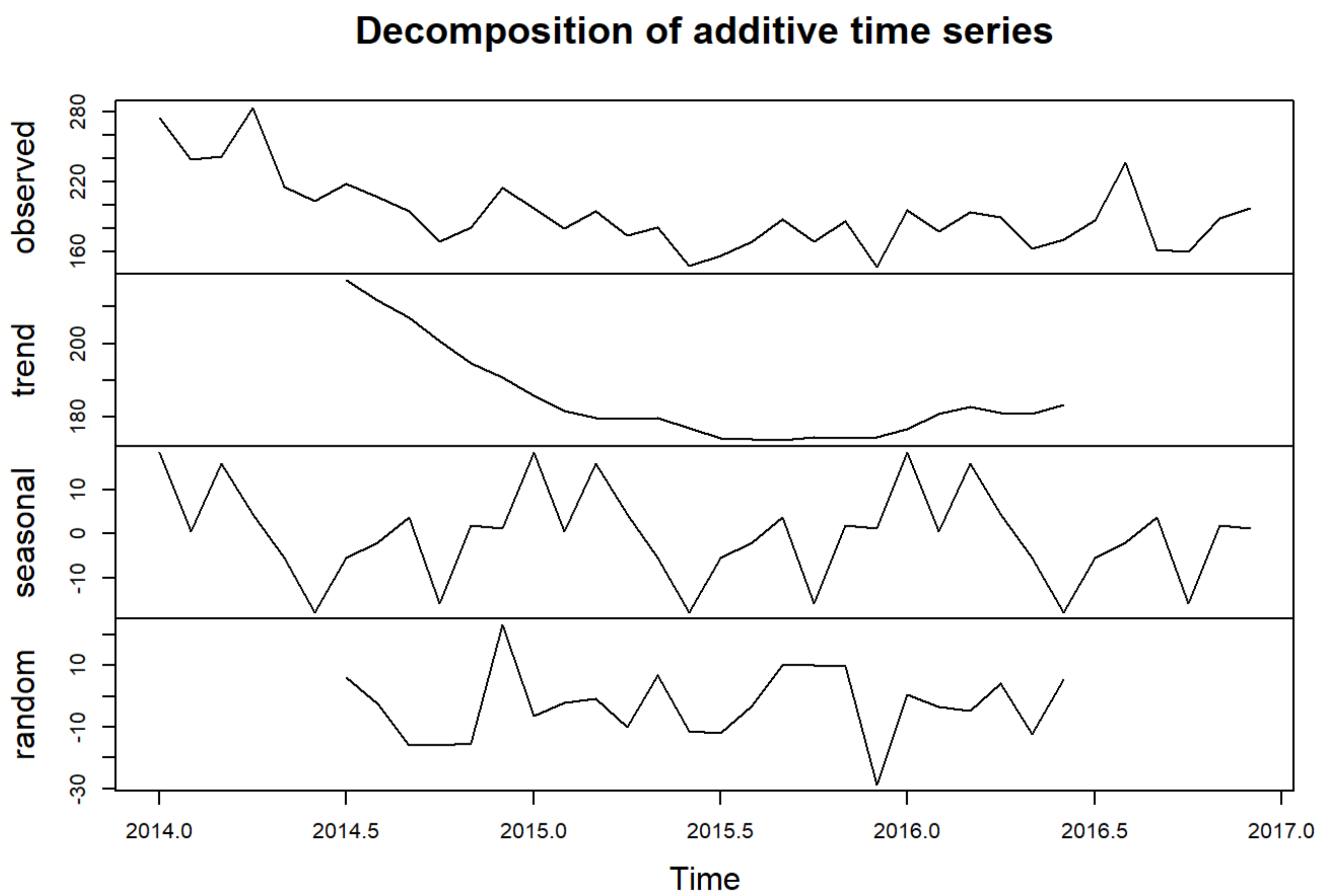
Holt-Winters filtering
Observed / Fitted
200
180
160
140
120
2015.0
2015.5
2016.0
2016.5
Time

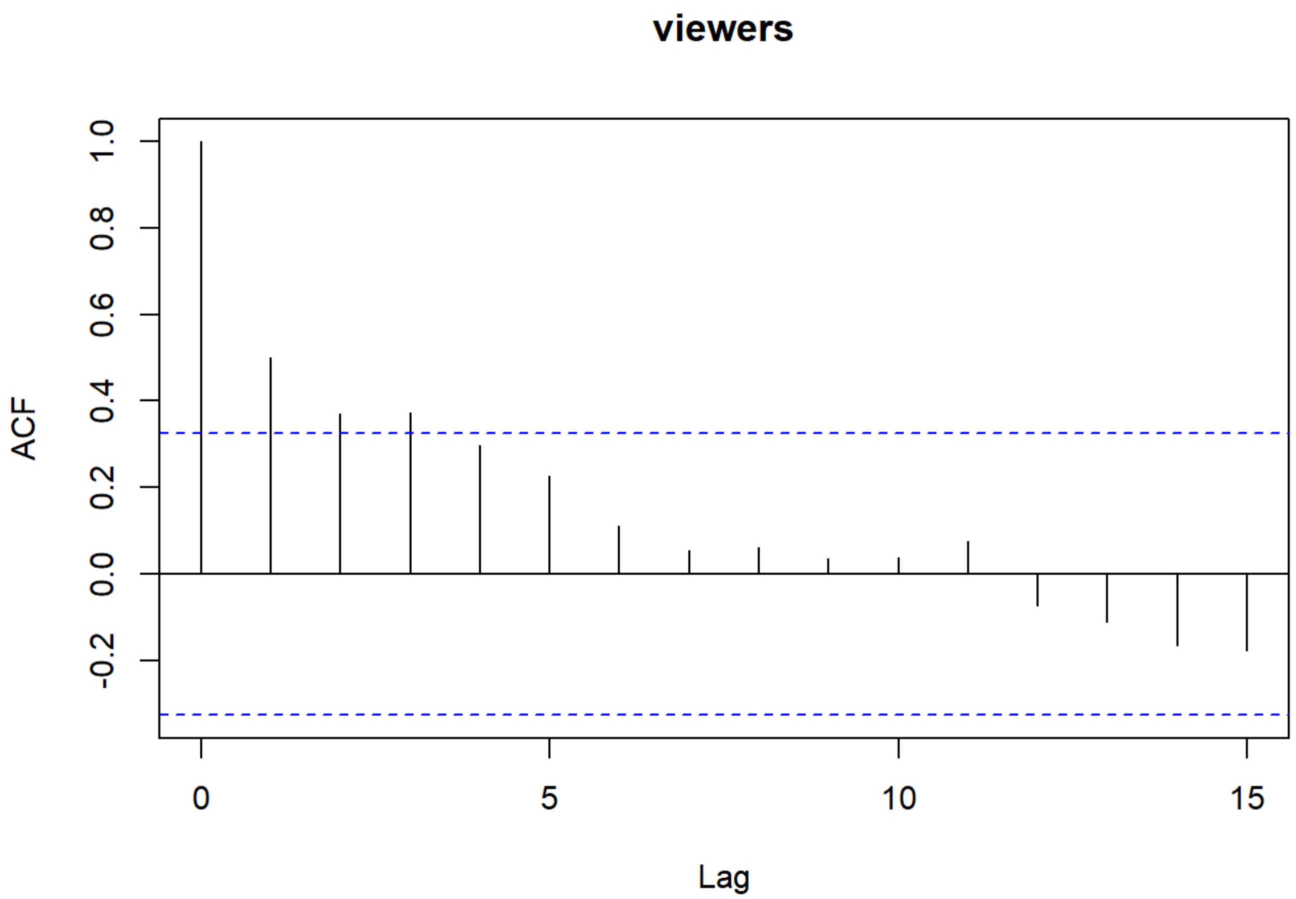
Decomposition of additive time series
observed
trend
seasonal
random
1.0
0.0
-1.0
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

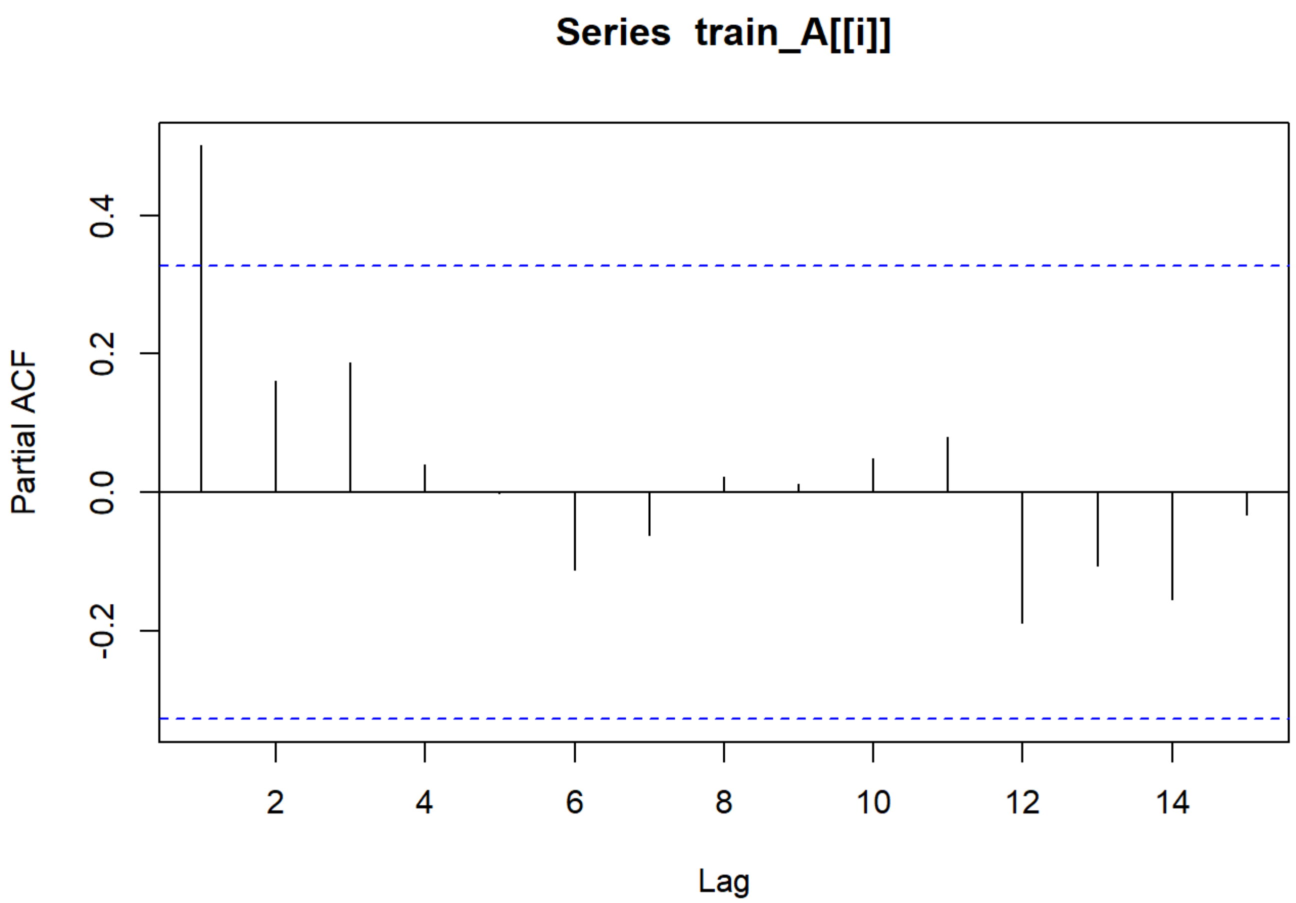


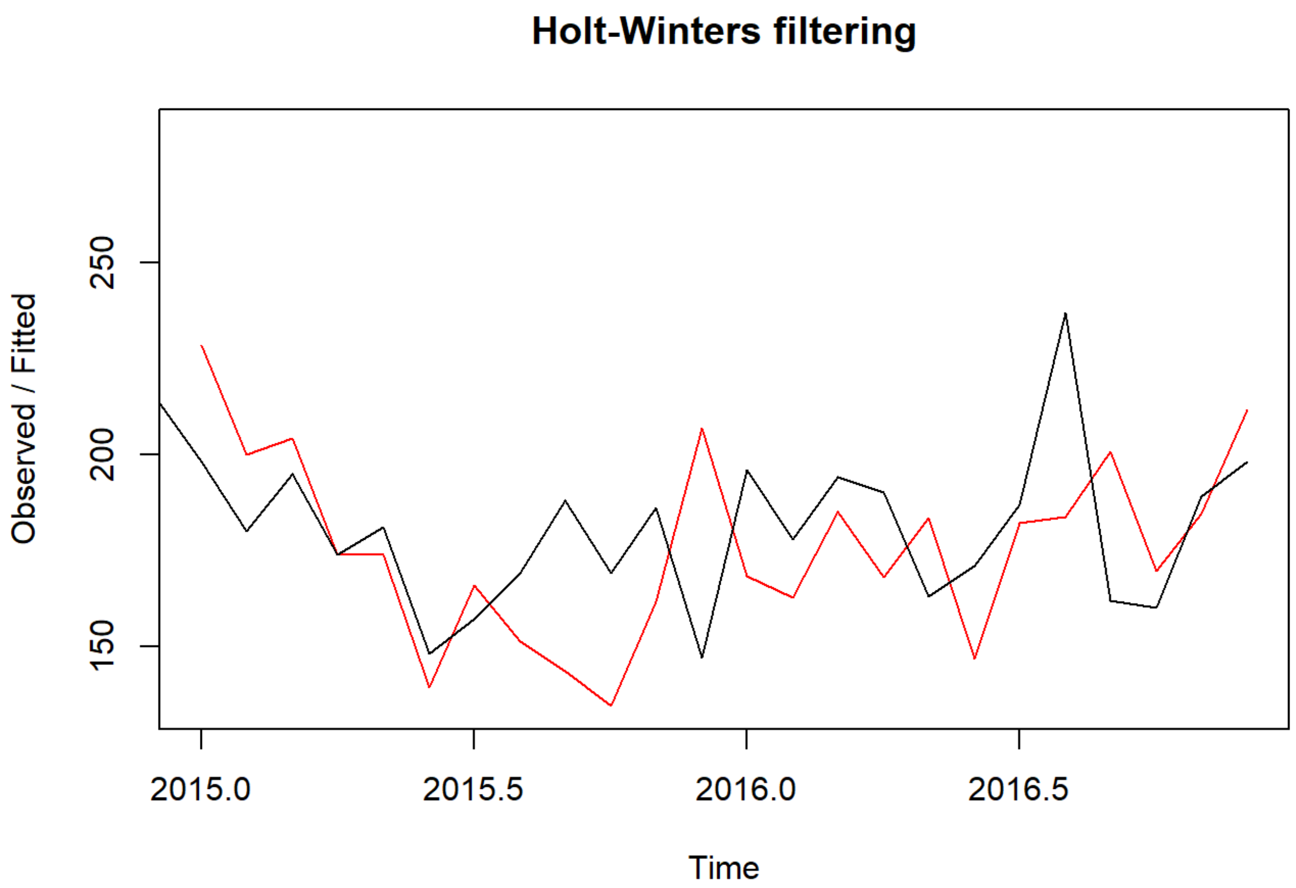
Holt-Winters filtering
Observed / Fitted
1.0
0.5
0.0
-0.5
-1.0
2015.0
2015.5
2016.0
2016.5
Time

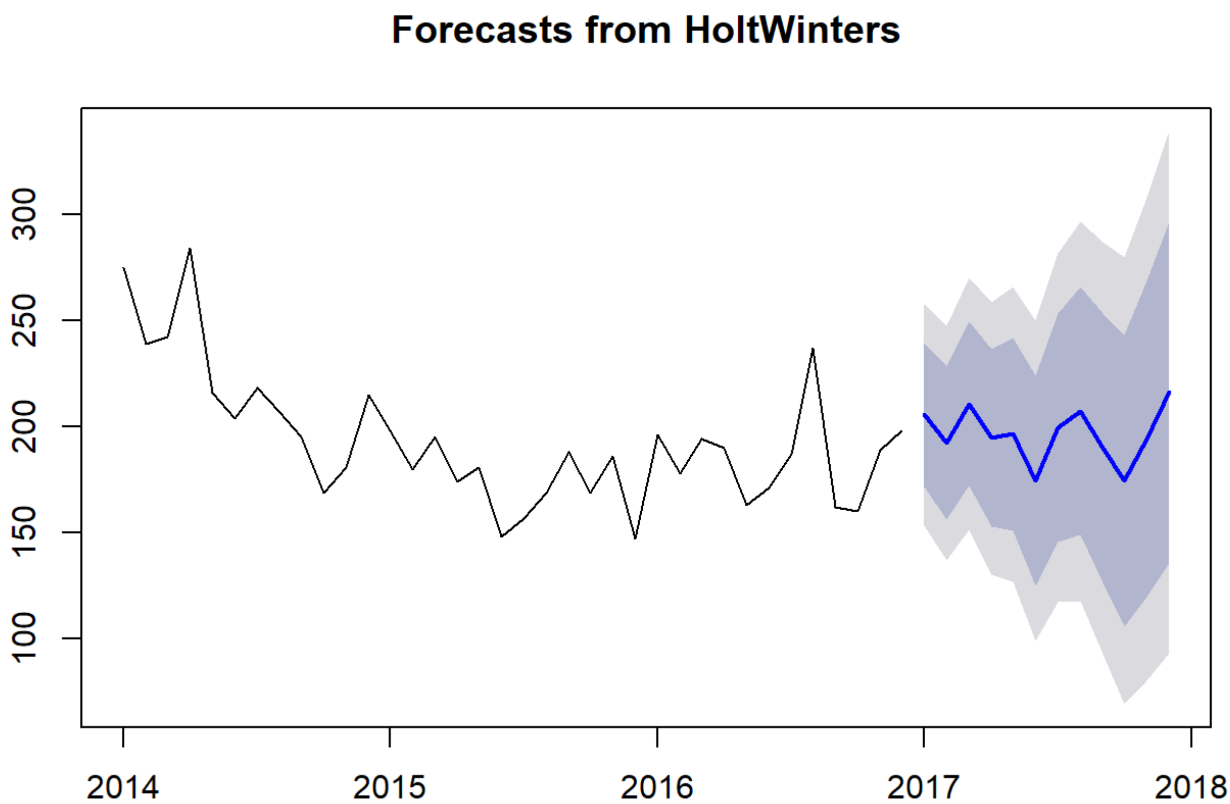



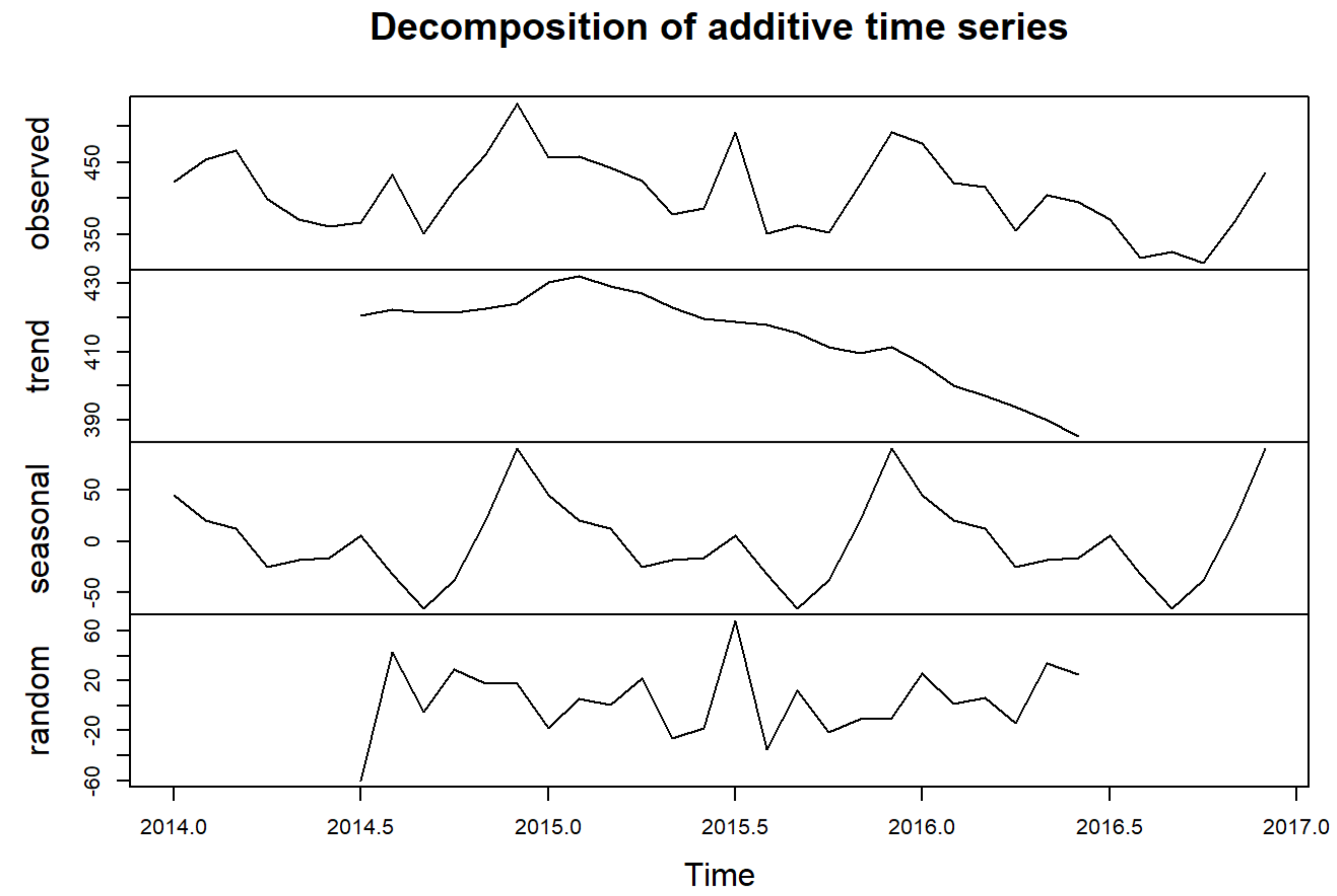
Decomposition of additive time series
observed
280
220
160
trend
200
180
seasonal
10
0
-10
random
10
-10
-30
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time

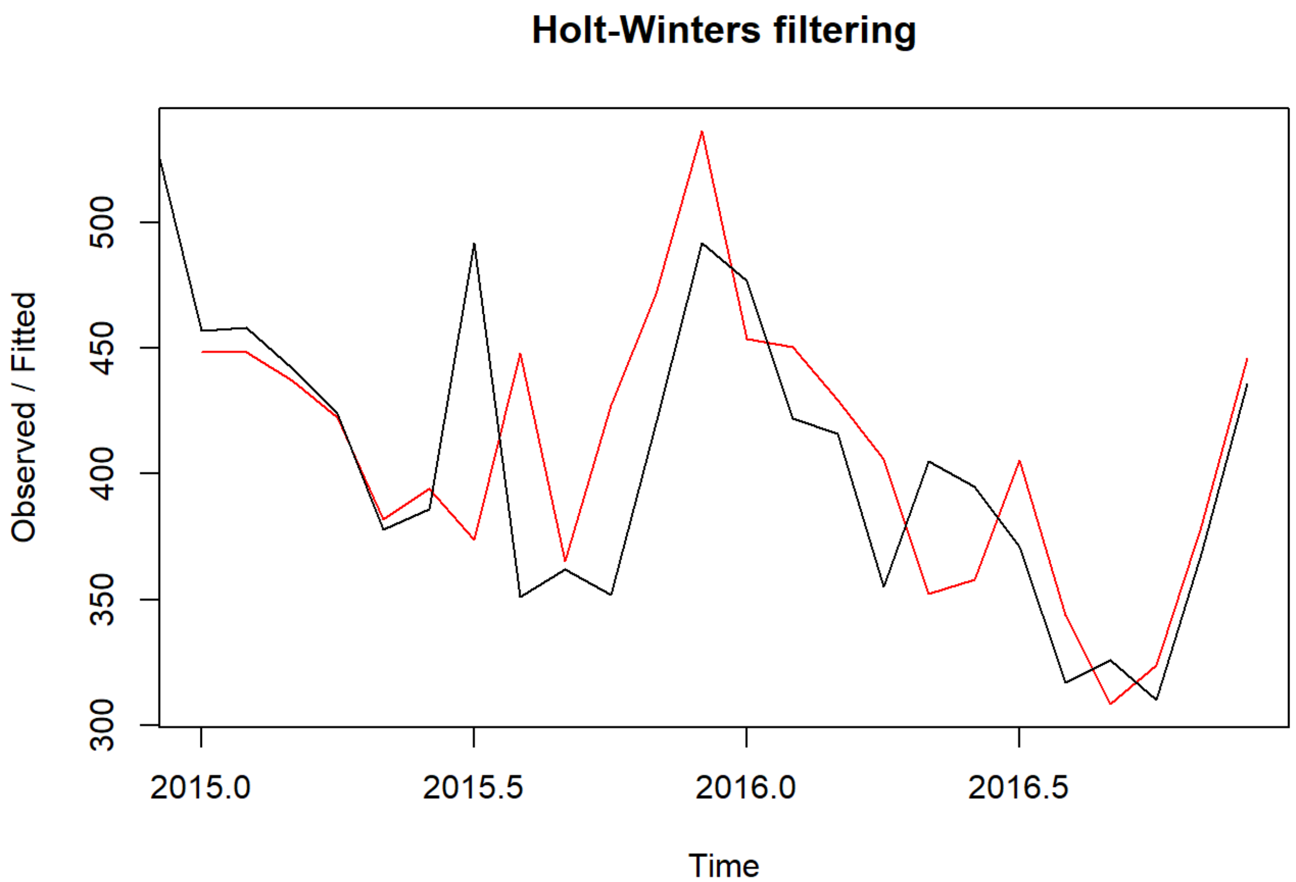

viewers
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
Lag

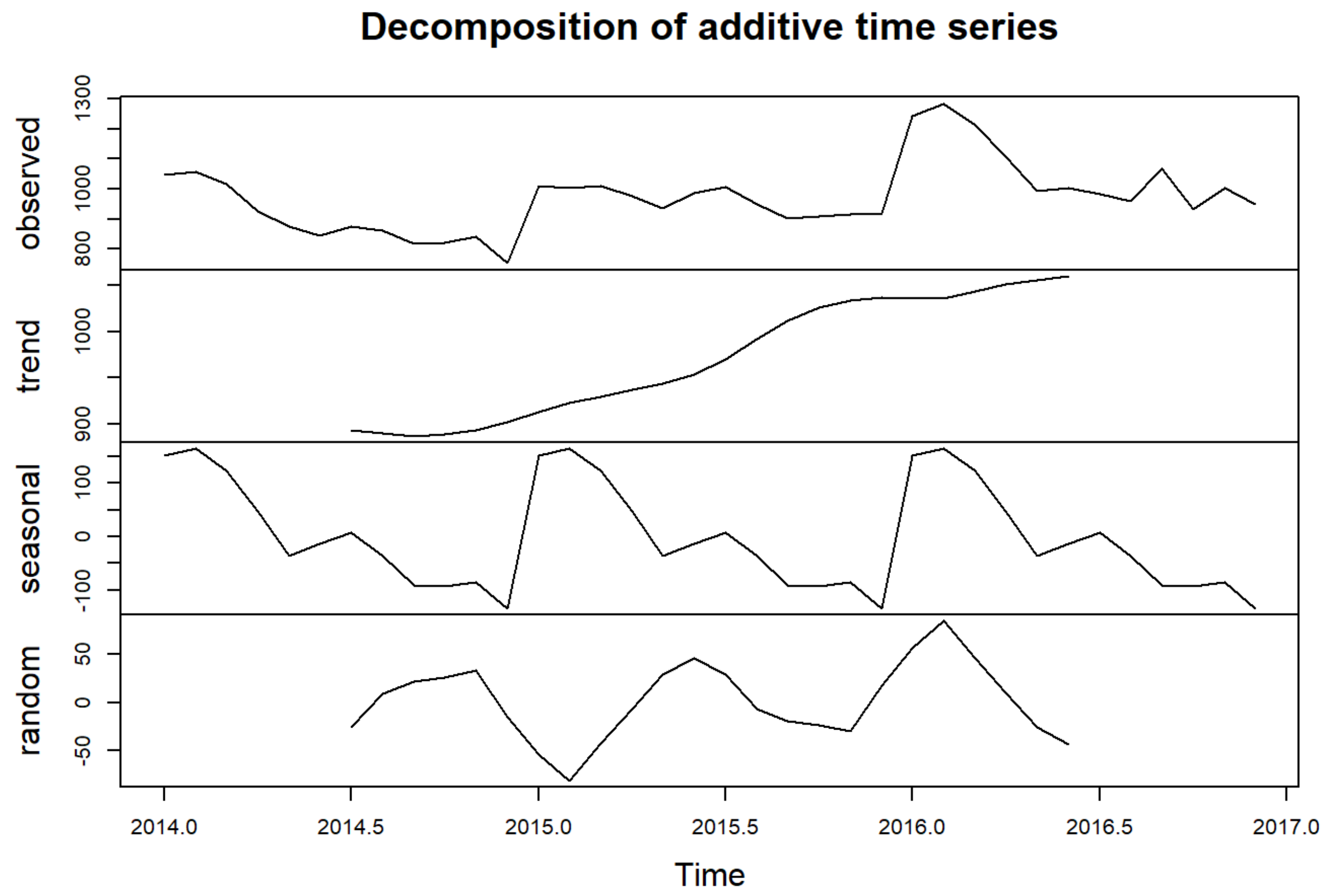

Series train_A[[i]]
Partial ACF
0.4
0.2
0.0
-0.2
2
4
6
8
10
12
14
Lag

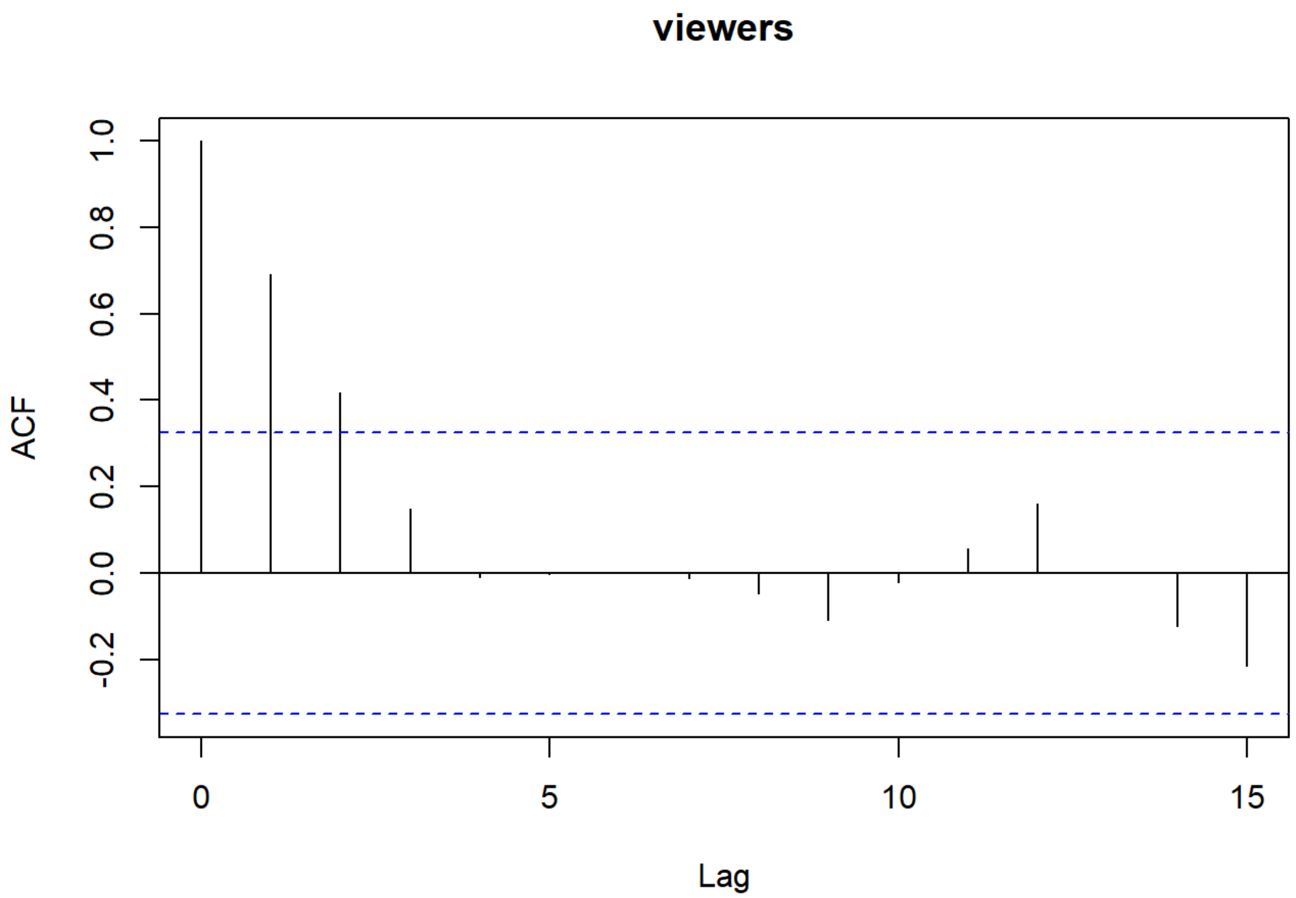

Holt-Winters filtering
Observed / Fitted
250
200
150
2015.0
2015.5
2016.0
2016.5
Time

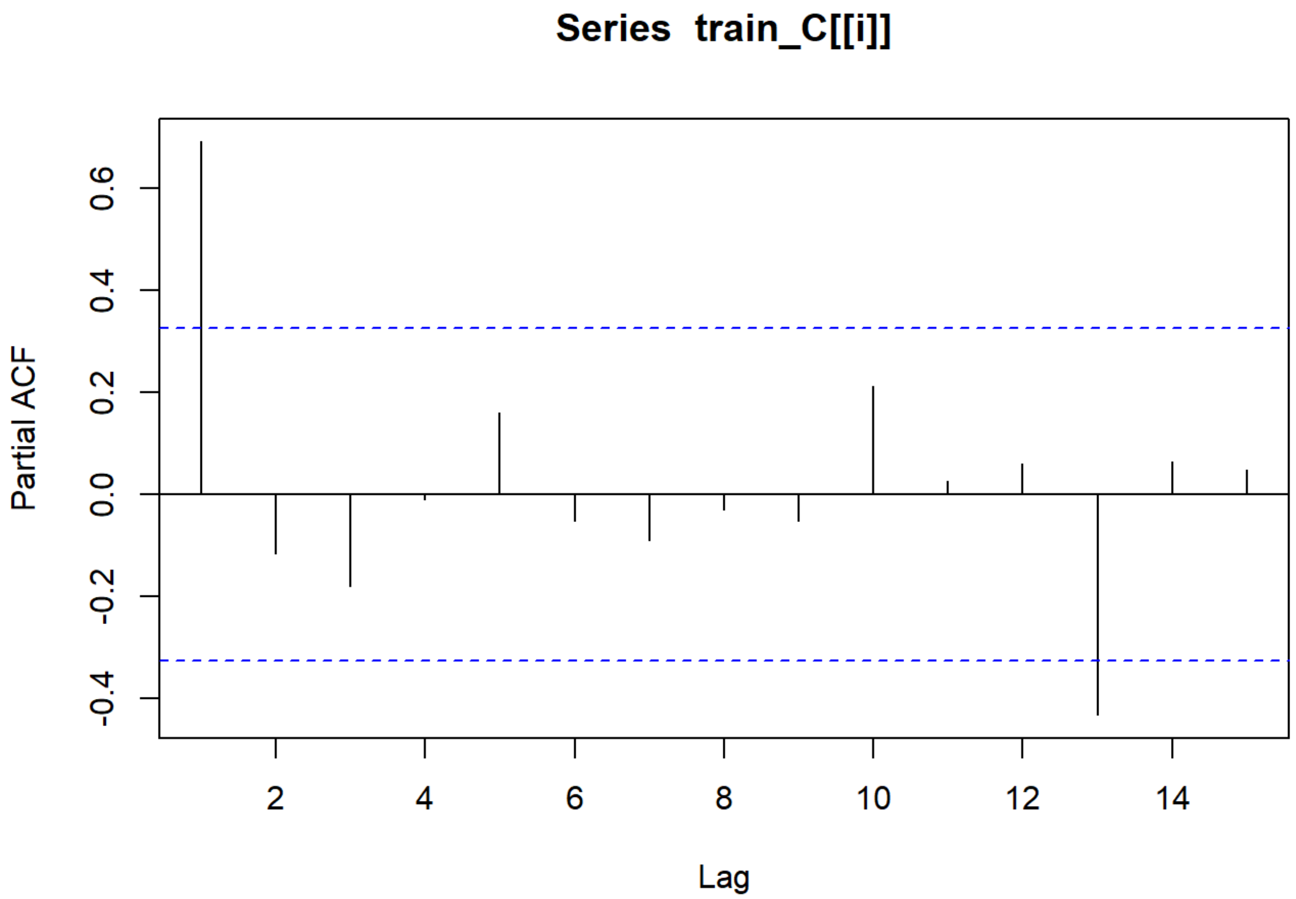

Forecasts from HoltWinters
300
250
200
150
100
2014
2015
2016
2017
2018

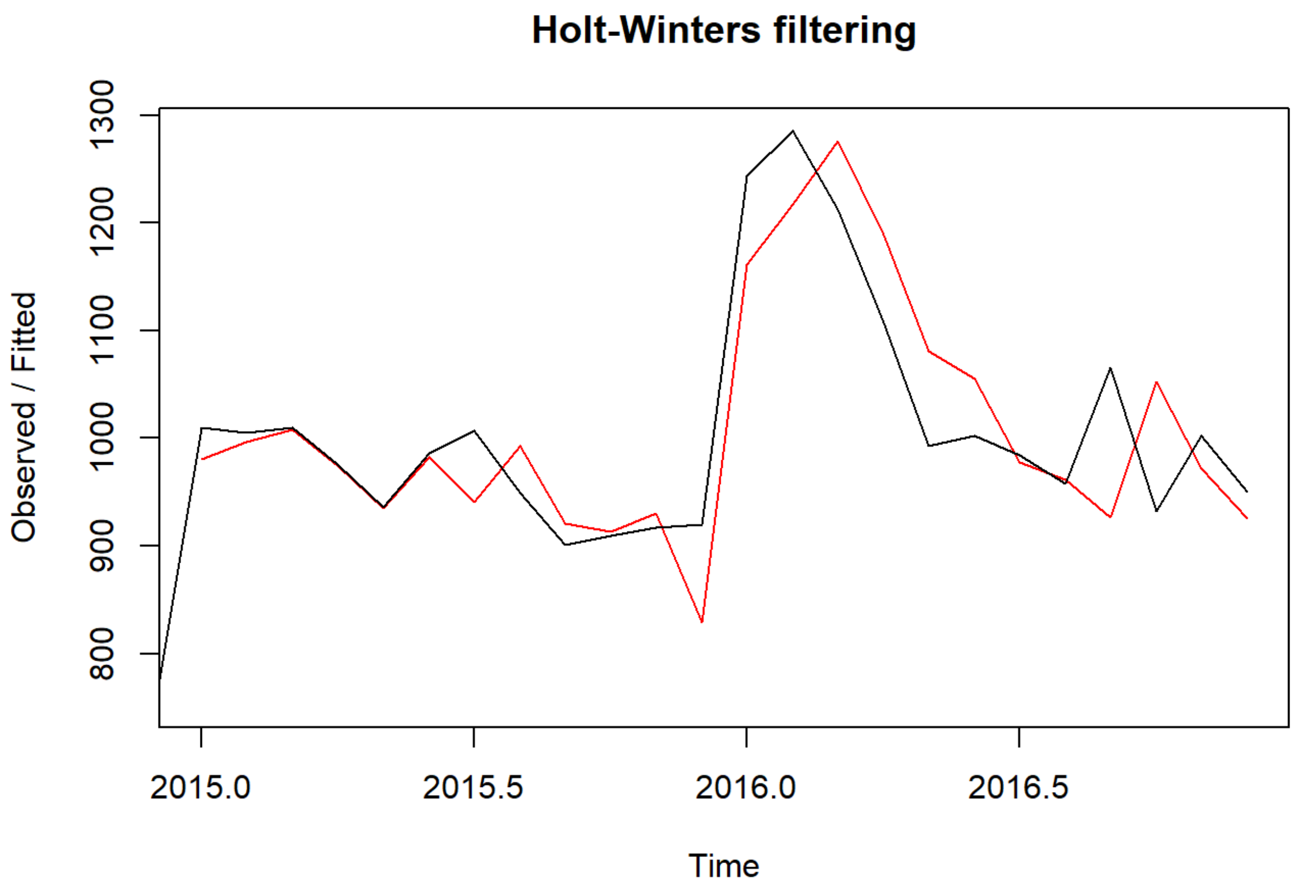

Decomposition of additive time series
observed
trend
seasonal
random
450
350
430
410
390
50
0
-50
60
20
-20
-60
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0
Time


Holt-Winters filtering
Observed / Fitted
500
450
400
350
300
2015.0
2015.5
2016.0
2016.5
Time

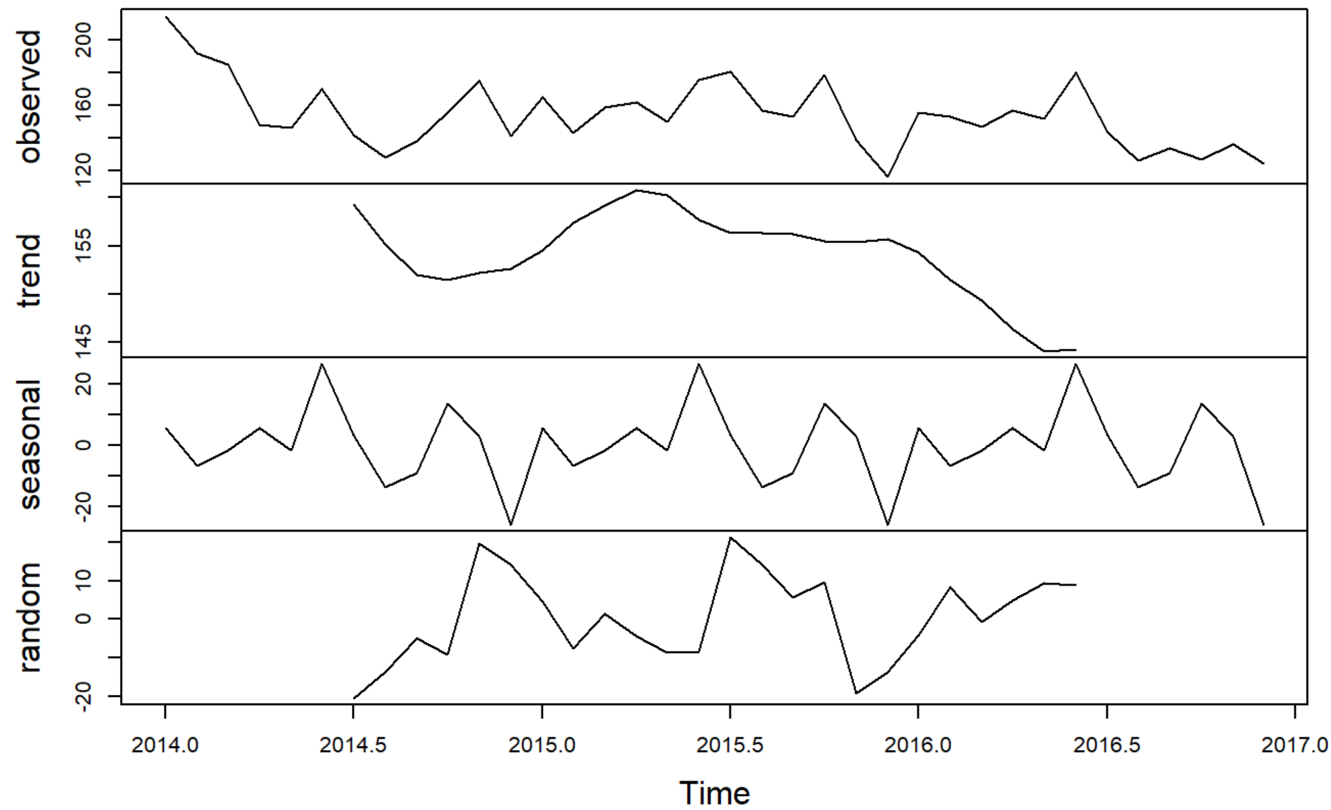

Decomposition of additive time series
observed
trend
seasonal
random
Time
2014.0
2014.5
2015.0
2015.5
2016.0
2016.5
2017.0


viewers
ACF
Lag
0
5
10
15

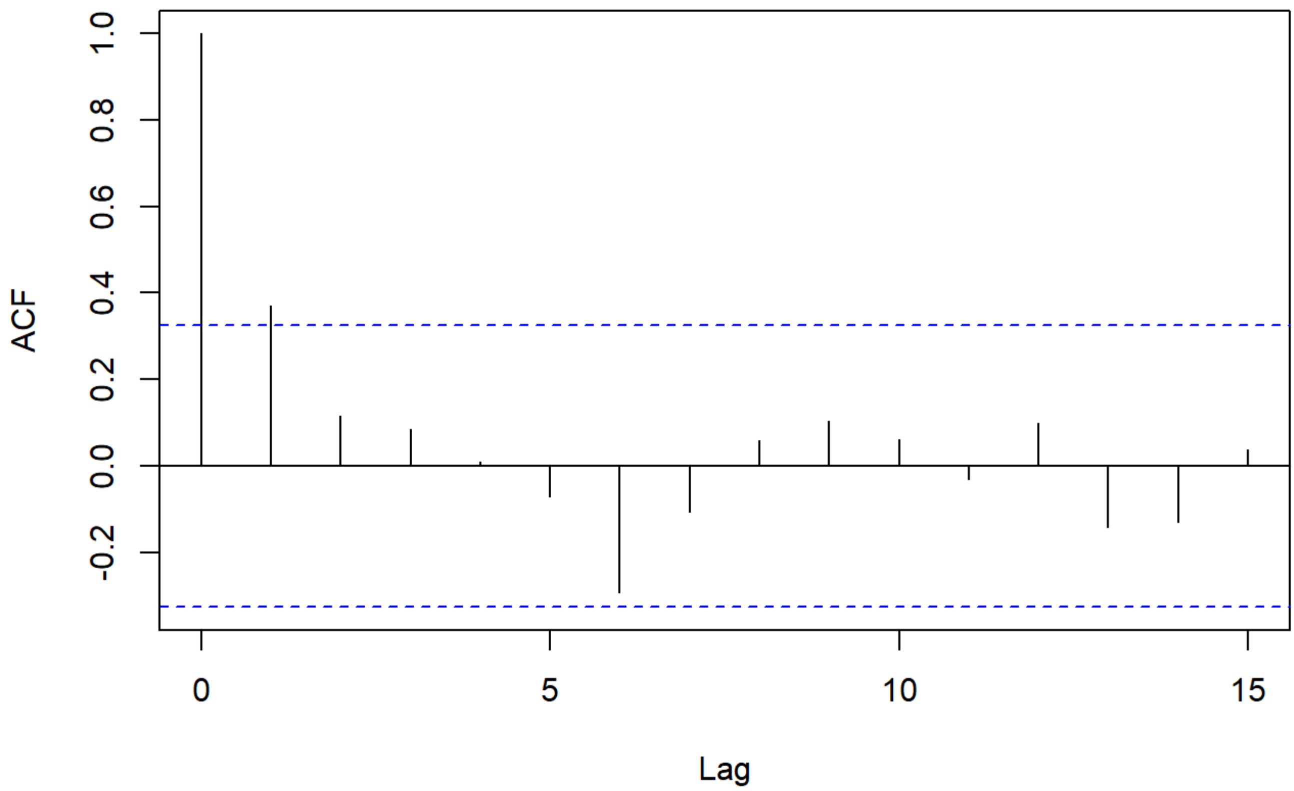

Series train_C[[i]]
Partial ACF
-0.4
-0.2
0.0
0.2
0.4
0.6
2
4
6
8
10
12
14
Lag

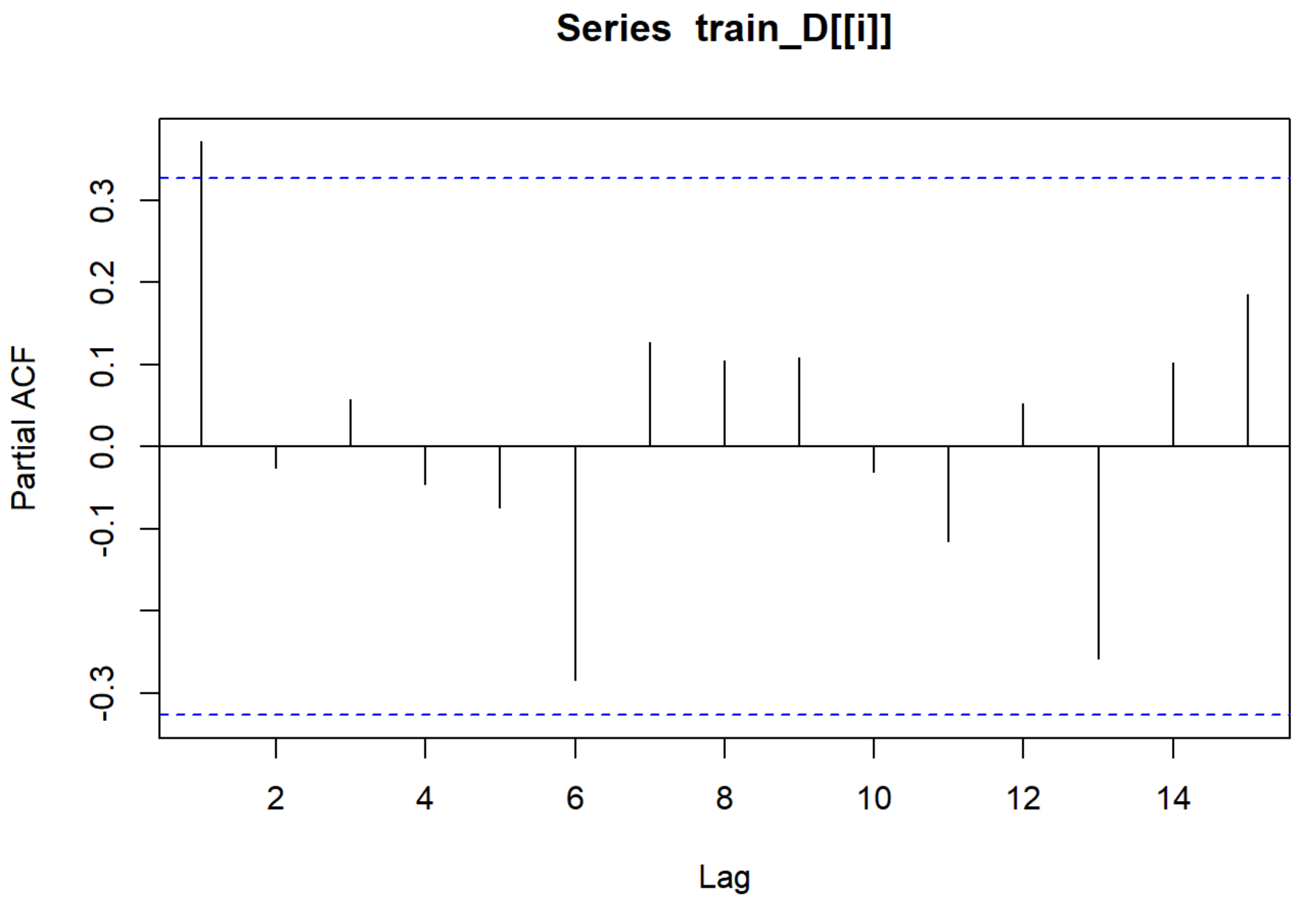

Holt-Winters filtering
Observed / Fitted
800
900
1000
1100
1200
1300
2015.0
2015.5
2016.0
2016.5
Time

## Decomposition of additive time series

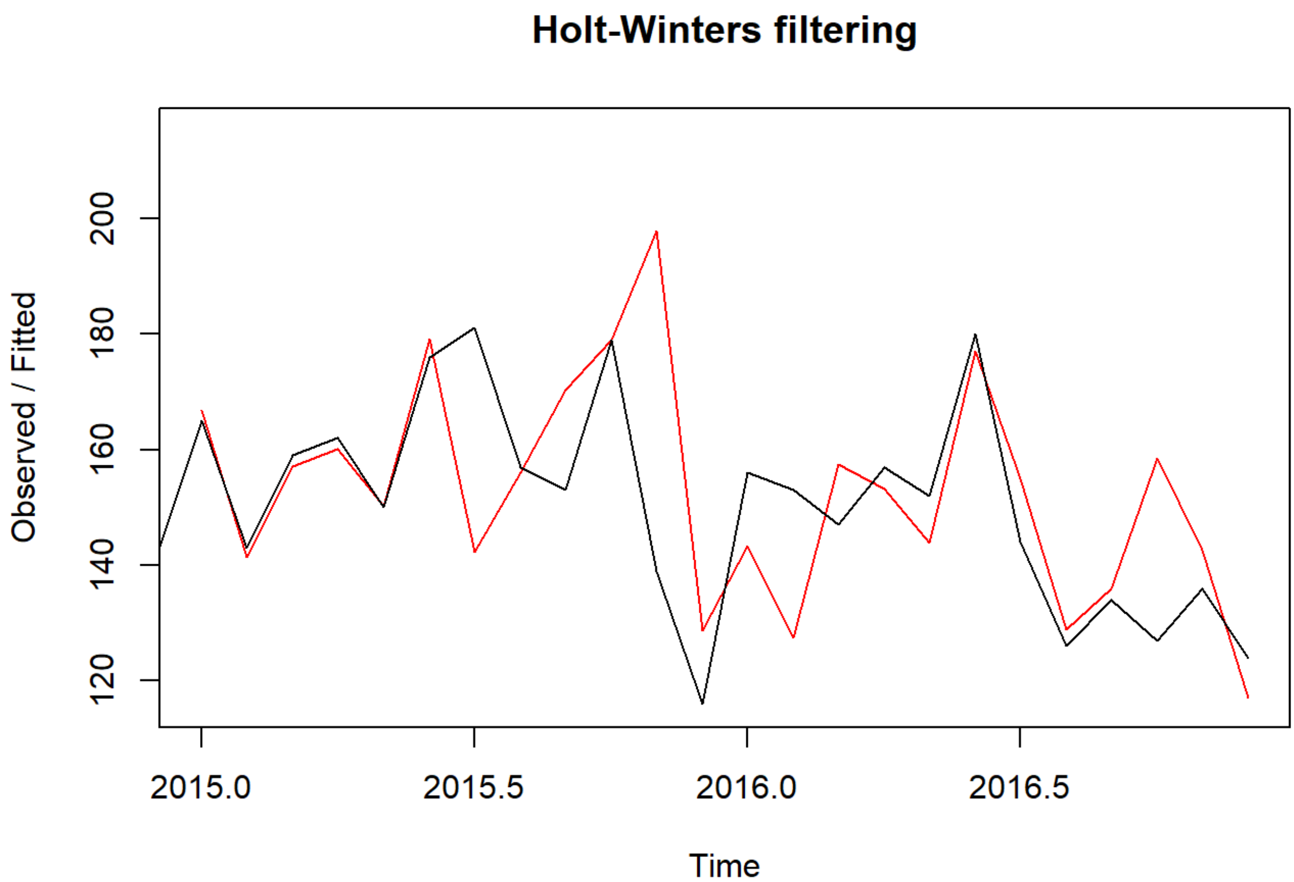



## viewers

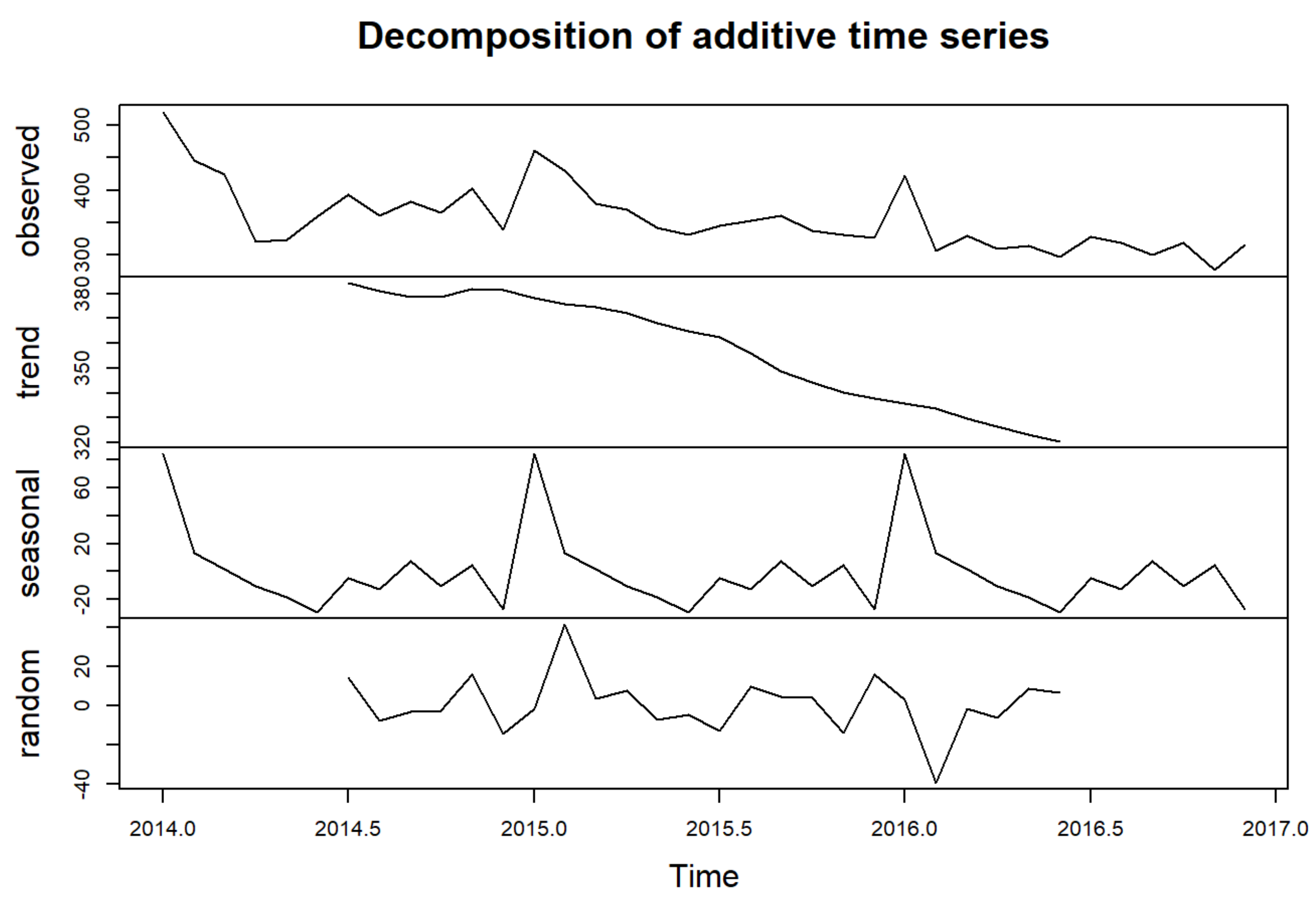


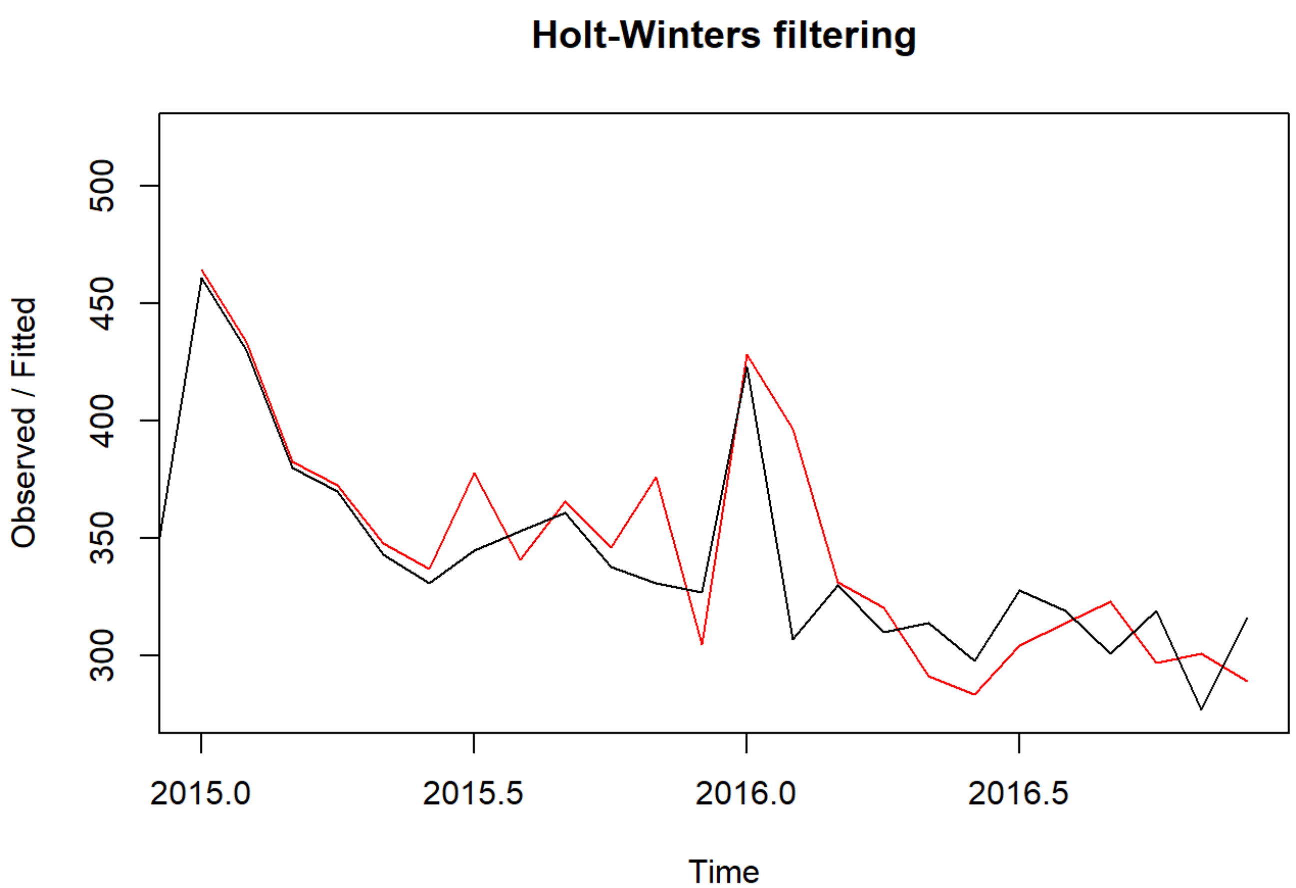


Series train_D[[i]]
Partial ACF
0.3
0.2
0.1
0.0
-0.1
-0.3
2
4
6
8
10
12
14
Lag

Holt-Winters filtering
Observed / Fitted
200
180
160
140
120
2015.0
2015.5
2016.0
2016.5
Time




making dataframe named final_result to

# display Mean absolute error for each dayparts

```
b1 <- t(as.data.frame(mse_A))
final_result_A <- data.frame(b1, d, network="A")
colnames(final_result_A) <- c("MAE","daypart","network")
rownames(final_result_A) <- 1:nrow(b1)
final_result_A
```

```
##          MAE                           daypart network
## 1  20.520219       M,T,W,R,F 1:00 PM - 4:00 PM       A
## 2  14.467713      M,T,W,R,F 10:00 AM - 1:00 PM       A
## 3  19.564695       M,T,W,R,F 4:00 PM - 6:00 PM       A
## 4  10.810388      M,T,W,R,F 6:00 AM - 10:00 AM       A
## 5  31.609346       M,T,W,R,F 6:00 PM - 8:00 PM       A
## 6  12.686683  M,T,W,R,F,S,Su 1:00 AM - 6:00 AM       A
## 7  37.530291 M,T,W,R,F,S,Su 11:00 PM - 1:00 AM       A
## 8  82.102585 M,T,W,R,F,S,Su 8:00 PM - 11:00 PM       A
## 9  39.827469            S,Su 1:00 PM - 8:00 PM       A
## 10  8.875389            S,Su 6:00 AM - 8:00 AM       A
## 11 42.664454            S,Su 8:00 AM - 1:00 PM       A
```

```
b2 <- t(as.data.frame(mse_B))
final_result_B <- data.frame(b2, d, network="B")
colnames(final_result_B) <- c("MAE","daypart","network")
rownames(final_result_B) <- 1:nrow(b2)
final_result_B
```

```
##          MAE                           daypart network
## 1   60.27782       M,T,W,R,F 1:00 PM - 4:00 PM       B
## 2   51.74338      M,T,W,R,F 10:00 AM - 1:00 PM       B
## 3   45.32363       M,T,W,R,F 4:00 PM - 6:00 PM       B
## 4   85.63665      M,T,W,R,F 6:00 AM - 10:00 AM       B
## 5   99.76095       M,T,W,R,F 6:00 PM - 8:00 PM       B
## 6   23.47888  M,T,W,R,F,S,Su 1:00 AM - 6:00 AM       B
## 7   28.41601 M,T,W,R,F,S,Su 11:00 PM - 1:00 AM       B
## 8   99.05151 M,T,W,R,F,S,Su 8:00 PM - 11:00 PM       B
## 9  103.75708            S,Su 1:00 PM - 8:00 PM       B
## 10 203.00000            S,Su 6:00 AM - 8:00 AM       B
## 11  74.74314            S,Su 8:00 AM - 1:00 PM       B
```

```
b3 <- t(as.data.frame(mse_C))
final_result_C <- data.frame(b3, d, network="C")
colnames(final_result_C) <- c("MAE","daypart","network")
rownames(final_result_C) <- 1:nrow(b3)
final_result_C
```

```
##          MAE                          daypart network
## 1   93.10595       M,T,W,R,F 1:00 PM - 4:00 PM       C
## 2   56.29067      M,T,W,R,F 10:00 AM - 1:00 PM       C
## 3   65.99625       M,T,W,R,F 4:00 PM - 6:00 PM       C
## 4   36.28251      M,T,W,R,F 6:00 AM - 10:00 AM       C
## 5   99.73155       M,T,W,R,F 6:00 PM - 8:00 PM       C
## 6   28.49202  M,T,W,R,F,S,Su 1:00 AM - 6:00 AM       C
## 7   68.66555 M,T,W,R,F,S,Su 11:00 PM - 1:00 AM       C
## 8  178.72917 M,T,W,R,F,S,Su 8:00 PM - 11:00 PM       C
## 9  215.25947            S,Su 1:00 PM - 8:00 PM       C
## 10  48.63877            S,Su 6:00 AM - 8:00 AM       C
## 11 153.17970            S,Su 8:00 AM - 1:00 PM       C
```

```
b4 <- t(as.data.frame(mse_D))
final_result_D <- data.frame(b4, d, network="D")
colnames(final_result_D) <- c("MAE","daypart","network")
rownames(final_result_D) <- 1:nrow(b4)
final_result_D
```

```
##          MAE                          daypart network
## 1   13.07586       M,T,W,R,F 1:00 PM - 4:00 PM       D
## 2   10.77540      M,T,W,R,F 10:00 AM - 1:00 PM       D
## 3   15.02938       M,T,W,R,F 4:00 PM - 6:00 PM       D
## 4  190.80968      M,T,W,R,F 6:00 AM - 10:00 AM       D
## 5   14.73406       M,T,W,R,F 6:00 PM - 8:00 PM       D
## 6   12.72243  M,T,W,R,F,S,Su 1:00 AM - 6:00 AM       D
## 7   28.73740 M,T,W,R,F,S,Su 11:00 PM - 1:00 AM       D
## 8   92.76801 M,T,W,R,F,S,Su 8:00 PM - 11:00 PM       D
## 9   18.49259            S,Su 1:00 PM - 8:00 PM       D
## 10  21.82742            S,Su 6:00 AM - 8:00 AM       D
## 11  19.66620            S,Su 8:00 AM - 1:00 PM       D
```

```
b5 <- t(as.data.frame(mse_E))
final_result_E <- data.frame(b5, d, network="E")
colnames(final_result_E) <- c("MAE","daypart","network")
rownames(final_result_E) <- 1:nrow(b5)
final_result_E
```

```
##          MAE                          daypart network
## 1   36.18410       M,T,W,R,F 1:00 PM - 4:00 PM       E
## 2   17.68645      M,T,W,R,F 10:00 AM - 1:00 PM       E
## 3   52.38683       M,T,W,R,F 4:00 PM - 6:00 PM       E
## 4   86.44478      M,T,W,R,F 6:00 AM - 10:00 AM       E
## 5   53.56170       M,T,W,R,F 6:00 PM - 8:00 PM       E
## 6   40.78742  M,T,W,R,F,S,Su 1:00 AM - 6:00 AM       E
## 7   73.21512 M,T,W,R,F,S,Su 11:00 PM - 1:00 AM       E
## 8  124.14011 M,T,W,R,F,S,Su 8:00 PM - 11:00 PM       E
## 9   68.41505            S,Su 1:00 PM - 8:00 PM       E
## 10 195.33333            S,Su 6:00 AM - 8:00 AM       E
## 11  52.75050            S,Su 8:00 AM - 1:00 PM       E
```