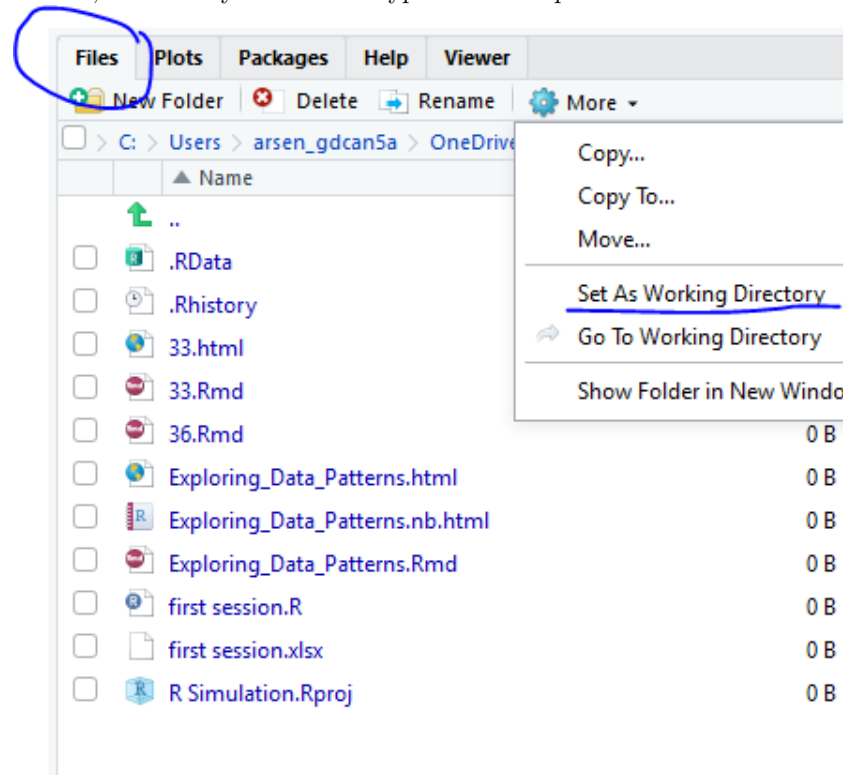


Data Patterns

This section covers sessions 1-2, chapters 2-3 of HW. Covered topics: - getting data into R - making a time series - exploring autocorrelation - how to do formulas from p.41-42 of HW - naive forecasting method - moving averages - exponential smoothing - Holt's linear smoothing - Winter's method - Winters-Holt

Load Data into R and transform to Time Series

First, set your working directory to wherever your excel file is, otherwise you'll have to type in the complete file



path. Also save your R project and your R script there.

Now you need to create an object and read the data from an excel file. If you typed the values from the book, type them as one series (one column). If you are using someone's file, transform them to one column. You don't need the years and quarters. Here is how my excel file looks after transforming:

Series						
0.17	1988Q1	1988	Q1		1988	
15.13	1988Q2	1988	Q2		1989	
26.59	1988Q3	1988	Q3			
16.07	1988Q4	1988	Q4			
19.64	1989Q1	1989	Q1			
19.24	1989Q2	1989	Q2			
24.57	1989Q3	1989	Q3			
8.11	1989Q4	1989	Q4			
5.09	1990Q1	1990	Q1			
23.53	1990Q2	1990	Q2			
23.04	1990Q3	1990	Q3			
-4.58	1990Q4	1990	Q4			
-8.21	1991Q1	1991	Q1			
10.57	1991Q2	1991	Q2			
15.72	1991Q3	1991	Q3			
8.84	1991Q4	1991	Q4			
13.48	1992Q1	1992	Q1			
23.48	1992Q2	1992	Q2			
26.89	1992Q3	1992	Q3			
27.17	1992Q4	1992	Q4			

There are two tabs in the file and I concatenated the Year+Quarter. Now we want to import the data from Sheet1 to R.

```
#For this, we use the package readxl and its function read_excel
#first, apply the function to the file
#create an object called firstdata0 and apply the function to it
#we have to specify the file name. This argument is a string, therefore use quotation marks ""
firstdata0 <- readxl::read_excel("first session.xlsx")
firstdata0
```

```
## # A tibble: 12 x 18
##   Year   `1st` `2nd` `3rd`  `4th` X__1 X__2 X__3 X__4 X__5 X__6
##   <dbl> <dbl> <dbl> <dbl> <dbl> <chr> <lgl> <lgl> <lgl> <lgl> <lgl>
## 1 1988  0.170 15.1 26.6 16.1 1988Q1 NA    NA    NA    NA    NA
## 2 1989 19.6 19.2 24.6  8.11 1988Q2 NA    NA    NA    NA    NA
## 3 1990  5.09 23.5 23.0 - 4.58 1988Q3 NA    NA    NA    NA    NA
## 4 1991 - 8.21 10.6 15.7  8.84 1988Q4 NA    NA    NA    NA    NA
## 5 1992 13.5 23.5 26.9 27.2 <NA> NA    NA    NA    NA    NA
## 6 1993 24.9 42.2 48.8 38.4 <NA> NA    NA    NA    NA    NA
## 7 1994 41.8 58.5 58.6 20.3 <NA> NA    NA    NA    NA    NA
## 8 1995 11.8 59.7 67.7 43.4 <NA> NA    NA    NA    NA    NA
## 9 1996 33.0 85.3 60.9 28.2 <NA> NA    NA    NA    NA    NA
## 10 1997 50.9 93.8 92.5 80.6 <NA> NA    NA    NA    NA    NA
## 11 1998 70.0 133 130 100 <NA> NA    NA    NA    NA    NA
## 12 1999 95.8 158 127 93.8 <NA> NA    NA    NA    NA    NA
## # ... with 7 more variables: X__7 <lgl>, X__8 <lgl>, X__9 <lgl>,
```

```
## # X__10 <dbl>, X__11 <dbl>, X__12 <dbl>, X__13 <dbl>
```

Clearly that's not what we want. Our goal is to get the time series in a friendly form.

```
#remove firstdata0
remove(firstdata0)
#add some inputs to the function
#We additionally specify the file name, which sheet to take the data from, and the range. Why the range
firstdata <- readxl::read_excel("first session.xlsx", sheet='Sheet1', range = "A1:A48")
#this displays the first five entries
head(firstdata, n=5)
```

```
## # A tibble: 5 x 1
##   Series
##   <dbl>
## 1  0.170
## 2 15.1
## 3 26.6
## 4 16.1
## 5 19.6
```

Now the data is loaded into R. Let's check what object type we have

```
str(firstdata)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame': 47 obs. of 1 variable:
## $ Series: num 0.17 15.13 26.59 16.07 19.64 ...
```

This is a data frame. We however want a timeseries because then we can use a number of specific functions.

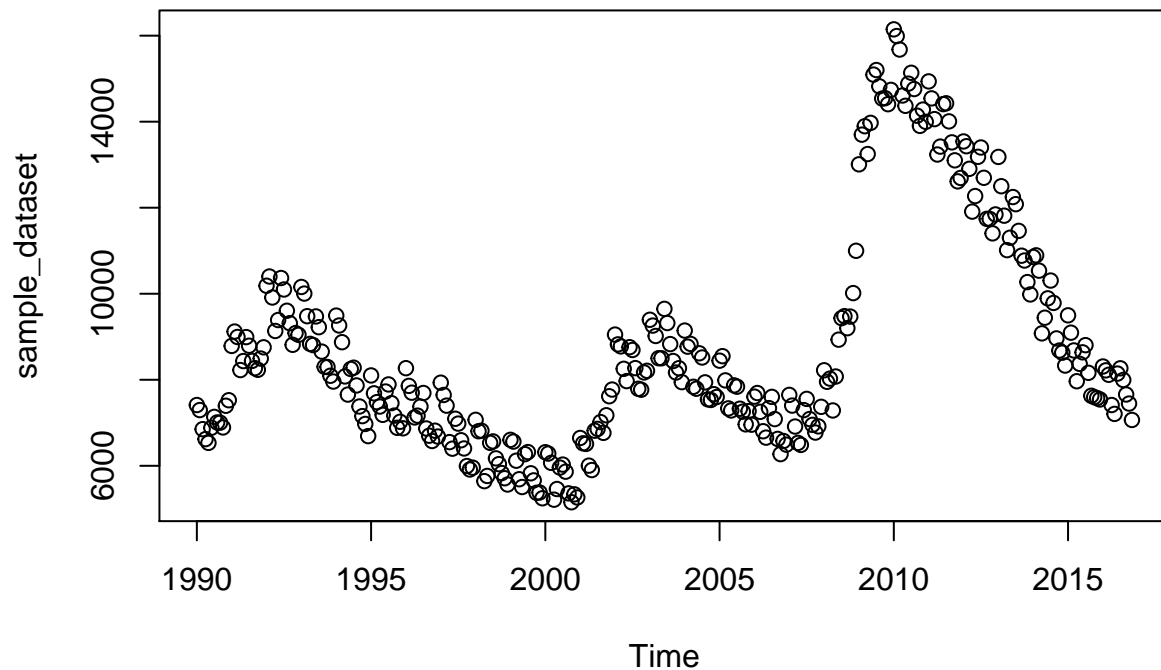
```
#to make a time series, create a new object and apply the ts function to it like this:
series <- ts(firstdata$Series, frequency=4, start=1988)
#as you can see, we defined the frequency of observations as 4 per year and the starting year as 1988.
#let's display the object
series
```

```
##      Qtr1  Qtr2  Qtr3  Qtr4
## 1988  0.17 15.13 26.59 16.07
## 1989 19.64 19.24 24.57  8.11
## 1990  5.09 23.53 23.04 -4.58
## 1991 -8.21 10.57 15.72  8.84
## 1992 13.48 23.48 26.89 27.17
## 1993 24.93 42.15 48.83 38.37
## 1994 41.85 58.52 58.62 20.34
## 1995 11.83 59.72 67.72 43.36
## 1996 33.00 85.32 60.86 28.16
## 1997 50.87 93.83 92.51 80.55
## 1998 70.01 133.39 129.64 100.38
## 1999 95.85 157.76 126.98
```

Let's plot a series (standard series of R-base).

```
#we use a generic plot function, there are many more.
#we use type = "p" for points in the scatterplot. Other types are available, use Help in Rstudio(F1) to
#main is the title of the plot
library(seasonal)
sample_dataset <- unemp
plot(sample_dataset, type="p", main="First plot")
```

First plot



Autocorrelation

To do this, we use the acf function from the stats package, which is pre-loaded.

```
# Load packages
library(zoo)
```

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

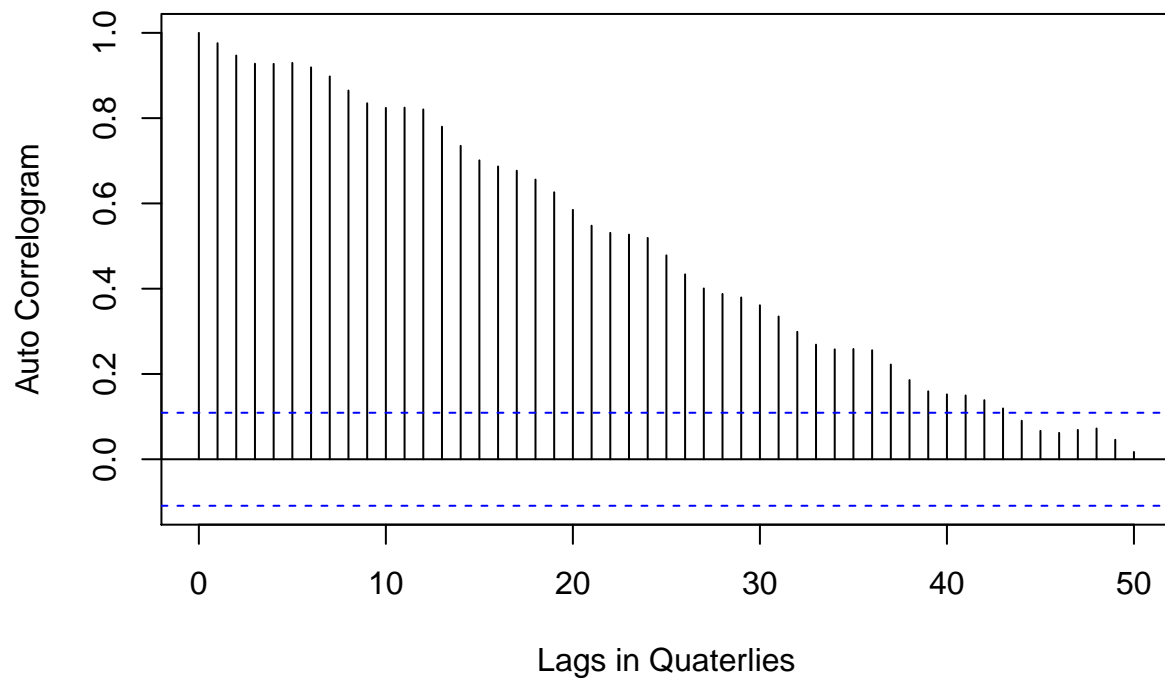
```
library(forecast)
```

```
# We specify the series, then we want to first look at the ACF, then we want to see it plotted. All unt
acf(coredata(sample_dataset), plot=FALSE, lag.max =10)
```

```
##
## Autocorrelations of series 'coredata(sample_dataset)', by lag
##
##   0    1    2    3    4    5    6    7    8    9   10
## 1.000 0.976 0.947 0.928 0.927 0.930 0.919 0.898 0.865 0.835 0.824
```

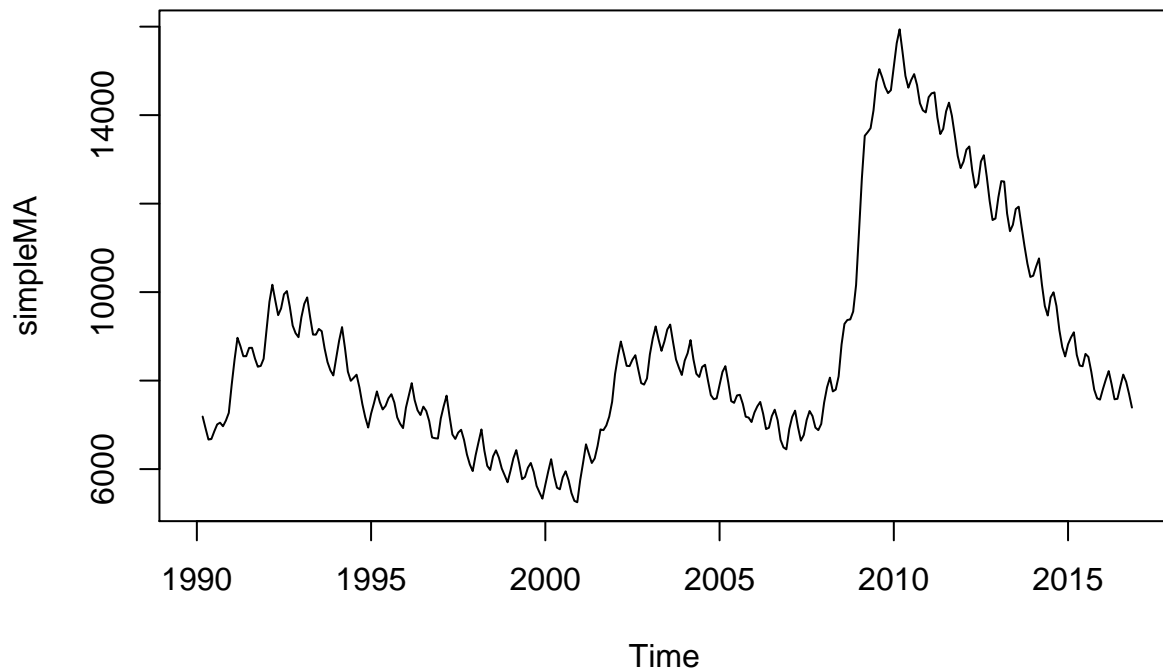
```
acf(coredata(sample_dataset), plot=TRUE, lag.max=50, xlim=c(0,50), ylab="Auto Correlogram", xlab="Lags :"
```

Series coredata(sample_dataset)



For forecasting we use the “TTR” package. Make sure to load this package. For the example we will be using the dataset “austres” that is preloaded in R. Fromt here you can use the package as shown below. Note that we are using an moving average of 3.

```
library(TTR)
simpleMA <- SMA(sample_dataset, n=3)
plot.ts(simpleMA)
```

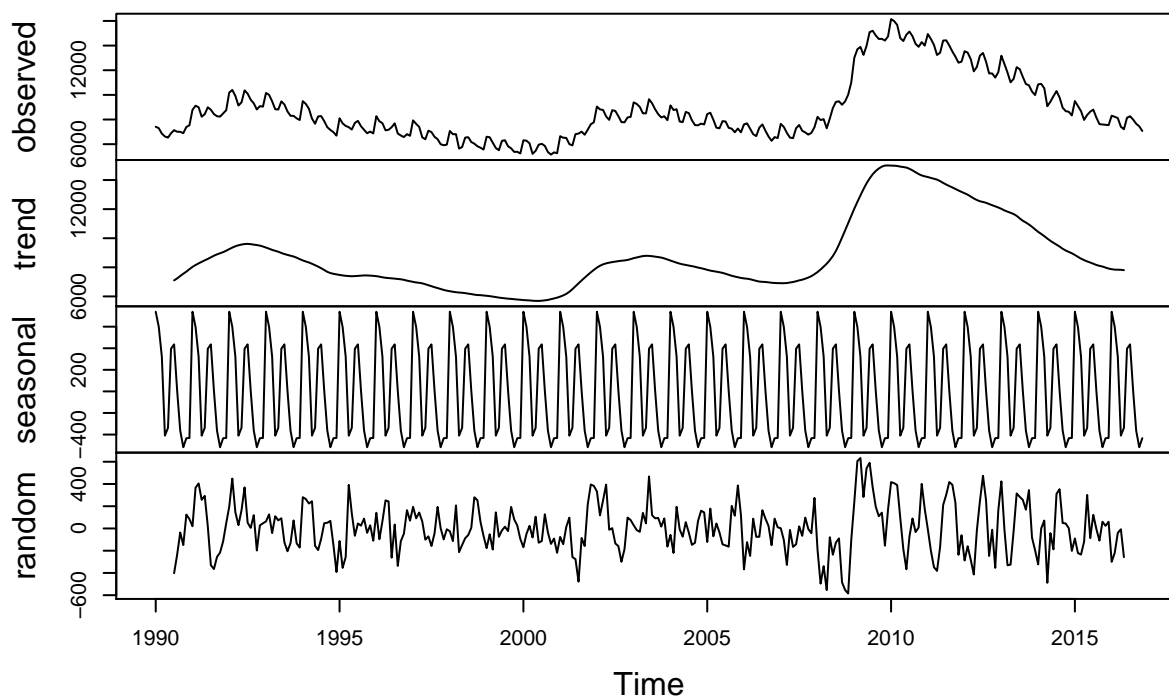


For decomposition of your forecast, it is important to analyse the seasonality, trend and randomness of your historic data. This can easily be done in R by calling the `decompose` function.

```
decomposition_of_historic_data <- decompose(sample_dataset)
```

```
plot(decomposition_of_historic_data)
```

Decomposition of additive time series



In order to create predictions we can use the HoltWinters Method. This is the most evolved version of the exponential smoothing methods. For simplicity, realize that beta and gamma can be set to zero, disabling the seasonal and/or trend component, reducing it to simpler technique.

```
exp <- HoltWinters(sample_dataset, beta = 0, gamma = 0)
exp_seasonal <- HoltWinters(sample_dataset, gamma = 0)
exp_seasonal_trend <- HoltWinters(sample_dataset)

print(exp)
```

```
## Holt-Winters exponential smoothing with trend and additive seasonal component.
##
## Call:
## HoltWinters(x = sample_dataset, beta = 0, gamma = 0)
##
## Smoothing parameters:
##  alpha: 0.9999498
##  beta : 0
##  gamma: 0
##
## Coefficients:
##           [,1]
## a    7437.15162
## b     137.37602
## s1   -409.19097
## s2     696.01736
## s3     901.43403
```

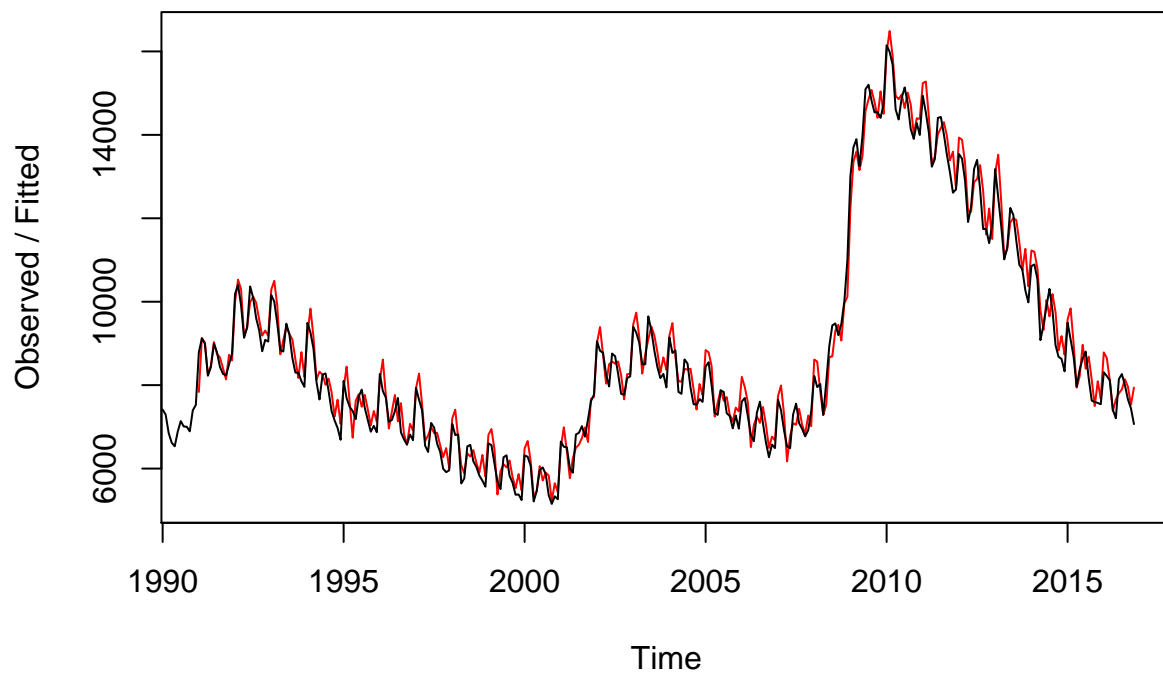
```
## s4 663.01736
## s5 -214.60764
## s6 -107.19097
## s7 352.80903
## s8 -29.10764
## s9 -291.39931
## s10 -461.73264
## s11 -728.94097
## s12 -371.10764
```

```
predictions <- exp$fitted
head(predictions)
```

```
##           xhat    level  trend  season
## Jan 1991 7837.925 7004.532 137.376 696.0174
## Feb 1991 9129.745 8090.935 137.376 901.4340
## Mar 1991 9019.960 8219.566 137.376 663.0174
## Apr 1991 8254.752 8331.984 137.376 -214.6076
## May 1991 8470.794 8440.609 137.376 -107.1910
## Jun 1991 9032.378 8542.193 137.376 352.8090
```

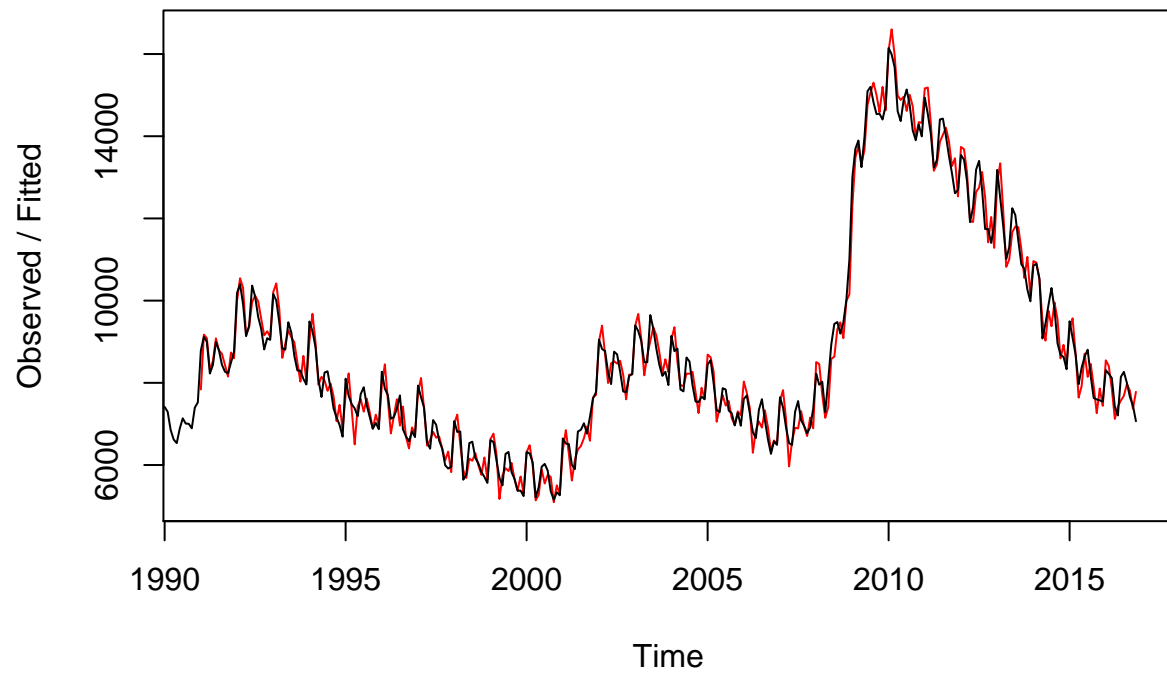
```
plot(exp)
```

Holt-Winters filtering



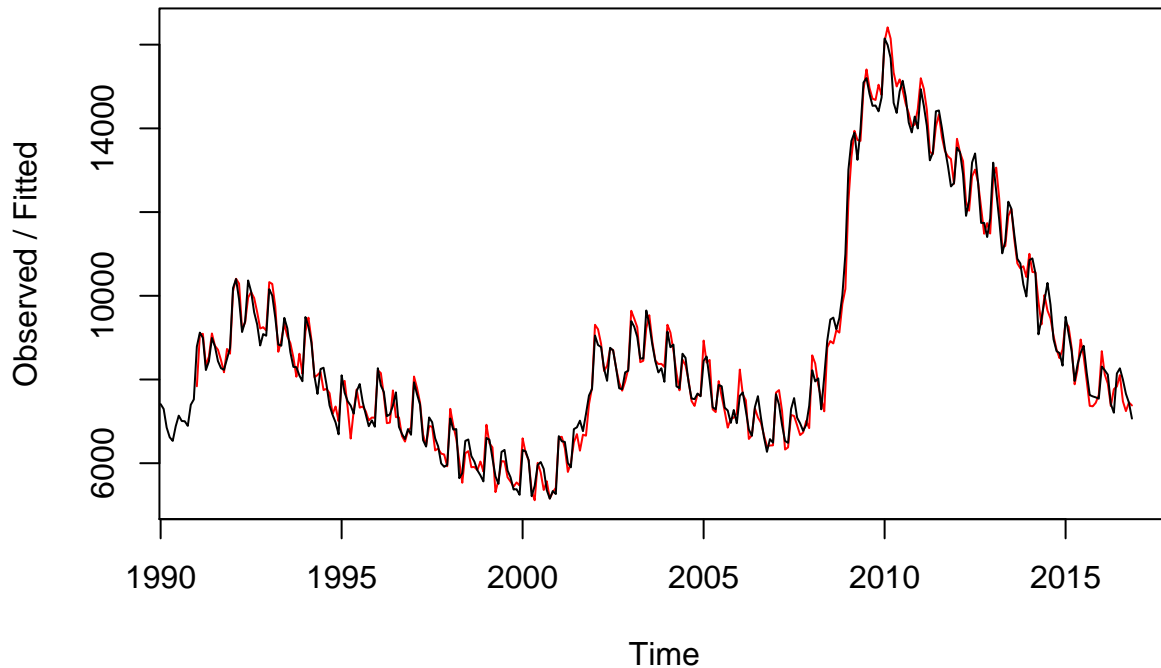
```
plot(exp_seasonal)
```


Holt-Winters filtering



```
plot(exp_seasonal_trend)
```

Holt-Winters filtering



```
cat("SSE exp", exp$SSE, "\n", "SSE exp Seasonality", exp_seasonal$SSE, "\n", "SSE exp Seasonality and Trend", exp_seasonal_and_trend$SSE, "\n")
```

```
## SSE exp 41957605
## SSE exp Seasonality 35865368
## SSE exp Seasonality and Trend 25231887
```

In order to calculate all the performance measures for the prediction a couple of numbers need to be retrieved. The formula $v = n - m$ relates to the R objects as n = the amount of values, m = the amount of coefficient. v represents the residual degrees of freedom. In order to calculate everything the following steps need to be conducted:

```
n <- length(exp$fitted)
m <- length(exp$coefficients)
v <- n - m
```

```
cat("With this formula we have established the values for n and m, those being", n, "and", m, "therefore we can calculate the MSE")
```

```
## With this formula we have established the values for n and m, those being 1244 and 14 therefore we can calculate the MSE
```

```
# Calculate MSE
```

```
MSE <- exp$SSE / v
cat("MSE =", MSE)
```

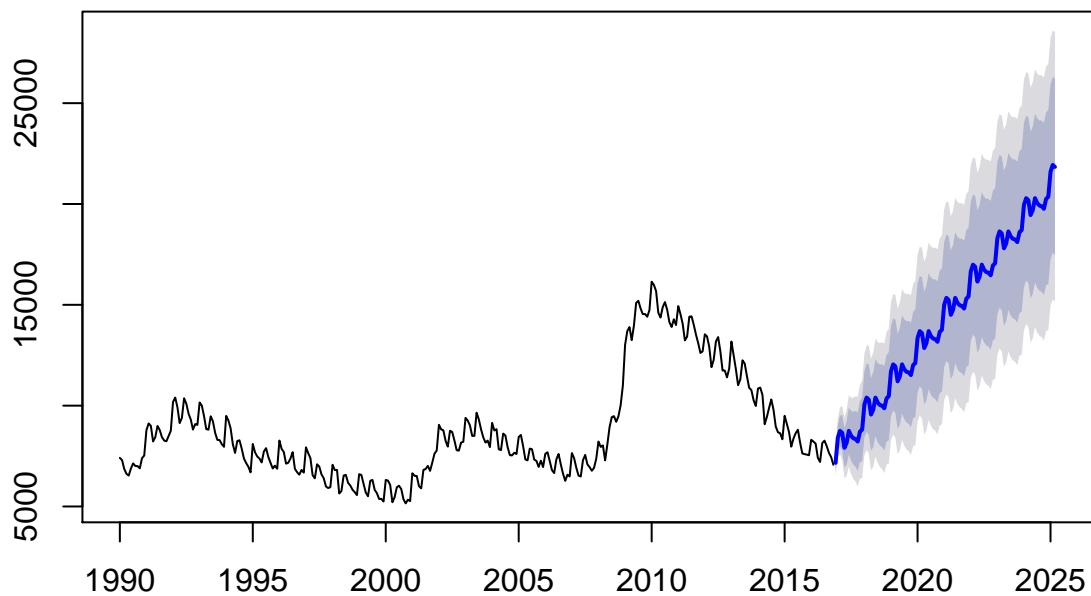
```
## MSE = 34111.87
```

In order to forecast the data for hundred periods, one can use the forecast package. The syntax works as follows:

```
exp_fore <- forecast::forecast(exp, h = 100)
exp_fore_trend_seasonal <- forecast::forecast(exp_seasonal_trend, h = 100)

plot(exp_fore, main="Forecast for Exponential Smothing (basic)")
```

Forecast for Exponential Smothing (basic)



```
plot(exp_fore_trend_seasonal, main = "Forecast for HoltWinters method with Trend and Seasonality")
```

Forecast for HoltWinters method with Trend and Seasonality

