# University of Salford, MSc Data Science

**Module:** Applied Statistics and Data Visualisation

**Date:** Trimester 1, 2025-2026

**Session:** Workshop Week 9

**Topic:** Time Series Analysis in R

**Tools:** RStudio

**Instructors:** Dr Kaveh Kiani, Nathan Topping (Based on a book by Dr Avril Coghlan)

## Objectives:

After completing this workshop, you will be able to:

- Plot Time Series
- Decompose Time Series
- Forecast Time Series Using Smoothing Methods

# Contents

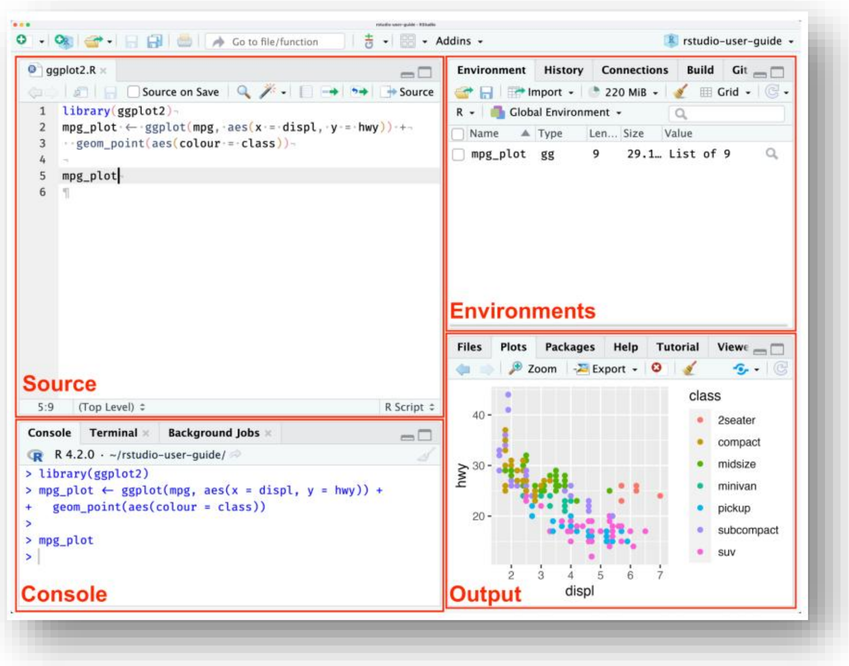
**For your own benefit, we strongly encourage you to type out the R scripts yourself in RStudio, rather than copying and pasting them directly from the workshop notes. Typing the code helps reinforce key concepts, improves your understanding of the syntax, and strengthens your coding skills. While copying and pasting may seem faster, actively engaging with the code will lead to a deeper understanding and make you more proficient in R programming over time.**

**Take your time, experiment, and learn by doing!**

## Part 1: Working in RStudio

Take sometime later to read about the RStudio pane layout, but for now, just focus on knowing that there are **4 main panes**, **Source, Environments, Console and Output**

https://docs.posit.co/ide/user/ide/guide/ui/ui-panes.html

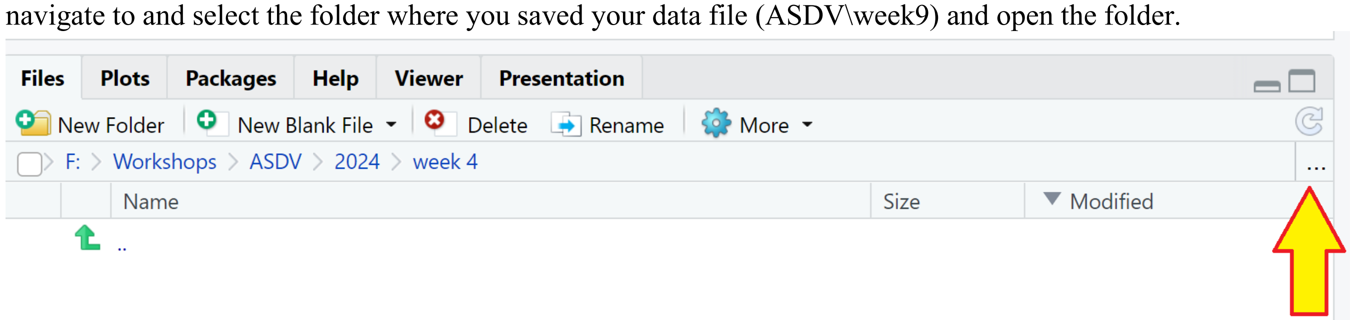


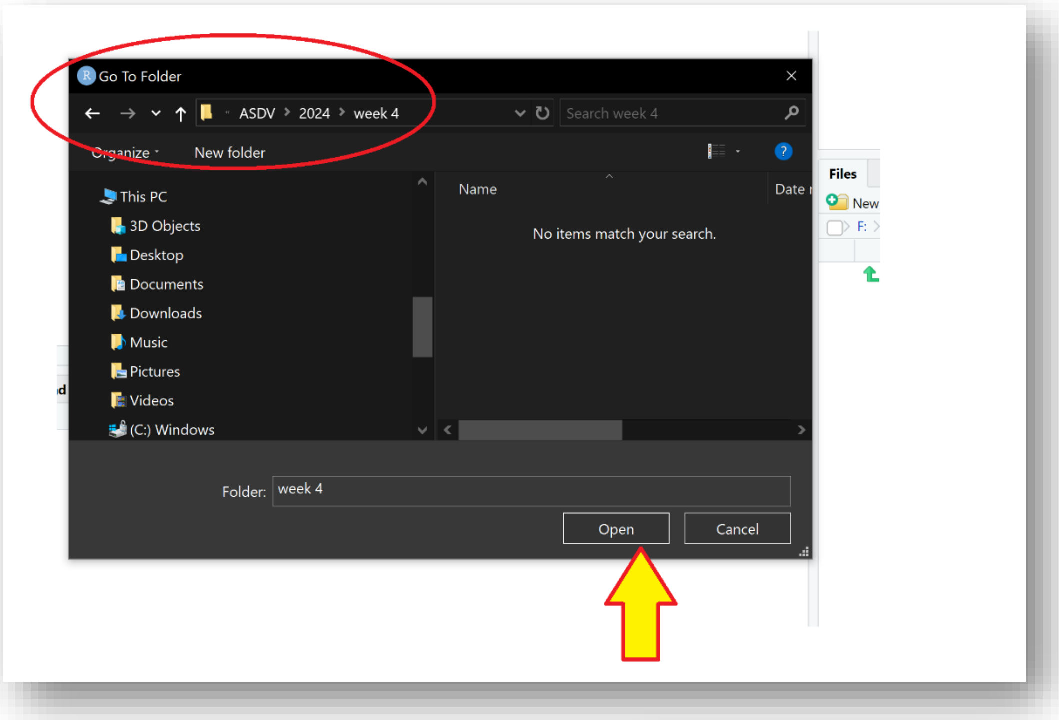

**You may work through the workshops as follows:**

1. Create a folder in the university PCs F drive or your personal OneDrive or your laptop to save datasets and R scripts. A good practice is to create a folder named **ASDV** (or similar) for all the R workshops that you will have throughout the trimester and then create a subfolder for each week. So, you can have **ASDV\Week9** for this week. Each week, you should **download the data for the week's workshop from Blackboard** and save it in this folder, as well as saving your scripts and the workshop materials in this folder too.

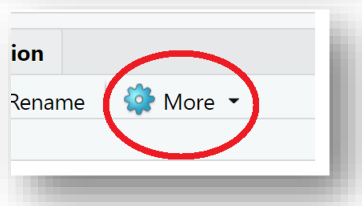
2. Start the RStudio

3. In the **Output Pane** (on the bottom right side of the RStudio window) click on the ellipse sign (…) to navigate to and select the folder where you saved your data file (ASDV\week9) and open the folder.

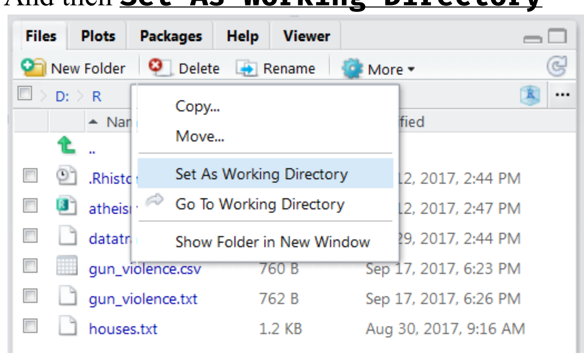





4. Then select the **More** tab




And then **`Set As Working Directory`**




5. From the **Source Pane** open a new R script window:

**`File → New File → R script`**

## Part 2: Packages

Packages are collections of R functions, data, and compiled code in a well-defined format. A package is either a **Base Package** or a **User Contributed Package**.

There are a set of **Base (or Standard) Packages** which are considered part of the R source code and automatically available as part of the R installation and we can directly use functions from the standard base packages.

However, the more we work with R, we will come to realize that there are many users contributed packages that have been created to add specific functionality. There are 10,000+ **User Contributed Packages** and growing. To use **User Contributed Packages** will require installation (Many packages can be installed from the **CRAN** repositories).

We will be using three packages throughout the workshop today.

1. stats
2. TTR
3. forecast

TTR and forecast packages are **User Contributed Packages**, and we must install and call them before using. Package 1, “stats” is a **Base Package**, and it is ready to use.

```
install.packages("TTR")

install.packages("forecast")


library(TTR)

library(forecast)
```

## Part 3: Source of the workshop:

The source of the workshop is second chapter of the:

**A Little Book of R For Time Series**
**Release 0.2**
**Avril Coghlan**
**Sep 10, 2018**

HTML version of the book:
https://a-little-book-of-r-for-time-series.readthedocs.io/en/latest/

PDF version of the book:
https://buildmedia.readthedocs.org/media/pdf/a-little-book-of-r-for-time-series/latest/a-little-book-of-r-for-time-series.pdf



Updates of the workshop notes compare to the book:

| The book | Workshop | Page |
|---|---|---|
| forecast.HoltWinters() | forecast() | 30,38,… |
| plot.forecast() | plot() | 30,38,… |
| acf(rainseriesforecasts2$residuals, lag.max=20) | acf(rainseriesforecasts2$residuals, lag.max=20 , na.action = na.pass) | 31, … |
| --- | Removing Null values | 34,... |
| Forecast.Arima() | forecast() | 60,… |

# Part 4: Chapter 2 - Using R for Time Series Analysis

## 2.1 Time Series Analysis

This booklet tells you how to use the R statistical software to carry out some simple analyses that are common in analysing time series data.

This booklet assumes that the reader has some basic knowledge of time series analysis, and the principal focus of the booklet is not to explain time series analysis, but rather to explain how to carry out these analyses using R.

If you are new to time series analysis, and want to learn more about any of the concepts presented here, I would highly recommend the Open University book "Time series" (product code M249/02), available from the Open University Shop.

In this booklet, I will be using time series data sets that have been kindly made available by Rob Hyndman in his Time Series Data Library at http://robjhyndman.com/TSDL/.

There is a pdf version of this booklet available at https://media.readthedocs.org/pdf/a-little-book-of-r-for-time-series/latest/a-little-book-of-r-for-time-series.pdf.

If you like this booklet, you may also like to check out my booklet on using R for biomedical statistics, http://a-little-book-of-r-for-biomedical-statistics.readthedocs.org/, and my booklet on using R for multivariate analysis, http://little-book-of-r-for-multivariate-analysis.readthedocs.org/.

## 2.2 Reading Time Series Data

The first thing that you will want to do to analyse your time series data will be to read it into R, and to plot the time series. You can read data into R using the scan() function, which assumes that your data for successive time points is in a simple text file with one column.

## Kings Data

For example, the file http://robjhyndman.com/tsdldata/misc/kings.dat contains data on the age of death of successive kings of England, starting with William the Conqueror (original source: Hipel and Mcleod, 1994).

The data set looks like this:

```
Age of Death of Successive Kings of England
#starting with William the Conqueror
#Source: McNeill, "Interactive Data Analysis"
60
43
67
50
56
42
50
65
68
43
65
34
...
```

Only the first few lines of the file have been shown. The first three lines contain some comment on the data, and we want to ignore this when we read the data into R. We can use this by using the "skip" parameter of the scan() function, which specifies how many lines at the top of the file to ignore. To read the file into R, ignoring the first three lines, we type:

```
> kings <- scan("http://robjhyndman.com/tsdldata/misc/kings.dat",skip=3)
> kings
  [1] 60 43 67 50 56 42 50 65 68 43 65 34 47 34 49 41 13 35 53 56 16 43 69 59 48
  [26] 59 86 55 68 51 33 49 67 77 81 67 71 81 68 70 77 56
```

In this case the age of death of 42 successive kings of England has been read into the variable 'kings'.

Once you have read the time series data into R, the next step is to store the data in a time series object in R, so that you can use R's many functions for analysing time series data. To store the data in a time series object, we use the ts() function in R. For example, to store the data in the variable 'kings' as a time series object in R, we type:

```
> kingstimeseries <- ts(kings)
> kingstimeseries
  Time Series:
  Start = 1
  End = 42
  Frequency = 1
  [1] 60 43 67 50 56 42 50 65 68 43 65 34 47 34 49 41 13 35 53 56 16 43 69 59 48
  [26] 59 86 55 68 51 33 49 67 77 81 67 71 81 68 70 77 56
```

## Births Data

Sometimes the time series data set that you have may have been collected at regular intervals that were less than one year, for example, monthly or quarterly. In this case, you can specify the number of times that data was collected per year by using the 'frequency' parameter in the ts() function. For monthly time series data, you set frequency=12, while for quarterly time series data, you set frequency=4.

You can also specify the first year that the data was collected, and the first interval in that year by using the 'start' parameter in the ts() function. For example, if the first data point corresponds to the second quarter of 1986, you would set start=c(1986,2).

An example is a data set of the number of births per month in New York city, from January 1946 to December 1959 (originally collected by Newton). This data is available in the file http://robjhyndman.com/tsdldata/data/nybirths.dat We can read the data into R, and store it as a time series object, by typing:

```
> births <- scan("http://robjhyndman.com/tsdldata/data/nybirths.dat")
> birthstimeseries <- ts(births, frequency=12, start=c(1946,1))
> birthstimeseries
    Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct    Nov    Dec
 1946 26.663 23.598 26.931 24.740 25.806 24.364 24.477 23.901 23.175 23.227 21.672␣
→21.870
 1947 21.439 21.089 23.709 21.669 21.752 20.761 23.479 23.824 23.105 23.110 21.759␣
→22.073
 1948 21.937 20.035 23.590 21.672 22.222 22.123 23.950 23.504 22.238 23.142 21.059␣
→21.573
 1949 21.548 20.000 22.424 20.615 21.761 22.874 24.104 23.748 23.262 22.907 21.519␣
→22.025
 1950 22.604 20.894 24.677 23.673 25.320 23.583 24.671 24.454 24.122 24.252 22.084␣
→22.991
 1951 23.287 23.049 25.076 24.037 24.430 24.667 26.451 25.618 25.014 25.110 22.964␣
→23.981
 1952 23.798 22.270 24.775 22.646 23.988 24.737 26.276 25.816 25.210 25.199 23.162␣
→24.707
 1953 24.364 22.644 25.565 24.062 25.431 24.635 27.009 26.606 26.268 26.462 25.246␣
→25.180
 1954 24.657 23.304 26.982 26.199 27.210 26.122 26.706 26.878 26.152 26.379 24.712␣
→25.688
 1955 24.990 24.239 26.721 23.475 24.767 26.219 28.361 28.599 27.914 27.784 25.693␣
→26.881
 1956 26.217 24.218 27.914 26.975 28.527 27.139 28.982 28.169 28.056 29.136 26.291␣
→26.987
 1957 26.589 24.848 27.543 26.896 28.878 27.390 28.065 28.141 29.048 28.484 26.634␣
→27.735
 1958 27.132 24.924 28.963 26.589 27.931 28.009 29.229 28.759 28.405 27.945 25.912␣
→26.619
 1959 26.076 25.286 27.660 25.951 26.398 25.565 28.865 30.000 29.261 29.012 26.992␣
→27.897
```

## Souvenir Data

Similarly, the file http://robjhyndman.com/tsdldata/data/fancy.dat contains monthly sales for a souvenir shop at a beach resort town in Queensland, Australia, for January 1987-December 1993 (original data from Wheelwright and Hyndman, 1998). We can read the data into R by typing:

```
> souvenir <- scan("http://robjhyndman.com/tsdldata/data/fancy.dat")
> souvenirtimeseries <- ts(souvenir, frequency=12, start=c(1987,1))
> souvenirtimeseries
  Jan       Feb       Mar       Apr       May       Jun       Jul
                                                                        Aug       Sep
→       Oct       Nov       Dec
 1987   1664.81   2397.53   2840.71   3547.29   3752.96   3714.74   4349.61   3566.
→34   5021.82   6423.48   7600.60  19756.21
 1988   2499.81   5198.24   7225.14   4806.03   5900.88   4951.34   6179.12   4752.
→15   5496.43   5835.10  12600.08  28541.72
 1989   4717.02   5702.63   9957.58   5304.78   6492.43   6630.80   7349.62   8176.
→62   8573.17   9690.50  15151.84  34061.01
 1990   5921.10   5814.58  12421.25   6369.77   7609.12   7224.75   8121.22   7979.
→25   8093.06   8476.70  17914.66  30114.41
 1991   4826.64   6470.23   9638.77   8821.17   8722.37  10209.48  11276.55  12552.
→22  11637.39  13606.89  21822.11  45060.69
 1992   7615.03   9849.69  14558.40  11587.33   9332.56  13082.09  16732.78  19888.
→61  23933.38  25391.35  36024.80  80721.71
 1993  10243.24  11266.88  21826.84  17357.33  15997.79  18601.53  26155.15  28586.
→52  30505.41  30821.33  46634.38 104660.67
```

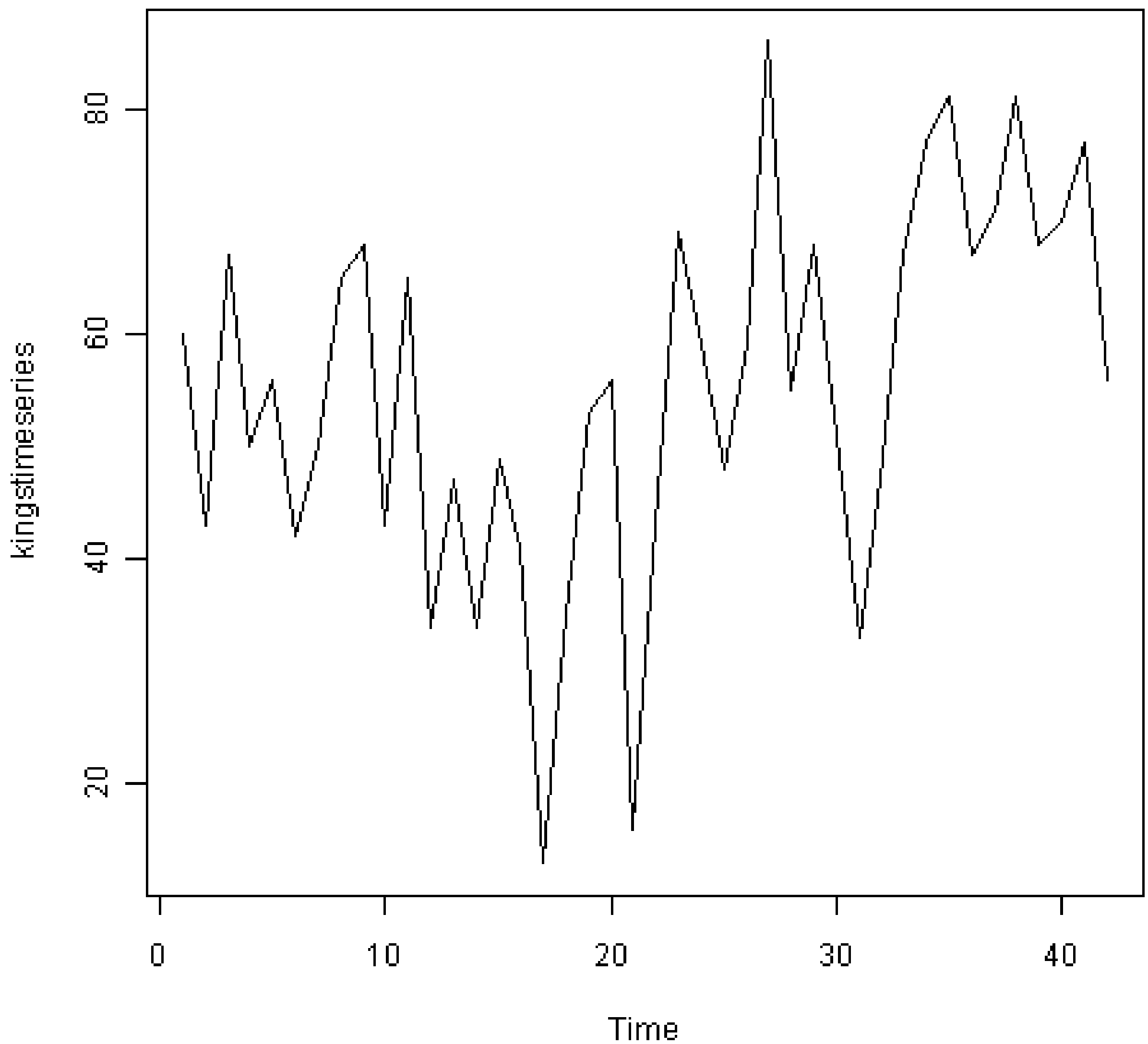
# Plotting Time Series

## 2.3 Plotting Time Series

Once you have read a time series into R, the next step is usually to make a plot of the time series data, which you can do with the plot.ts() function in R.

For example, to plot the time series of the age of death of 42 successive kings of England, we type:

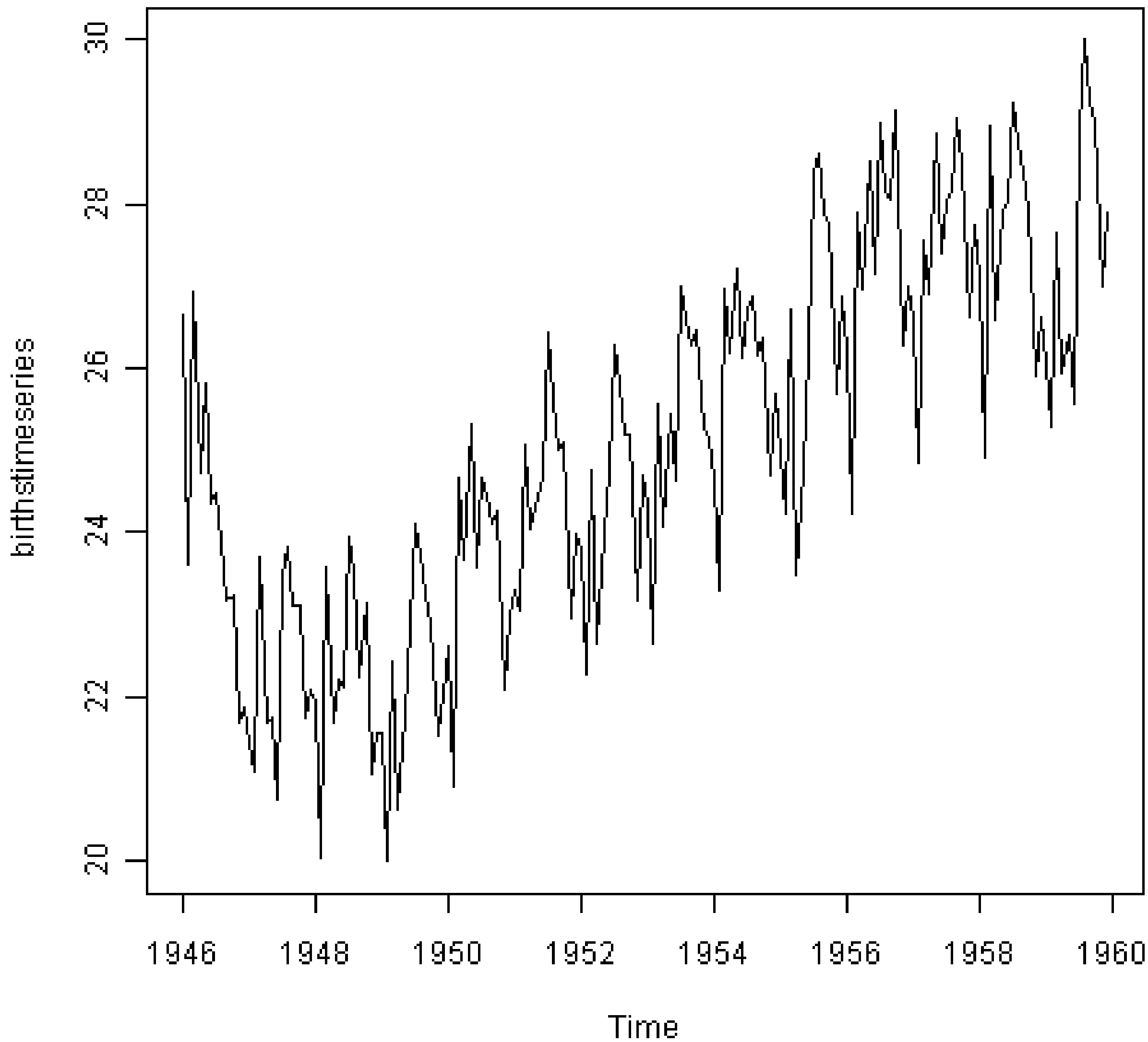
```
> plot.ts(kingstimeseries)
```




We can see from the time plot that this time series could probably be described using an additive model, since the random fluctuations in the data are roughly constant in size over time.

Likewise, to plot the time series of the number of births per month in New York city, we type:

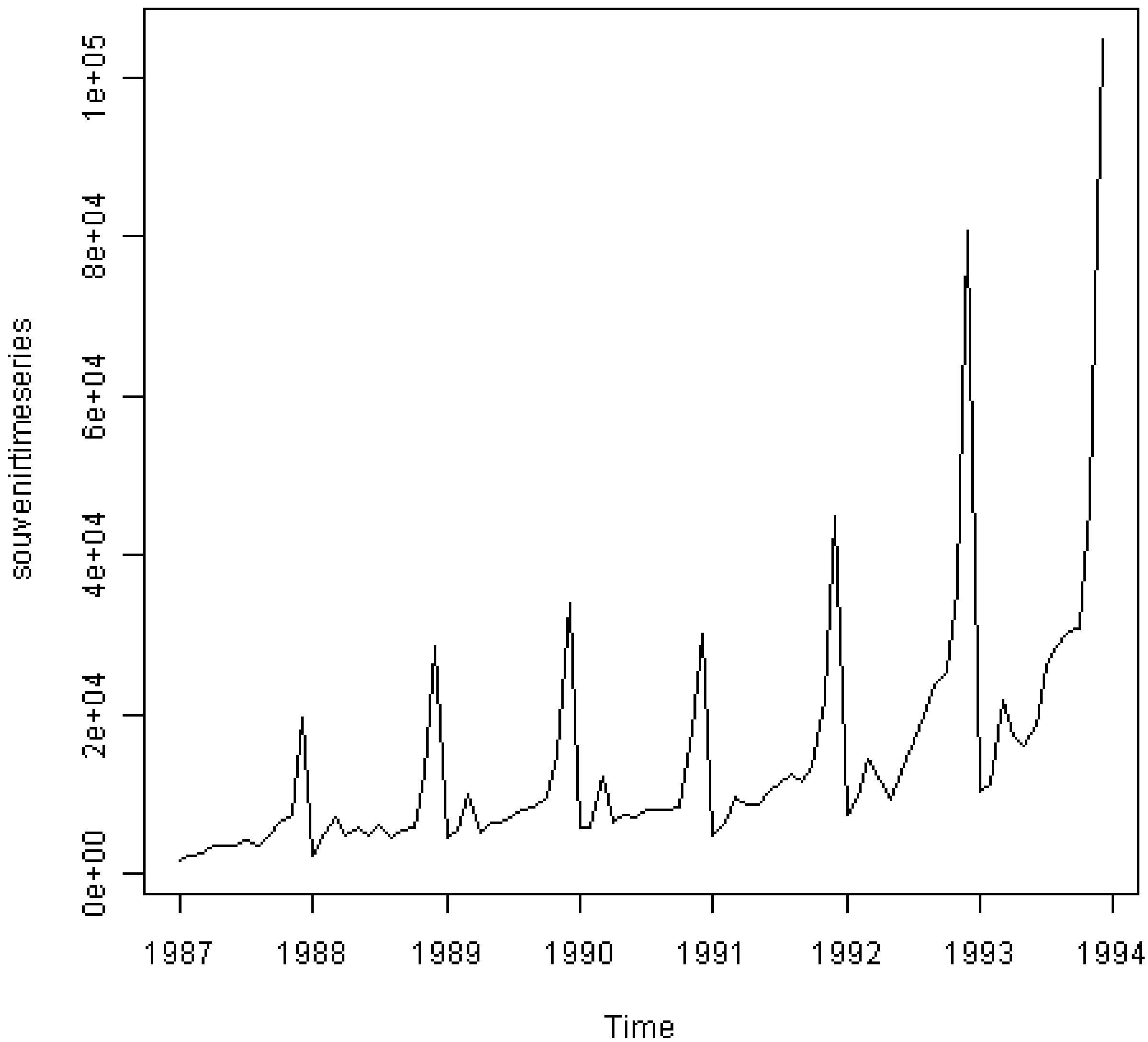
```
> plot.ts(birthstimeseries)
```




We can see from this time series that there seems to be seasonal variation in the number of births per month: there is a peak every summer, and a trough every winter. Again, it seems that this time series could probably be described using an additive model, as the seasonal fluctuations are roughly constant in size over time and do not seem to depend on the level of the time series, and the random fluctuations also seem to be roughly constant in size over time.

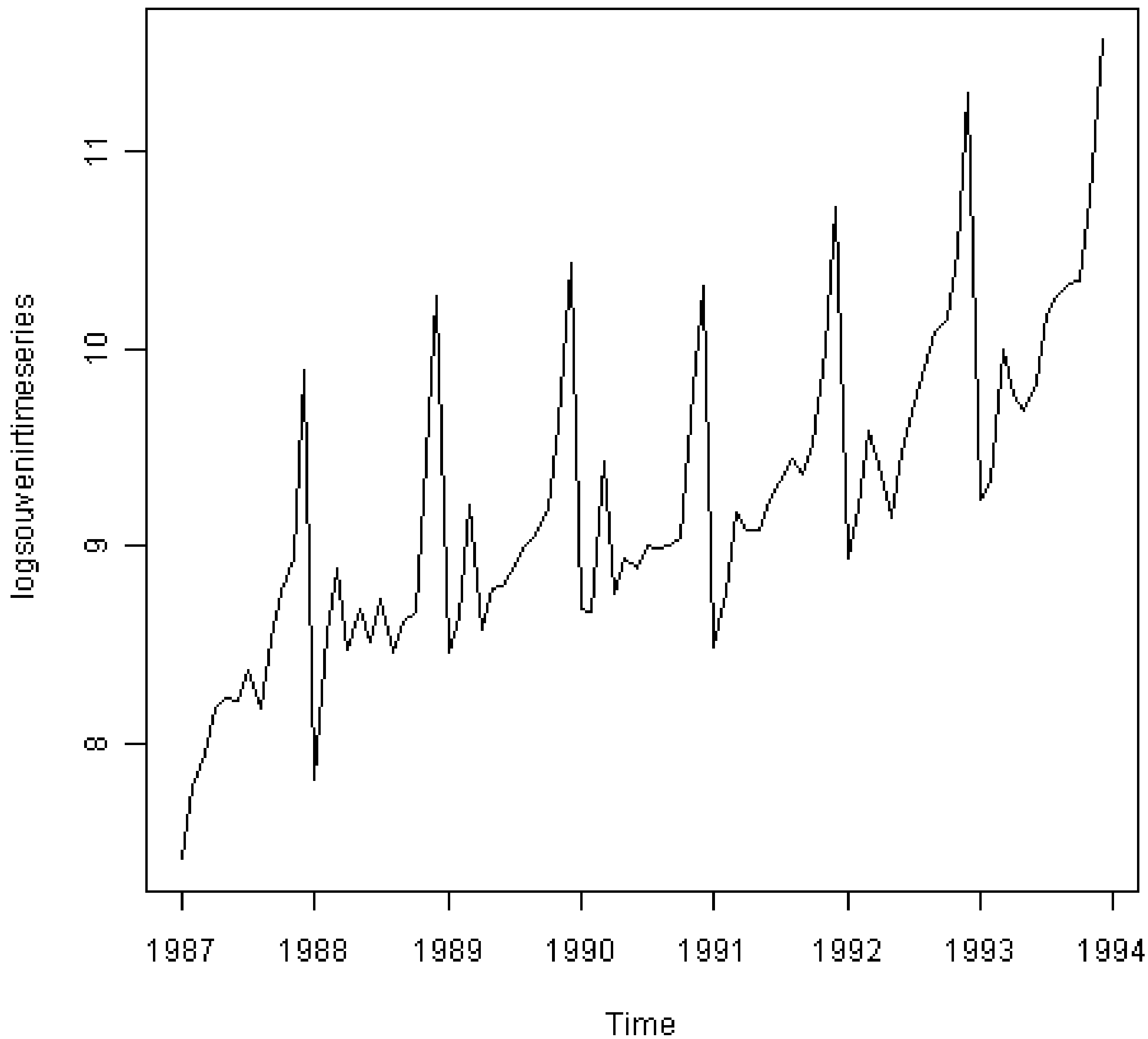
Similarly, to plot the time series of the monthly sales for the souvenir shop at a beach resort town in Queensland, Australia, we type:

```
> plot.ts(souvenirtimeseries)
```




In this case, it appears that an additive model is not appropriate for describing this time series, since the size of the seasonal fluctuations and random fluctuations seem to increase with the level of the time series. Thus, we may need to transform the time series in order to get a transformed time series that can be described using an additive model. For example, we can transform the time series by calculating the natural log of the original data:

```
> logsouvenirtimeseries <- log(souvenirtimeseries)
> plot.ts(logsouvenirtimeseries)
```




Here we can see that the size of the seasonal fluctuations and random fluctuations in the log-transformed time series seem to be roughly constant over time, and do not depend on the level of the time series. Thus, the log-transformed time series can probably be described using an additive model.

# Decomposing Time Series

## 2.4 Decomposing Time Series

Decomposing a time series means separating it into its constituent components, which are usually a trend component and an irregular component, and if it is a seasonal time series, a seasonal component.

### 2.4.1 Decomposing Non-Seasonal Data

A non-seasonal time series consists of a trend component and an irregular component. Decomposing the time series involves trying to separate the time series into these components, that is, estimating the the trend component and the irregular component.

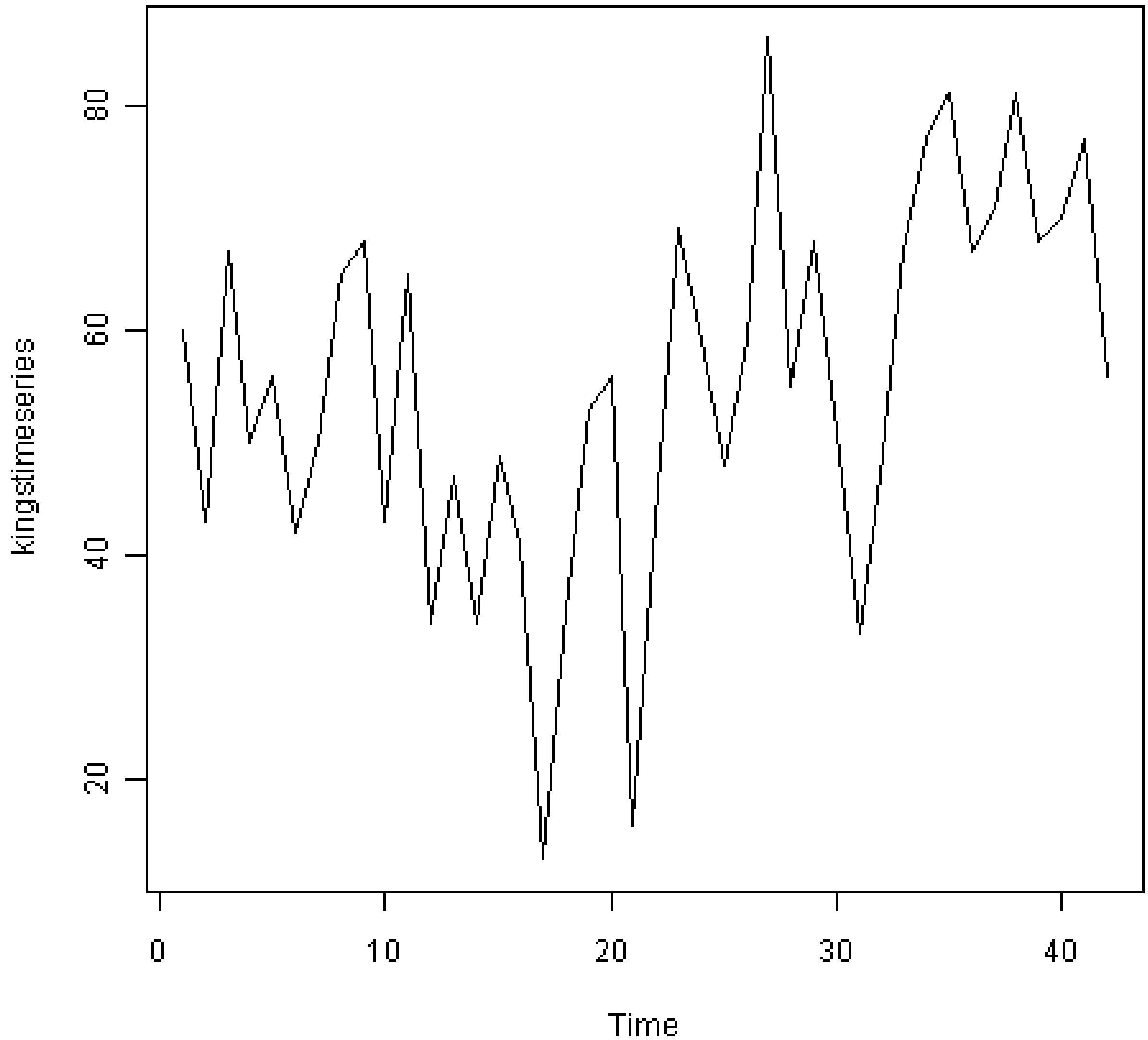
To estimate the trend component of a non-seasonal time series that can be described using an additive model, it is common to use a smoothing method, such as calculating the simple moving average of the time series.

The SMA() function in the "TTR" R package can be used to smooth time series data using a simple moving average. To use this function, we first need to install the "TTR" R package (for instructions on how to install an R package, see How to install an R package). Once you have installed the "TTR" R package, you can load the "TTR" R package by typing:

```
> library("TTR")
```

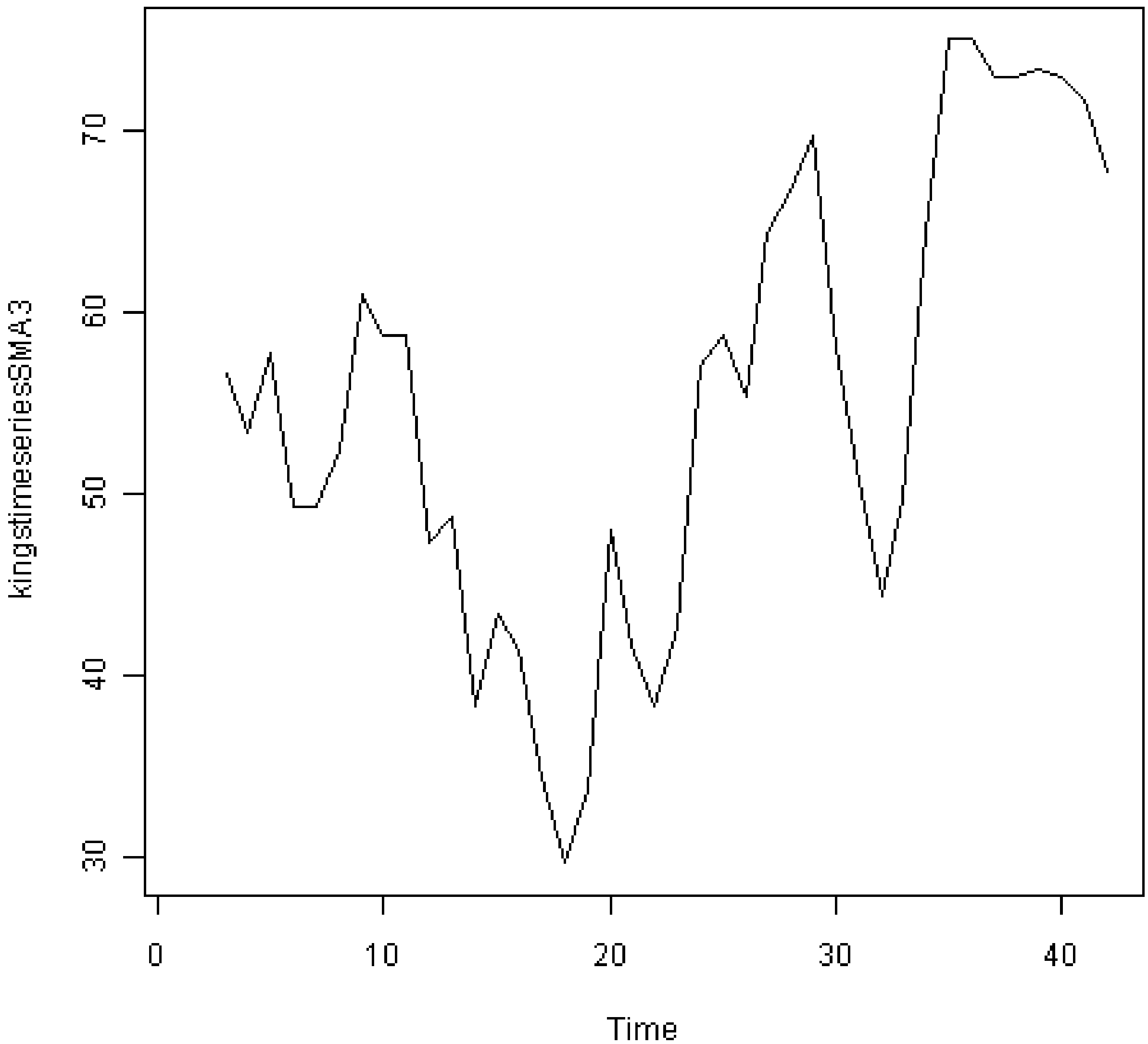
You can then use the "SMA()" function to smooth time series data. To use the SMA() function, you need to specify the order (span) of the simple moving average, using the parameter "n". For example, to calculate a simple moving average of order 5, we set n=5 in the SMA() function.

For example, as discussed above, the time series of the age of death of 42 successive kings of England appears is non-seasonal, and can probably be described using an additive model, since the random fluctuations in the data are roughly constant in size over time:



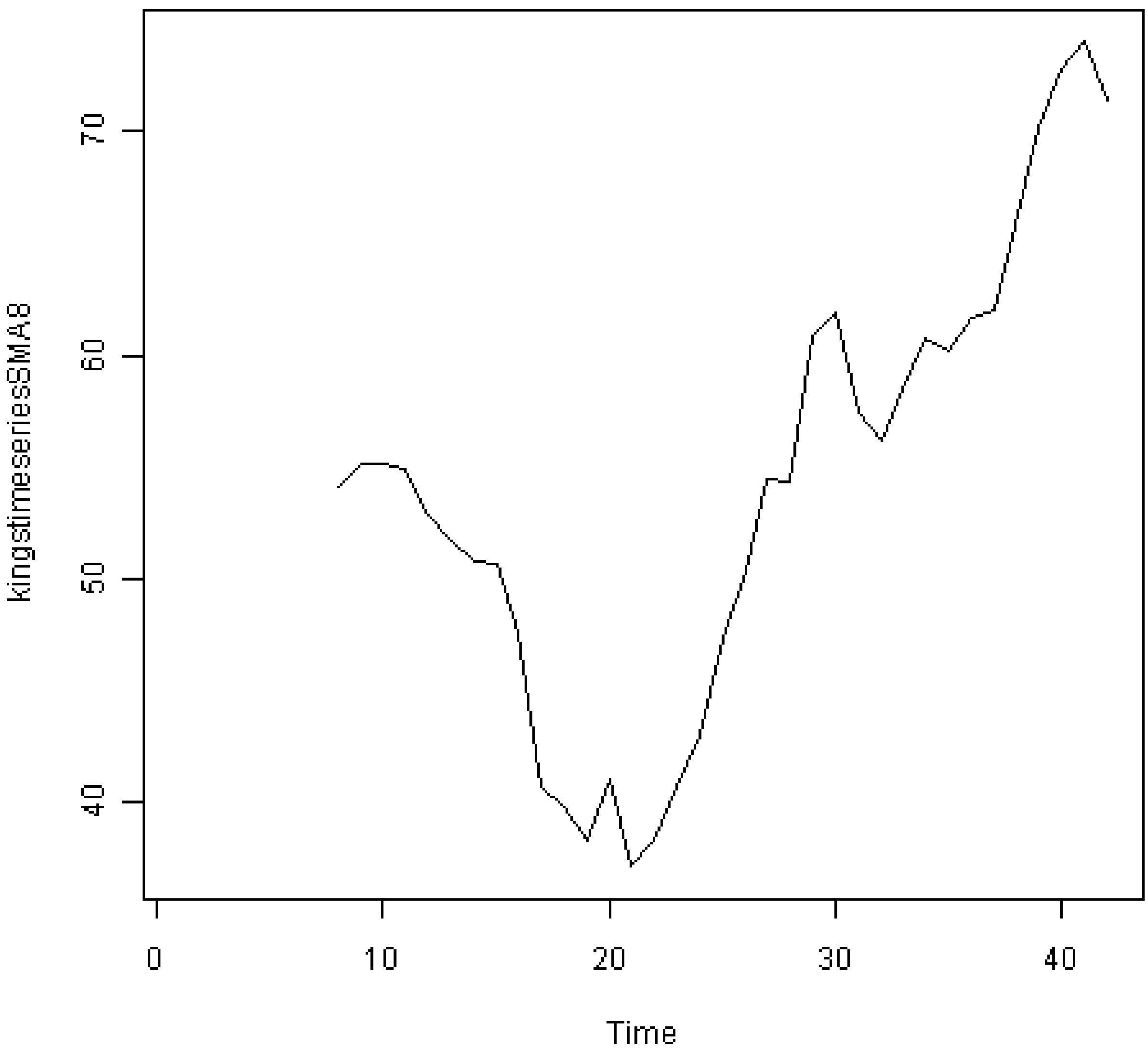

Thus, we can try to estimate the trend component of this time series by smoothing using a simple moving average. To smooth the time series using a simple moving average of order 3, and plot the smoothed time series data, we type:

```
> kingstimeseriesSMA3 <- SMA(kingstimeseries,n=3)
> plot.ts(kingstimeseriesSMA3)
```




There still appears to be quite a lot of random fluctuations in the time series smoothed using a simple moving average of order 3. Thus, to estimate the trend component more accurately, we might want to try smoothing the data with a simple moving average of a higher order. This takes a little bit of trial-and-error, to find the right amount of smoothing. For example, we can try using a simple moving average of order 8:

```
> kingstimeseriesSMA8 <- SMA(kingstimeseries,n=8)
> plot.ts(kingstimeseriesSMA8)
```




The data smoothed with a simple moving average of order 8 gives a clearer picture of the trend component, and we can see that the age of death of the English kings seems to have decreased from about 55 years old to about 38 years old during the reign of the first 20 kings, and then increased after that to about 73 years old by the end of the reign of the 40th king in the time series.

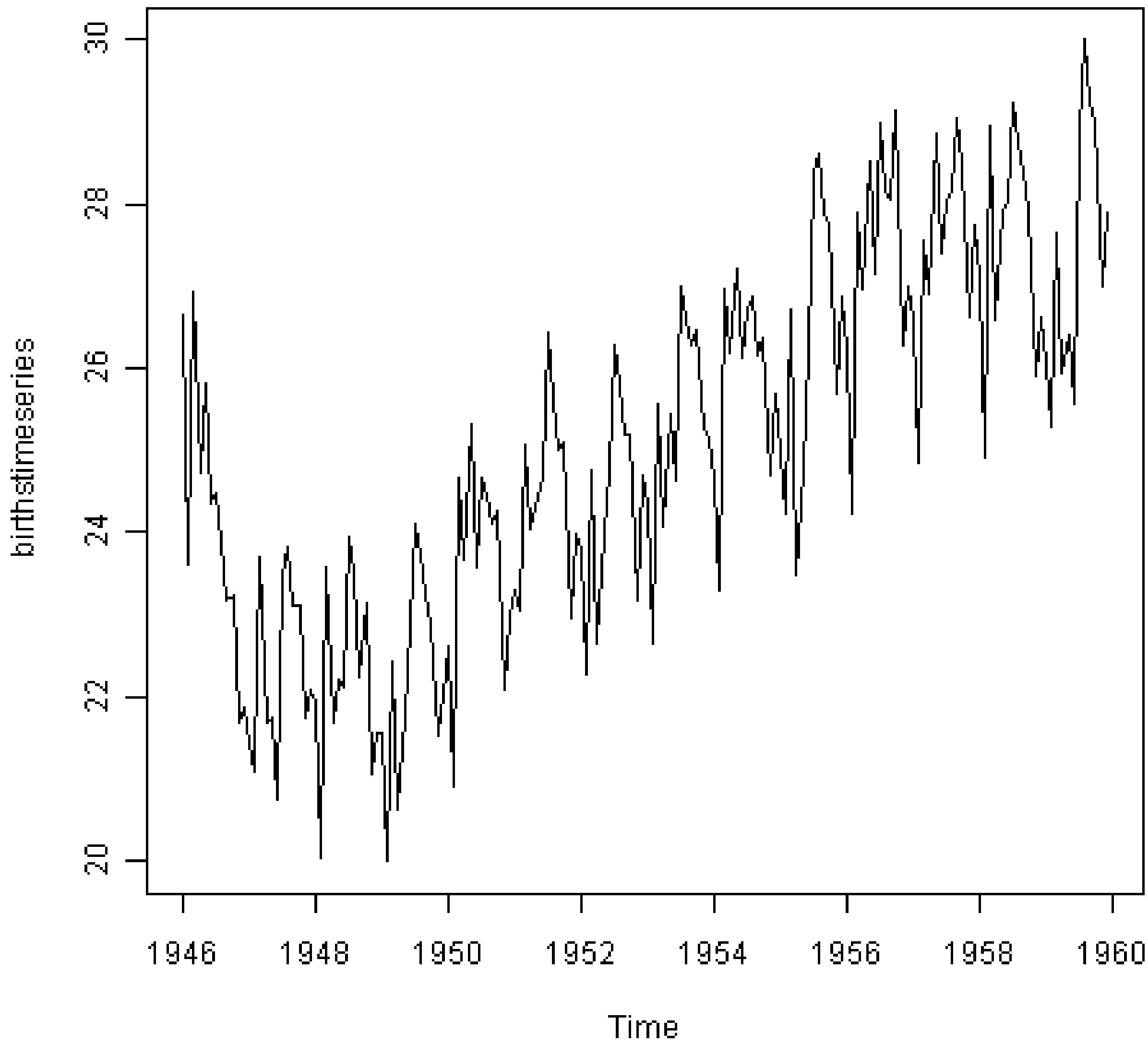
### 2.4.2 Decomposing Seasonal Data

A seasonal time series consists of a trend component, a seasonal component and an irregular component. Decomposing the time series means separating the time series into these three components: that is, estimating these three components.

To estimate the trend component and seasonal component of a seasonal time series that can be described using an additive model, we can use the "decompose()" function in R. This function estimates the trend, seasonal, and irregular components of a time series that can be described using an additive model.

The function "decompose()" returns a list object as its result, where the estimates of the seasonal component, trend component and irregular component are stored in named elements of that list objects, called "seasonal", "trend", and "random" respectively.

For example, as discussed above, the time series of the number of births per month in New York city is seasonal with a peak every summer and trough every winter, and can probably be described using an additive model since the seasonal and random fluctuations seem to be roughly constant in size over time:




To estimate the trend, seasonal and irregular components of this time series, we type:

```
> birthstimeseriescomponents <- decompose(birthstimeseries)
```

The estimated values of the seasonal, trend and irregular components are now stored in variables birthstimeseriescomponents$seasonal, birthstimeseriescomponents$trend and birthstimeseriescomponents$random. For example, we can print out the estimated values of the seasonal component by typing:

```
> birthstimeseriescomponents$seasonal # get the estimated values of the seasonal␣
→component
        Jan        Feb        Mar        Apr        May        Jun        Jul       ␣
→Aug        Sep        Oct        Nov        Dec
1946 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1947 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
```

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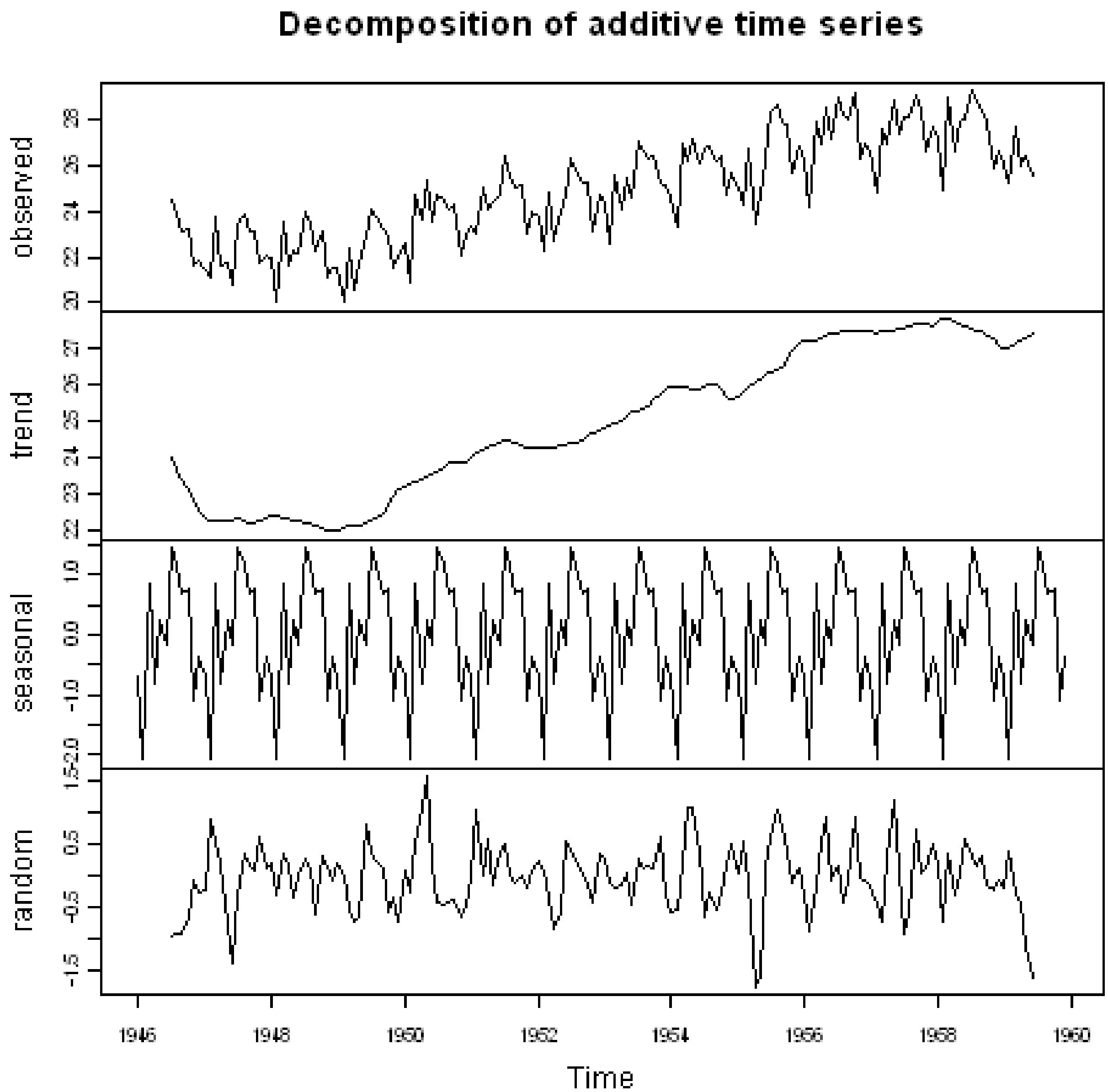
```
1948 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1949 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1950 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1951 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1952 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1953 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1954 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1955 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1956 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1957 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1958 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
1959 -0.6771947 -2.0829607  0.8625232 -0.8016787  0.2516514 -0.1532556  1.4560457  1.
→1645938  0.6916162  0.7752444 -1.1097652 -0.3768197
```

The estimated seasonal factors are given for the months January-December, and are the same for each year. The largest seasonal factor is for July (about 1.46), and the lowest is for February (about -2.08), indicating that there seems to be a peak in births in July and a trough in births in February each year.

We can plot the estimated trend, seasonal, and irregular components of the time series by using the "plot()" function, for example:

```
> plot(birthstimeseriescomponents)
```




The plot above shows the original time series (top), the estimated trend component (second from top), the estimated seasonal component (third from top), and the estimated irregular component (bottom). We see that the estimated trend component shows a small decrease from about 24 in 1947 to about 22 in 1948, followed by a steady increase from then on to about 27 in 1959.

### 2.4.3 Seasonally Adjusting

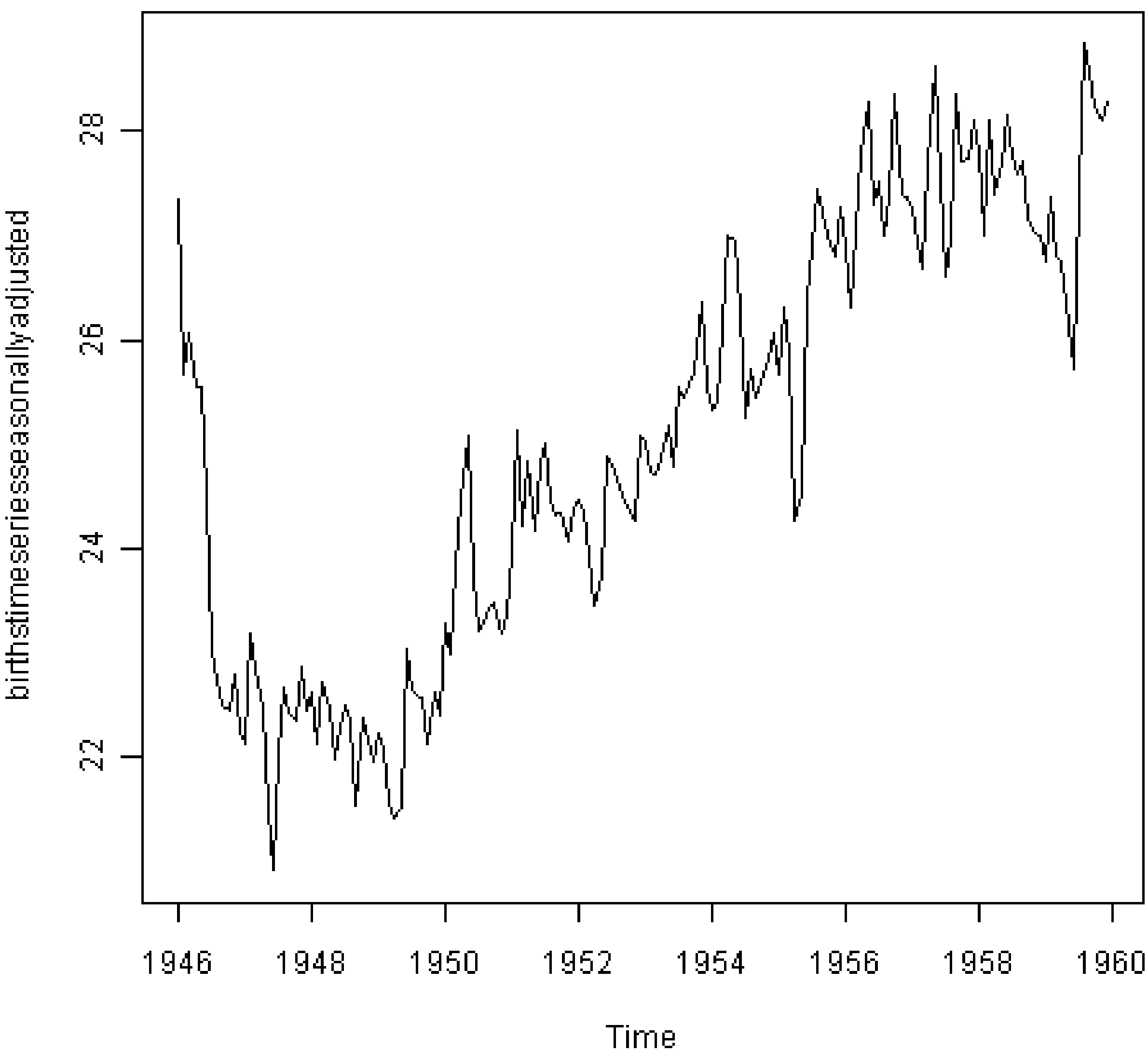
If you have a seasonal time series that can be described using an additive model, you can seasonally adjust the time series by estimating the seasonal component and subtracting the estimated seasonal component from the original time series. We can do this using the estimate of the seasonal component calculated by the "decompose()" function.

For example, to seasonally adjust the time series of the number of births per month in New York city, we can estimate the seasonal component using "decompose()", and then subtract the seasonal component from the original time series:

```
birthstimeseriescomponents <- decompose(birthstimeseries)
birthstimeseriesseasonallyadjusted <- birthstimeseries - birthstimeseriescomponents$seasonal
```

We can then plot the seasonally adjusted time series using the "plot()" function, by typing:

```
> plot(birthstimeseriesseasonallyadjusted)
```




You can see that the seasonal variation has been removed from the seasonally adjusted time series. The seasonally adjusted time series now just contains the trend component and an irregular component.

# Forecasts using Smoothing

## 2.5 Forecasts using Exponential Smoothing

Exponential smoothing can be used to make short-term forecasts for time series data.

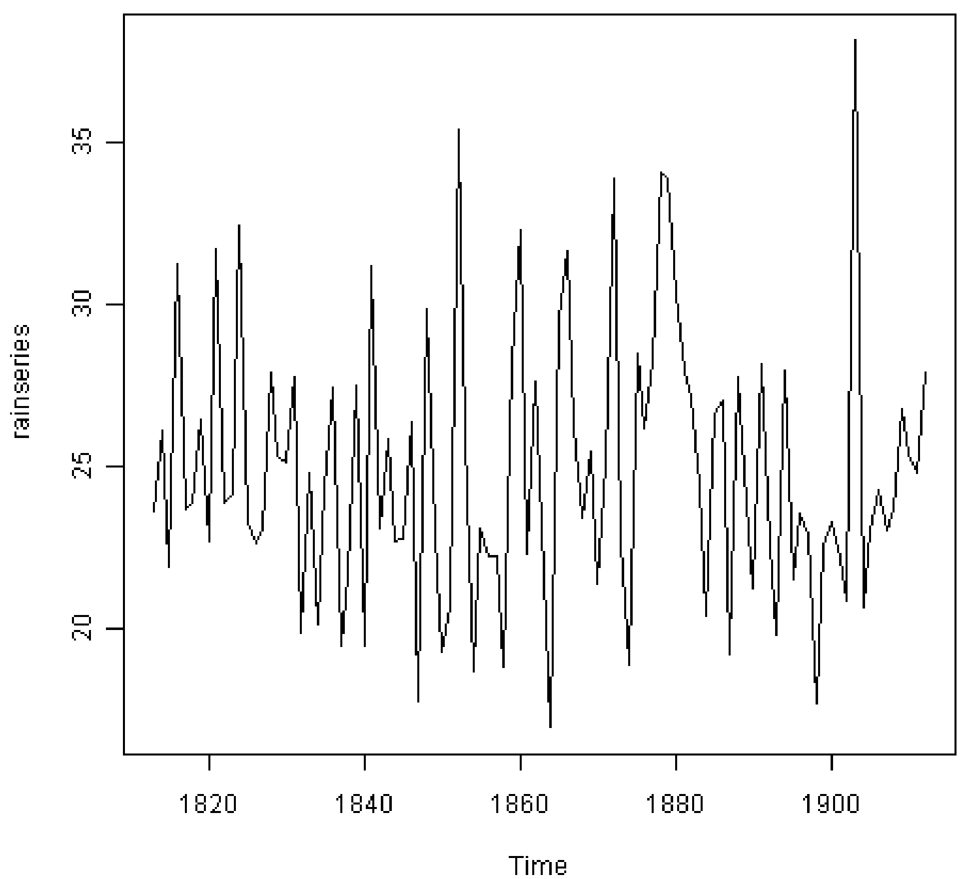
### 2.5.1 Simple Exponential Smoothing. Holt-Winters Exponential Smoothing (additive model with no trend and no seasonality)

If you have a time series that can be described using an additive model with constant level and no seasonality, you can use simple exponential smoothing to make short-term forecasts.

The simple exponential smoothing method provides a way of estimating the level at the current time point. Smoothing is controlled by the parameter alpha; for the estimate of the level at the current time point. The value of alpha; lies between 0 and 1. Values of alpha that are close to 0 mean that little weight is placed on the most recent observations when making forecasts of future values.

For example, the file http://robjhyndman.com/tsdldata/hurst/precip1.dat contains total annual rainfall in inches for London, from 1813-1912 (original data from Hipel and McLeod, 1994). We can read the data into R and plot it by typing:

```
> rain <- scan("http://robjhyndman.com/tsdldata/hurst/precip1.dat",skip=1)
> rainseries <- ts(rain,start=c(1813))
> plot.ts(rainseries)
```




You can see from the plot that there is roughly constant level (the mean stays constant at about 25 inches). The random fluctuations in the time series seem to be roughly constant in size over time, so it is probably appropriate to describe the data using an additive model. Thus, we can make forecasts using simple exponential smoothing.

To make forecasts using simple exponential smoothing in R, we can fit a simple exponential smoothing predictive model using the "HoltWinters()" function in R. To use HoltWinters() for simple exponential smoothing, we need to set the parameters beta=FALSE and gamma=FALSE in the HoltWinters() function (the beta and gamma parameters are used for Holt's exponential smoothing, or Holt-Winters exponential smoothing, as described below).

The HoltWinters() function returns a list variable, that contains several named elements.

For example, to use simple exponential smoothing to make forecasts for the time series of annual rainfall in London, we type:

```
> rainseriesforecasts <- HoltWinters(rainseries, beta=FALSE, gamma=FALSE)
> rainseriesforecasts
  Smoothing parameters:
  alpha:  0.02412151
  beta :  FALSE
  gamma:  FALSE
  Coefficients:
    [,1]
  a 24.67819
```

The output of HoltWinters() tells us that the estimated value of the alpha parameter is about 0.024. This is very close to zero, telling us that the forecasts are based on both recent and less recent observations (although somewhat more weight is placed on recent observations).

**By default, HoltWinters() just makes forecasts for the same time period covered by our original time series**.

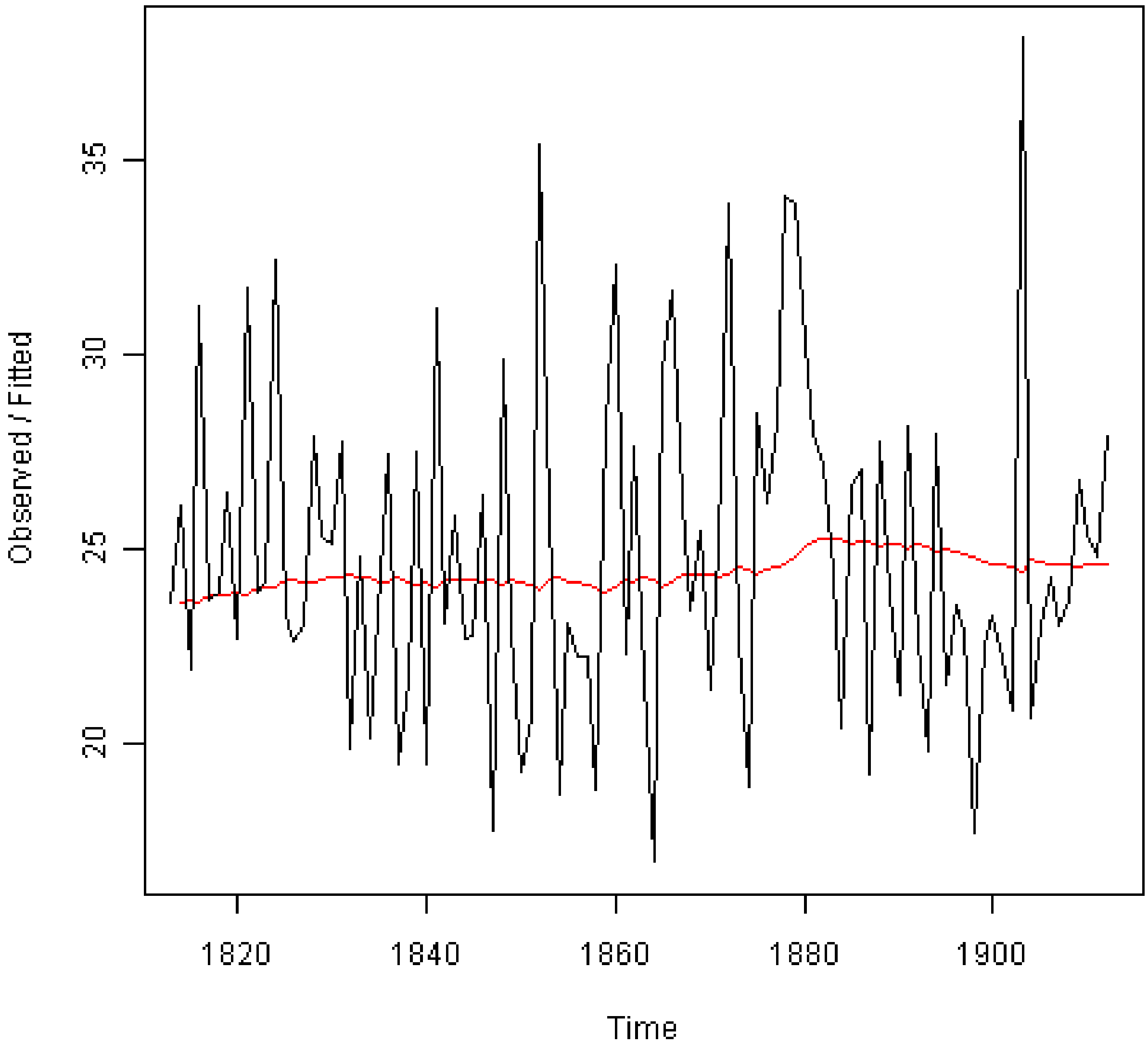
In this case, our original time series included rainfall for London from 1813-1912, so the forecasts are also for 1813-1912.

In the example above, we have stored the output of the HoltWinters() function in the list variable "rainseriesforecasts". The forecasts made by HoltWinters() are stored in a named element of this list variable called "fitted", so we can get their values by typing:

```
> rainseriesforecasts$fitted
  Time Series:
  Start = 1814
  End = 1912
  Frequency = 1
     xhat     level
  1814 23.56000 23.56000
  1815 23.62054 23.62054
  1816 23.57808 23.57808
  1817 23.76290 23.76290
  1818 23.76017 23.76017
  1819 23.76306 23.76306
  1820 23.82691 23.82691
  ...
  1905 24.62852 24.62852
  1906 24.58852 24.58852
  1907 24.58059 24.58059
  1908 24.54271 24.54271
  1909 24.52166 24.52166
  1910 24.57541 24.57541
  1911 24.59433 24.59433
  1912 24.59905 24.59905
```

We can plot the original time series against the forecasts by typing:

```
> plot(rainseriesforecasts)
```




**The plot shows the original time series in black, and the forecasts as a red line.** The time series of forecasts is much smoother than the time series of the original data here.

As a measure of the accuracy of the forecasts, we can calculate the sum of squared errors for the in-sample forecast errors, that is, the forecast errors for the time period covered by our original time series. The sum-of-squared-errors is stored in a named element of the list variable "rainseriesforecasts" called "SSE", so we can get its value by typing:

```
> rainseriesforecasts$SSE
  [1] 1828.855
```

That is, here the sum-of-squared-errors is 1828.855.

It is common in simple exponential smoothing to use the first value in the time series as the initial value for the level. For example, in the time series for rainfall in London, the first value is 23.56 (inches) for rainfall in 1813. You can specify the initial value for the level in the HoltWinters() function by using the "l.start" parameter. For example, to make forecasts with the initial value of the level set to 23.56, we type:

```
> HoltWinters(rainseries, beta=FALSE, gamma=FALSE, l.start=23.56)
```

As explained above, by default HoltWinters() just makes forecasts for the time period covered by the original data, which is **1813-1912** for the rainfall time series.

**We can make forecasts for further time points by using the "forecast()" function** in the R "forecast" package. To use the forecast() function, we first need to install the "forecast" R package.

Once you have installed the "forecast" R package, you can load the "forecast" R package by typing:

```
> library("forecast")
```

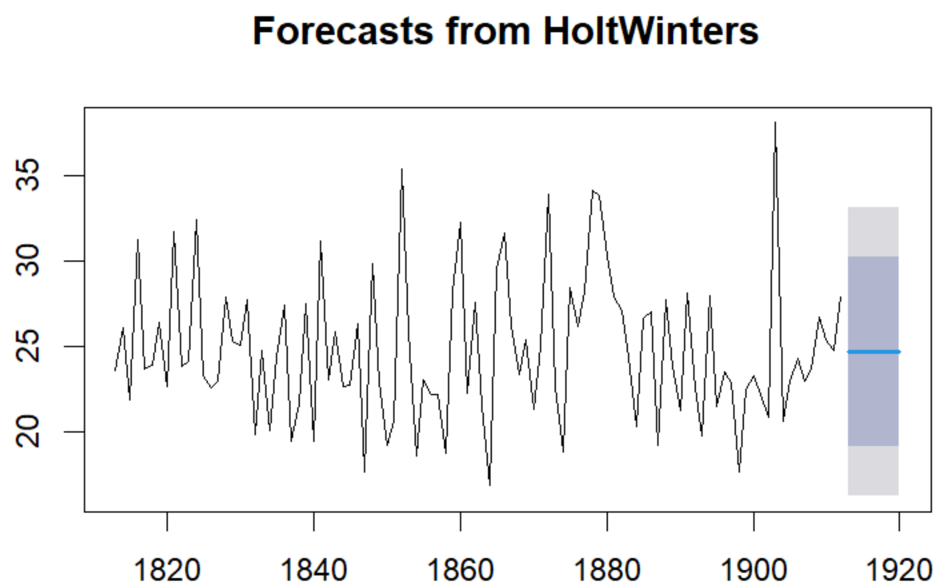
When using the forecast.HoltWinters() function, as its first argument (input), you pass it the predictive model that you have already fitted using the HoltWinters() function. For example, in the case of the rainfall time series, we stored the predictive model made using HoltWinters() in the variable "rainseriesforecasts". You specify how many further time points you want to make forecasts for by using the "h" parameter in forecast(). For example, to make a forecast of rainfall for the years 1814-1820 (8 more years) using forecast(), we type:

```
> rainseriesforecasts2 <- forecast(rainseriesforecasts, h=8)
> rainseriesforecasts2
 Point      Forecast     Lo 80     Hi 80     Lo 95     Hi 95
 1913        24.67819 19.17493 30.18145 16.26169 33.09470
 1914        24.67819 19.17333 30.18305 16.25924 33.09715
 1915        24.67819 19.17173 30.18465 16.25679 33.09960
 1916        24.67819 19.17013 30.18625 16.25434 33.10204
 1917        24.67819 19.16853 30.18785 16.25190 33.10449
 1918        24.67819 19.16694 30.18945 16.24945 33.10694
 1919        24.67819 19.16534 30.19105 16.24701 33.10938
 1920        24.67819 19.16374 30.19265 16.24456 33.11182
```

The forecast() function gives you the forecast for a year, a 80% prediction interval for the forecast, and a 95% prediction interval for the forecast. For example, the forecasted rainfall for 1920 is about 24.68 inches, with a 95% prediction interval of (16.24, 33.11).

To plot the predictions made by forecast(), we can use the "plot()" function:

```
> plot(rainseriesforecasts2)
```




Here the forecasts for 1913-1920 are plotted as a blue line, the 80% prediction interval as an purple shaded area, and the 95% prediction interval as a gray shaded area.

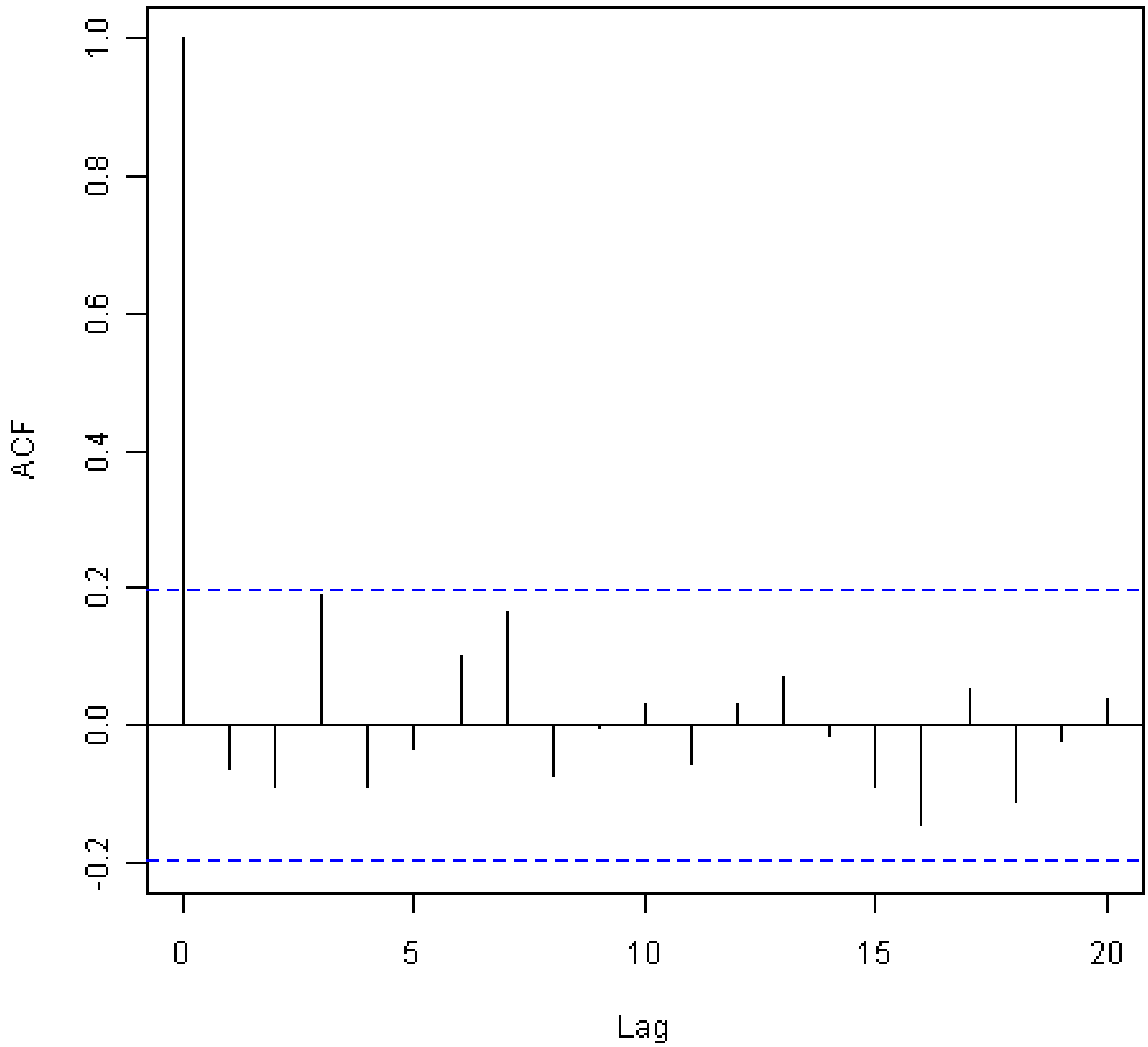
The 'forecast errors' are calculated as the observed values minus predicted values, for each time point. We can only calculate the forecast errors for the time period covered by our original time series, which is 1813-1912 for the rainfall data. As mentioned above, one measure of the accuracy of the predictive model is the sum-of-squared-errors (SSE) for the in-sample forecast errors.

The in-sample forecast errors are stored in the named element "residuals" of the list variable returned by forecast(). If the predictive model cannot be improved upon, there should be no correlations between forecast errors for successive predictions. In other words, **if there are correlations between forecast errors for successive predictions, it is likely that the simple exponential smoothing forecasts could be improved upon by another forecasting technique.**

To figure out whether this is the case, we can obtain a correlogram of the in-sample forecast errors for lags 1-20. We can calculate a correlogram of the forecast errors using the "acf()" function in R. To specify the maximum lag that we want to look at, we use the "lag.max" parameter in acf().

For example, to calculate a correlogram of the in-sample forecast errors for the London rainfall data for lags 1-20, we type:

```
> acf(rainseriesforecasts2$residuals, lag.max=20 , na.action = na.pass)
```



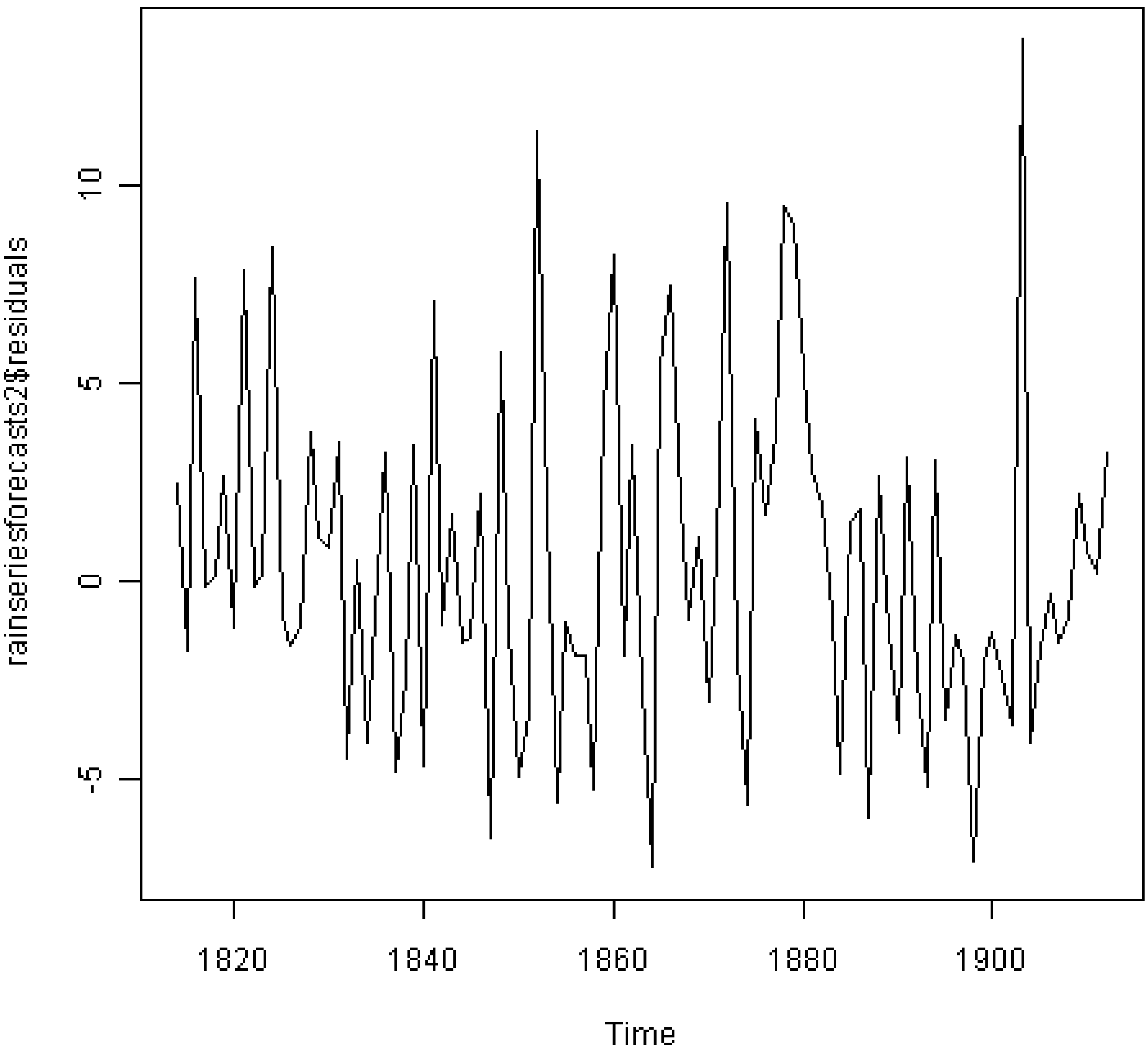

You can see from the sample correlogram that the autocorrelation at lag 3 is just touching the significance bounds. To test whether there is significant evidence for non-zero correlations at lags 1-20, we can carry out a Ljung-Box test. This can be done in R using the “Box.test()”, function. The maximum lag that we want to look at is specified using the “lag” parameter in the Box.test() function. For example, to test whether there are non-zero autocorrelations at lags 1-20, for the in-sample forecast errors for London rainfall data, we type:

```
> Box.test(rainseriesforecasts2$residuals, lag=20, type="Ljung-Box")
    Box-Ljung test
  data:  rainseriesforecasts2$residuals
  X-squared = 17.4008, df = 20, p-value = 0.6268
```

Here the Ljung-Box test statistic is 17.4, and the p-value is 0.6, so there is little evidence of non-zero autocorrelations in the in-sample forecast errors at lags 1-20.

To be sure that the predictive model cannot be improved upon, it is also a good idea to check whether the forecast errors are normally distributed with mean zero and constant variance. To check whether the forecast errors have constant variance, we can make a time plot of the in-sample forecast errors:

```
> plot.ts(rainseriesforecasts2$residuals)
```




The plot shows that the in-sample forecast errors seem to have roughly constant variance over time, although the size of the fluctuations in the start of the time series (1820-1830) may be slightly less than that at later dates (eg. 1840-1850).

To check whether the forecast errors are normally distributed with mean zero, we can plot a histogram of the forecast errors, with an overlaid normal curve that has mean zero and the same standard deviation as the distribution of forecast errors. To do this, we can define an R function "plotForecastErrors()", which we do on the following page.

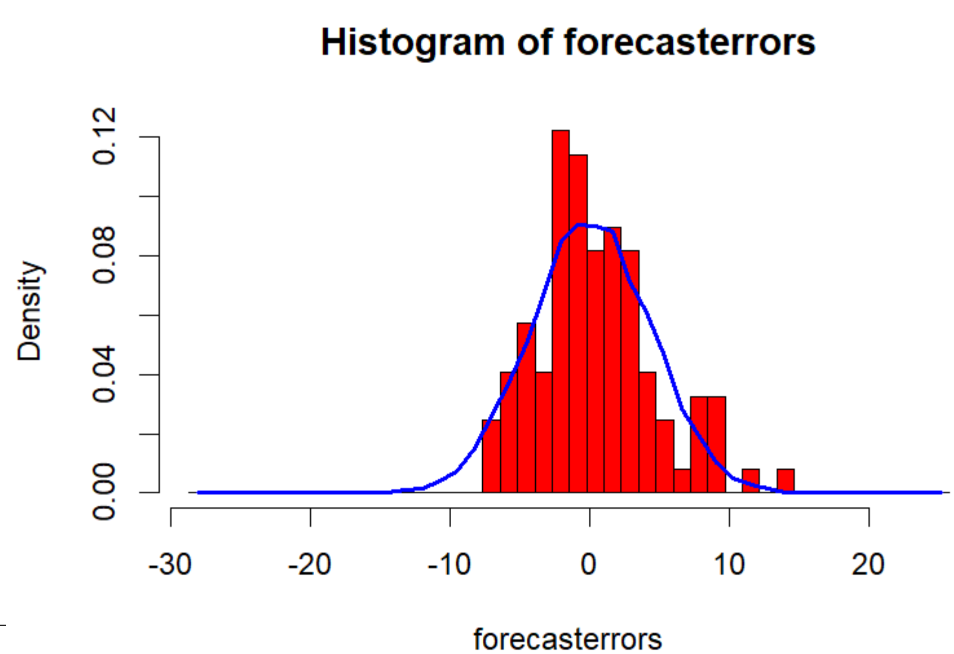
Copy and paste the entirety of the code below to define the function:

```
plotForecastErrors <- function(forecasterrors)
{
  # make a histogram of the forecast errors:
  mybinsize <- IQR(forecasterrors)/4
  mysd  <- sd(forecasterrors)
  mymin <- min(forecasterrors) - mysd*5
  mymax <- max(forecasterrors) + mysd*3
  # generate normally distributed data with mean 0 and standard deviation mysd
  mynorm <- rnorm(10000, mean=0, sd=mysd)
  mymin2 <- min(mynorm)
  mymax2 <- max(mynorm)
  if (mymin2 < mymin) { mymin <- mymin2 }
  if (mymax2 > mymax) { mymax <- mymax2 }
  # make a red histogram of the forecast errors, with the normally distributed data
overlaid:
    mybins <- seq(mymin, mymax, mybinsize)
    hist(forecasterrors, col="red", freq=FALSE, breaks=mybins)
  # freq=FALSE ensures the area under the histogram = 1
  # generate normally distributed data with mean 0 and standard deviation mysd
  myhist <- hist(mynorm, plot=FALSE, breaks=mybins)
  # plot the normal curve as a blue line on top of the histogram of forecast errors:
    points(myhist$mids, myhist$density, type="l", col="blue", lwd=2)
}
```

You will have to copy the function above into R in order to use it. You can then use plotForecastErrors() to plot a histogram (with overlaid normal curve) of the forecast errors for the rainfall predictions. First remove any Null Values from the residual vector:

```
> rainseriesforecasts2$residuals <-
  rainseriesforecasts2$residuals[!is.na(rainseriesforecasts2$residuals)]
```

```
> plotForecastErrors(rainseriesforecasts2$residuals)
```



The plot shows that the distribution of forecast errors is roughly centered on zero, and is more or less normally distributed, although it seems to be slightly skewed to the right compared to a normal curve. However, the right skew is relatively small, and so it is plausible that the forecast errors are normally distributed with mean zero.

The Ljung-Box test showed that there is little evidence of non-zero autocorrelations in the in-sample forecast errors, and the distribution of forecast errors seems to be normally distributed with mean zero. **This suggests that the simple exponential smoothing method provides an adequate predictive model for London rainfall, which probably cannot be improved upon.** Furthermore, the assumptions that the 80% and 95% predictions intervals were based upon (that there are no autocorrelations in the forecast errors, and the forecast errors are normally distributed with mean zero and constant variance) are probably valid.

### 2.5.2 Holt-Winters Exponential Smoothing (additive model with increasing or decreasing trend and no seasonality)

If you have a time series that can be described using an **additive model with increasing or decreasing trend and no seasonality,** you can use Holt's exponential smoothing to make short-term forecasts.

Holt's exponential smoothing estimates the level and slope at the current time point. Smoothing is controlled by two parameters, alpha, for the estimate of the level at the current time point, and beta for the estimate of the slope b of the trend component at the current time point. As with simple exponential smoothing, the paramters alpha and beta have values between 0 and 1, **and values that are close to 0 mean that little weight is placed on the most recent observations when making forecasts of future values.**

An example of a time series that can probably be described using an additive model with a trend and no seasonality is the time series of the **annual diameter of women's skirts at the hem, from 1866 to 1911**. The data is available in the file http://robjhyndman.com/tsdldata/roberts/skirts.dat (original data from Hipel and McLeod, 1994).

We can read in and plot the data in R by typing:

```
> skirts <- scan("http://robjhyndman.com/tsdldata/roberts/skirts.dat",skip=5)
> skirtsseries <- ts(skirts,start=c(1866))
> plot.ts(skirtsseries)
```

We can see from the plot that there was an increase in hem diameter from about 600 in 1866 to about 1050 in 1880, and that afterwards the hem diameter decreased to about 520 in 1911.

To make forecasts, we can fit a predictive model using the HoltWinters() function in R. To use HoltWinters() for Holt's exponential smoothing, we need to set the parameter gamma=FALSE (the gamma parameter is used for Holt-Winters exponential smoothing, as described below).

For example, to use Holt's exponential smoothing to fit a predictive model for skirt hem diameter, we type:

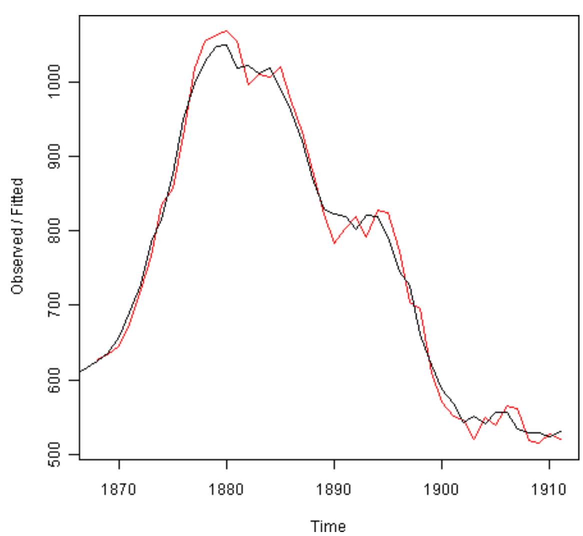
```
> skirtsseriesforecasts <- HoltWinters(skirtsseries, gamma=FALSE)
> skirtsseriesforecasts
  Smoothing parameters:
  alpha:  0.8383481
  beta :  1
  gamma:  FALSE
  Coefficients:
    [,1]
  a 529.308585
  b   5.690464
> skirtsseriesforecasts$SSE
```

```
  [1] 16954.18
```

The estimated value of alpha is 0.84, and of beta is 1.00. These are both high, telling us that both the estimate of the current value of the level, and of the slope b of the trend component, are based mostly upon very recent observations in the time series. This makes good intuitive sense, since the level and the slope of the time series both change quite a lot over time. The value of the sum-of-squared-errors for the in-sample forecast errors is 16954.

We can plot the original time series as a black line, with the forecasted values as a red line on top of that, by typing:

```
> plot(skirtsseriesforecasts)
```



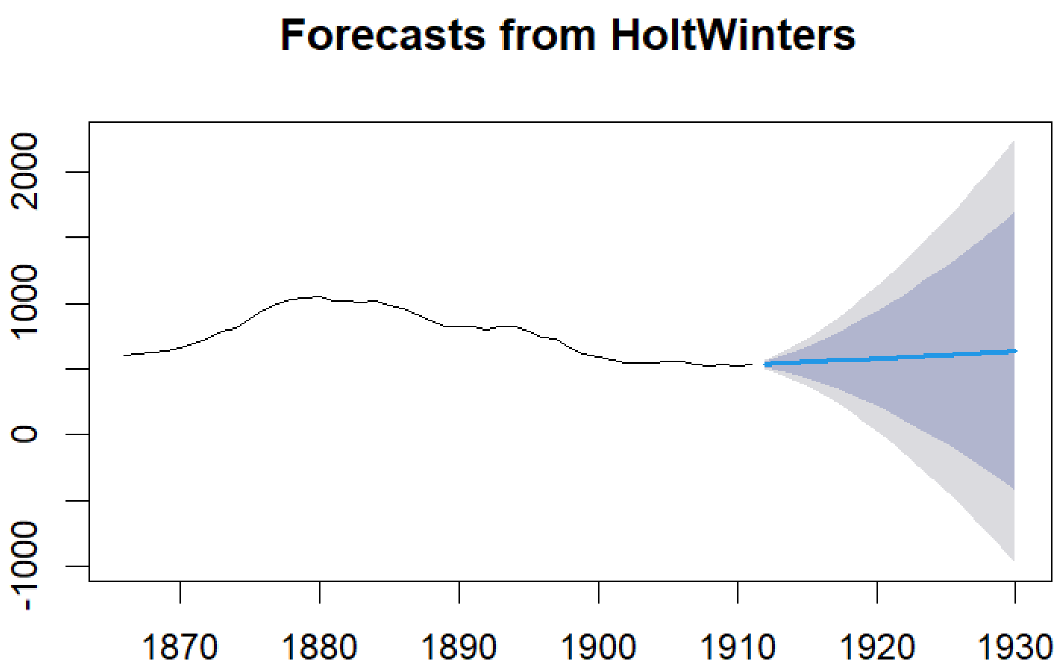

We can see from the picture that the in-sample forecasts agree pretty well with the observed values, although they tend to lag behind the observed values a little bit.

If you wish, you can specify the initial values of the level and the slope b of the trend component by using the "l.start" and "b.start" arguments for the HoltWinters() function. It is common to set the initial value of the level to the first value in the time series (608 for the skirts data), and the initial value of the slope to the second value minus the first value (9 for the skirts data). For example, to fit a predictive model to the skirt hem data using Holt's exponential smoothing, with initial values of 608 for the level and 9 for the slope b of the trend component, we type:

```
> HoltWinters(skirtsseries, gamma=FALSE, l.start=608, b.start=9)
```

As for simple exponential smoothing, we can make forecasts for future times not covered by the original time series by using the forecast() function in the "forecast" package. For example, our time series data for skirt hems was for 1866 to 1911, so we can make predictions for 1912 to 1930 (19 more data points), and plot them, by typing:

```
> skirtsseriesforecasts2 <- forecast(skirtsseriesforecasts, h=19)
> plot(skirtsseriesforecasts2)
```

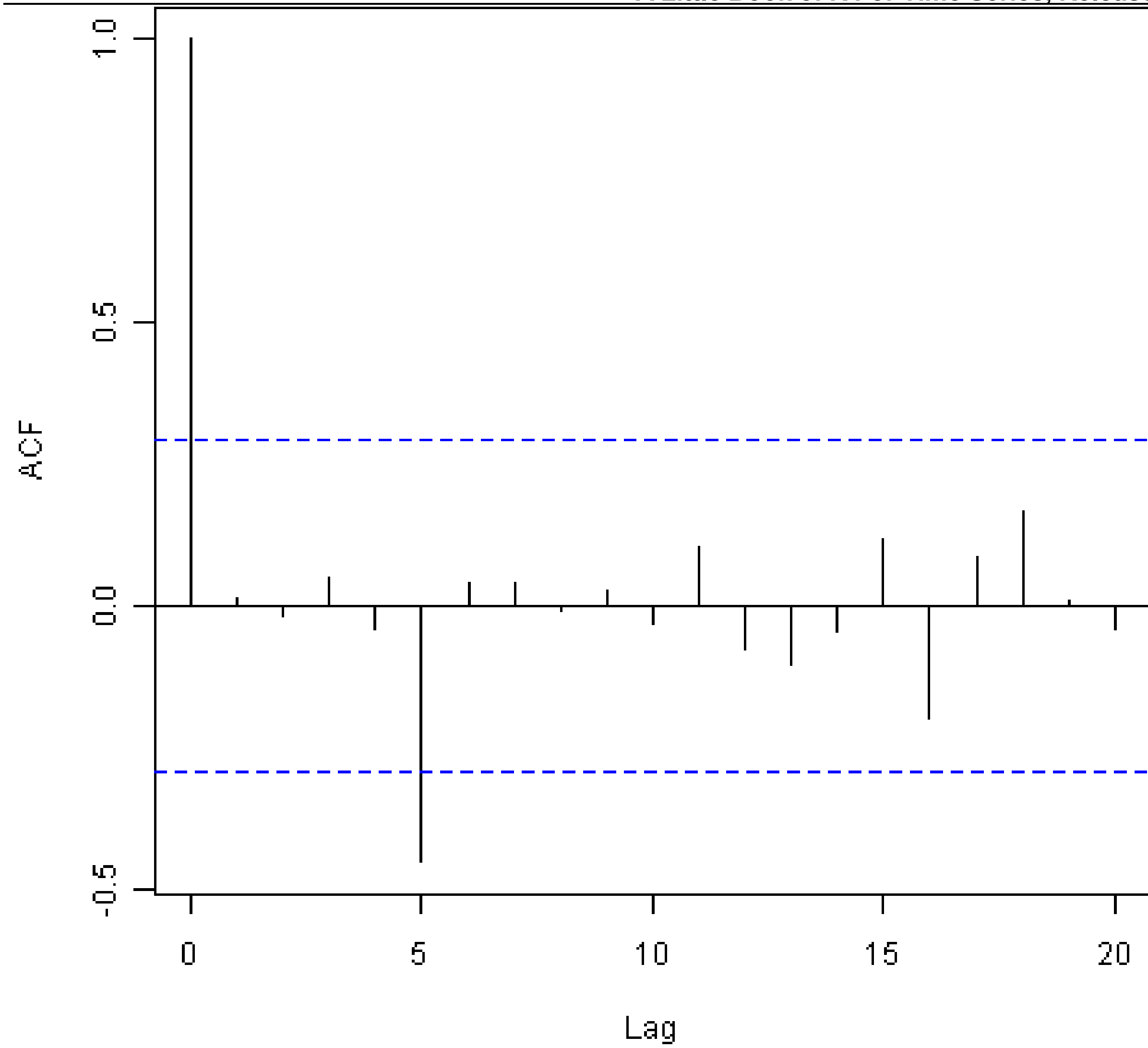



The forecasts are shown as a blue line, with the 80% prediction intervals as an purple shaded area, and the 95% prediction intervals as a gray shaded area.

As for simple exponential smoothing, we can check whether the predictive model could be improved upon by checking whether the in-sample forecast errors show non-zero autocorrelations at lags 1-20. For example, for the skirt hem data, we can make a correlogram, and carry out the Ljung-Box test, by typing (na.omit omits the null values):

```
> acf(na.omit(skirtsseriesforecasts2$residuals), lag.max=20)
> Box.test(na.omit(skirtsseriesforecasts2$residuals), lag=20, type="Ljung-Box")

    Box-Ljung test
  data:  skirtsseriesforecasts2$residuals
  X-squared = 19.7312, df = 20, p-value = 0.4749
```



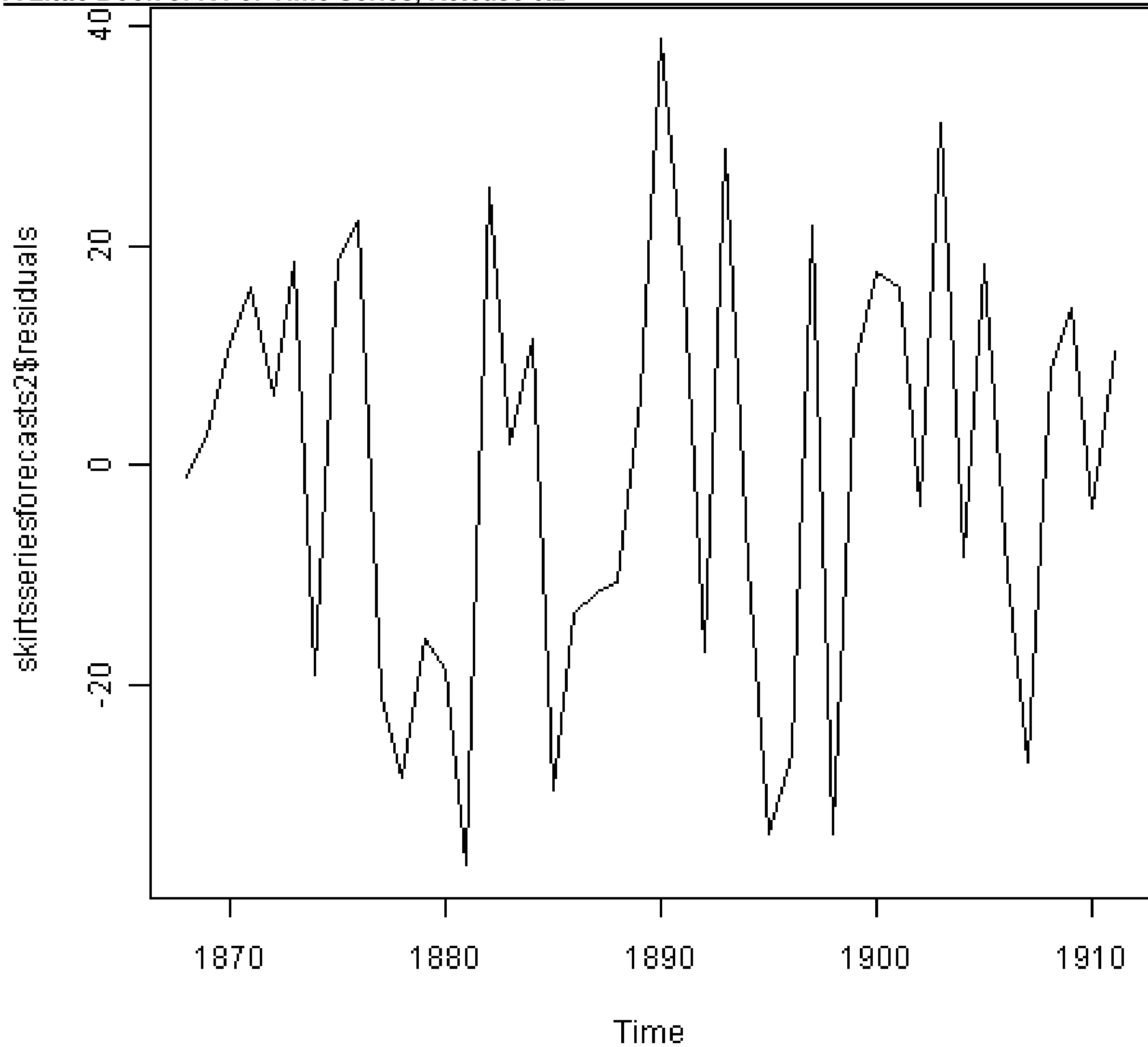

Here the correlogram shows that the sample **autocorrelation for the in-sample forecast errors at lag 5 exceeds the significance bounds**. However, we would expect one in 20 of the autocorrelations for the first twenty lags to exceed the 95% significance bounds by chance alone. Indeed, when we carry out the Ljung-Box test, the p-value is 0.47, indicating that there is little evidence of non-zero autocorrelations in the in-sample forecast errors at lags 1-20.

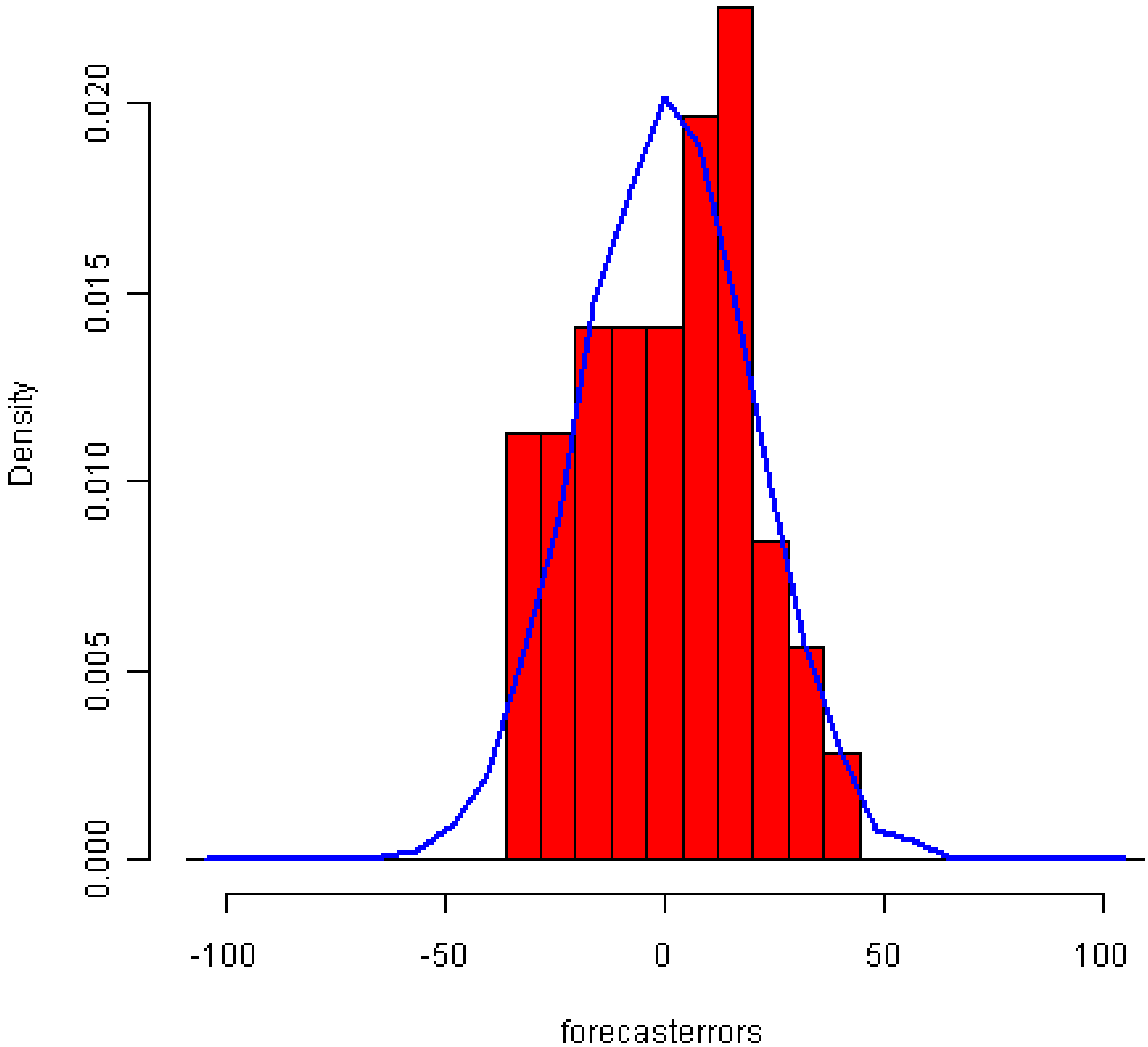
As for simple exponential smoothing, we should also check that the forecast errors have constant variance over time, and are normally distributed with mean zero. We can do this by making a time plot of forecast errors, and a histogram of the distribution of forecast errors with an overlaid normal curve:

```
plot.ts(skirtsseriesforecasts2$residuals) # make time series plot

skirtsseriesforecasts2$residuals <-
skirtsseriesforecasts2$residuals[!is.na(skirtsseriesforecasts2$residuals)]

plotForecastErrors(skirtsseriesforecasts2$residuals) # make a histogram
```


40
20
0
-20
skirtsseriesforecasts2$residuals
1870
1880
1890
1900
1910
Time




The time plot of forecast errors shows that the forecast errors have roughly constant variance over time. The histogram of forecast errors show that it is plausible that the forecast errors are normally distributed with mean zero and constant variance.

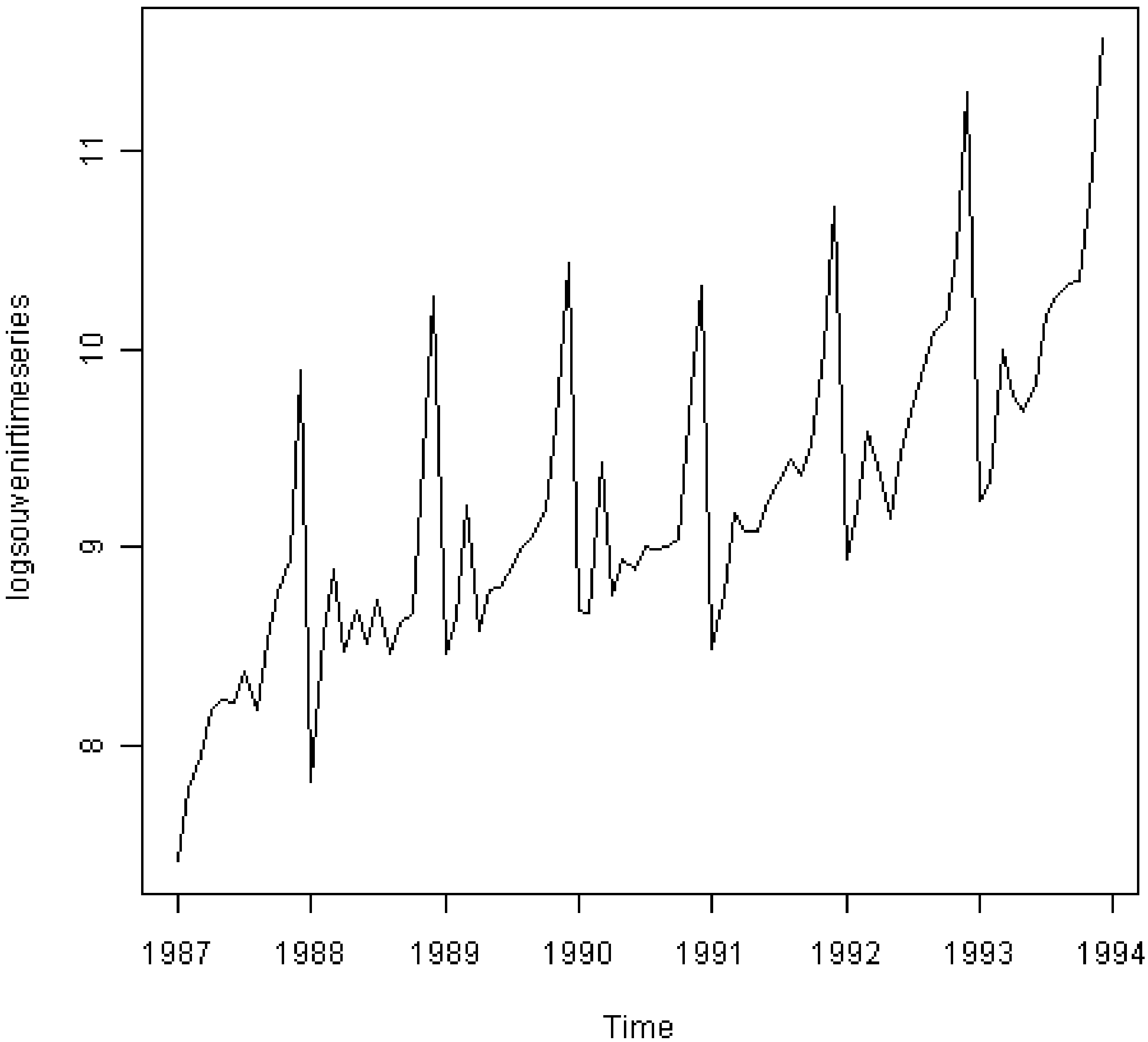
Thus, the Ljung-Box test shows that there is little evidence of autocorrelations in the forecast errors, while the time plot and histogram of forecast errors show that it is plausible that the forecast errors are normally distributed with mean zero and constant variance. Therefore, we can conclude that Holt's exponential smoothing provides an adequate predictive model for skirt hem diameters, which probably cannot be improved upon. In addition, it means that the assumptions that the 80% and 95% predictions intervals were based upon are probably valid.

### 2.5.3 Holt-Winters Exponential Smoothing (additive model with increasing or decreasing trend and seasonality)

If you have a time series that can be described using an **additive model with increasing or decreasing trend and seasonality**, you can use Holt-Winters exponential smoothing to make short-term forecasts.

Holt-Winters exponential smoothing estimates the level, slope and seasonal component at the current time point. Smoothing is controlled by three parameters: alpha, beta, and gamma, for the estimates of the level, slope b of the trend component, and the seasonal component, respectively, at the current time point. The parameters alpha, beta and gamma all have values between 0 and 1, and values that are close to 0 mean that relatively little weight is placed on the most recent observations when making forecasts of future values.

An example of a time series that can probably be described using an additive model with a trend and seasonality is the time series of the log of monthly sales for the souvenir shop at a beach resort town in Queensland, Australia (discussed above):



To make forecasts, we can fit a predictive model using the HoltWinters() function. For example, to fit a predictive model for the log of the monthly sales in the souvenir shop, we type:

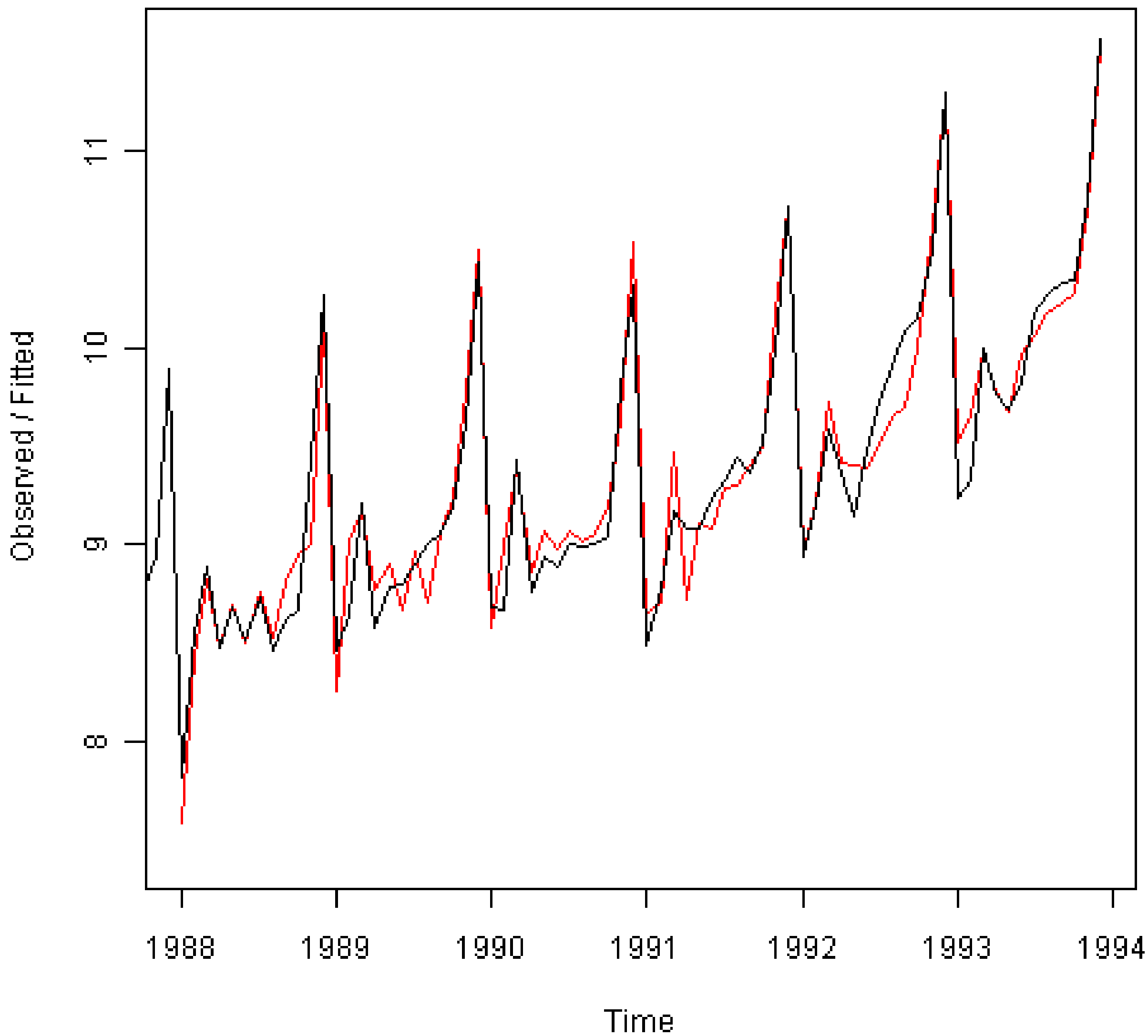
```
> logsouvenirtimeseries <- log(souvenirtimeseries)
> souvenirtimeseriesforecasts <- HoltWinters(logsouvenirtimeseries)
> souvenirtimeseriesforecasts
  Holt-Winters exponential smoothing with trend and additive seasonal component.
  Smoothing parameters:
  alpha:  0.413418
  beta :  0
  gamma:  0.9561275
  Coefficients:
       [,1]
```

```
   a    10.37661961
   b     0.02996319
   s1   -0.80952063
   s2   -0.60576477
   s3    0.01103238
   s4   -0.24160551
   s5   -0.35933517
   s6   -0.18076683
   s7    0.07788605
   s8    0.10147055
   s9    0.09649353
   s10   0.05197826
   s11   0.41793637
   s12   1.18088423
> souvenirtimeseriesforecasts$SSE
  2.011491
```

The estimated values of alpha, beta and gamma are 0.41, 0.00, and 0.96, respectively. The value of alpha (0.41) is relatively low, indicating that the estimate of the level at the current time point is based upon both recent observations and some observations in the more distant past. The value of beta is 0.00, indicating that the estimate of the slope b of the trend component is not updated over the time series, and instead is set equal to its initial value. This makes good intuitive sense, as the level changes quite a bit over the time series, but the slope b of the trend component remains roughly the same. In contrast, the value of gamma (0.96) is high, indicating that the estimate of the seasonal component at the current time point is just based upon very recent observations.

As for simple exponential smoothing and Holt's exponential smoothing, we can plot the original time series as a black line, with the forecasted values as a red line on top of that:

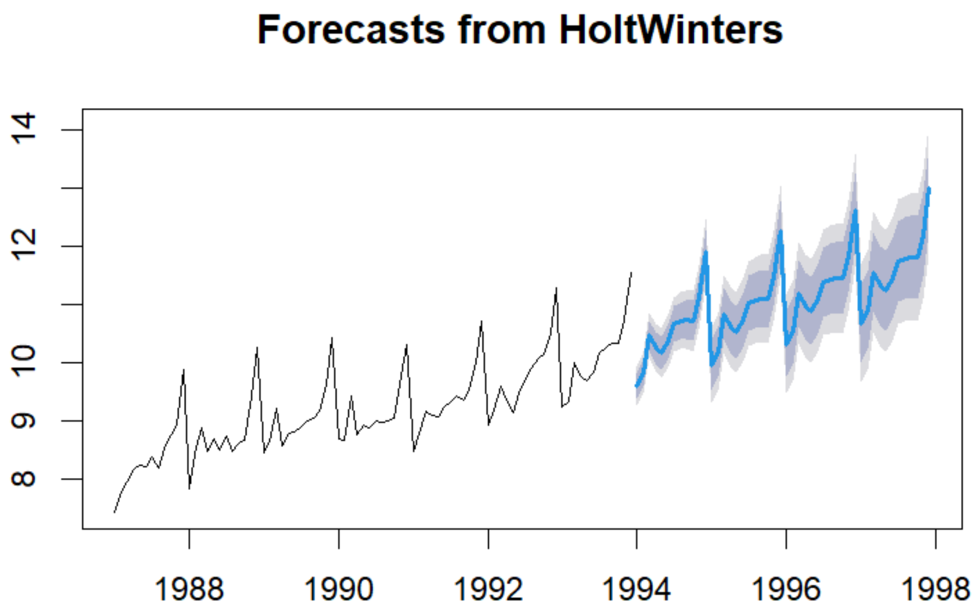
```
> plot(souvenirtimeseriesforecasts)
```




We see from the plot that the Holt-Winters exponential method is very successful in predicting the seasonal peaks, which occur roughly in November every year.

To make forecasts for future times not included in the original time series, we use the "forecast()" function in the "forecast" package. For example, the original data for the souvenir sales is from January 1987 to December 1993. If we wanted to make forecasts for January 1994 to December 1998 (48 more months), and plot the forecasts, we would type:

```
> souvenirtimeseriesforecasts2 <- forecast(souvenirtimeseriesforecasts,h=48)
> plot(souvenirtimeseriesforecasts2)
```

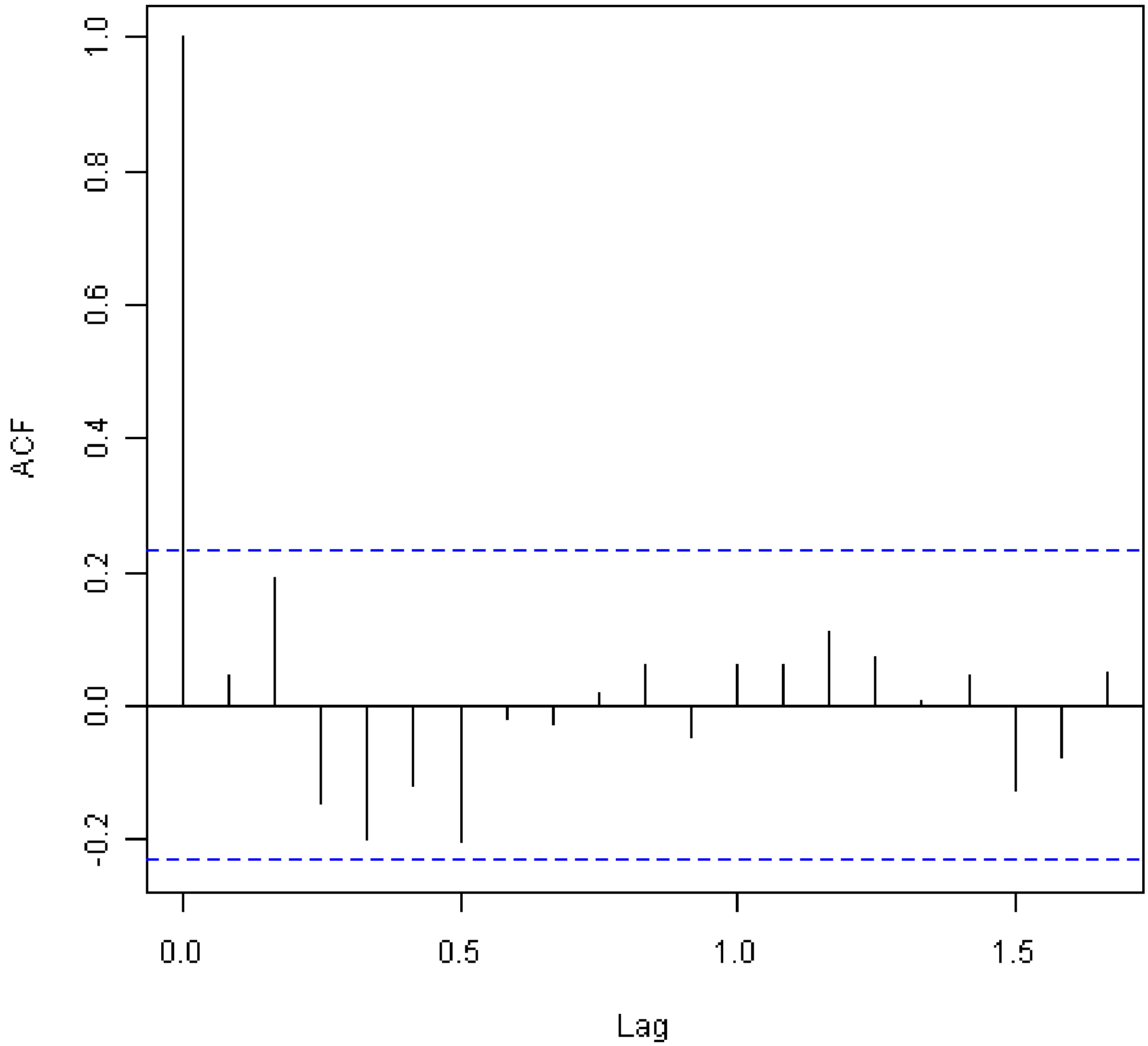



The forecasts are shown as a blue line, and the purple and gray shaded areas show 80% and 95% prediction intervals, respectively.

We can investigate whether the predictive model can be improved upon by checking whether the in-sample forecast errors show non-zero autocorrelations at lags 1-20, by making a correlogram and carrying out the Ljung-Box test:

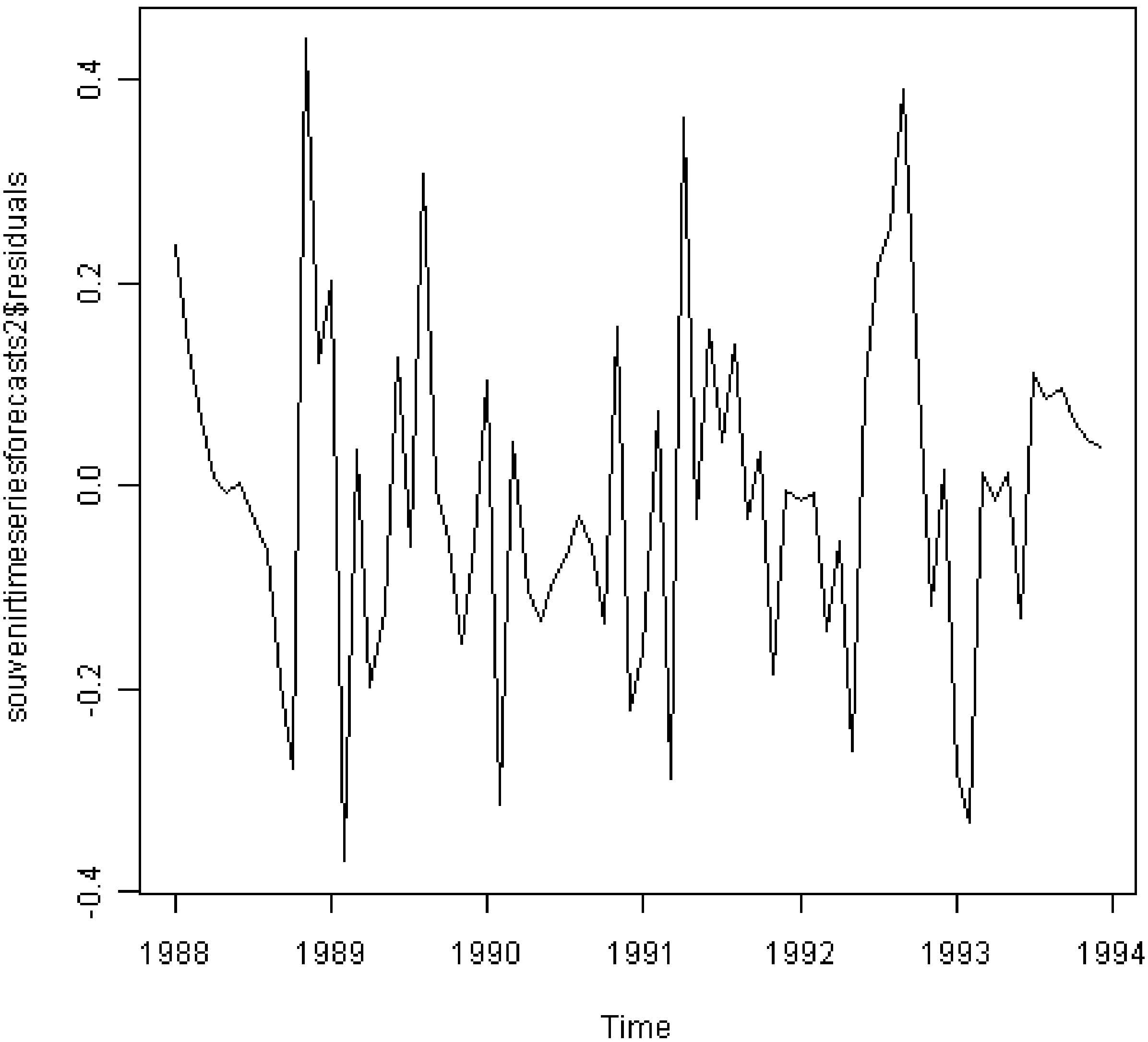
```
> acf(souvenirtimeseriesforecasts2$residuals, lag.max=20 , na.action = na.pass)
> Box.test(souvenirtimeseriesforecasts2$residuals, lag=20, type="Ljung-Box")

  Box-Ljung test
  data:  souvenirtimeseriesforecasts2$residuals
  X-squared = 17.5304, df = 20, p-value = 0.6183
```




The correlogram shows that the autocorrelations for the in-sample forecast errors do not exceed the significance bounds for lags 1-20. Furthermore, the p-value for Ljung-Box test is 0.6, indicating that there is little evidence of non-zero autocorrelations at lags 1-20.

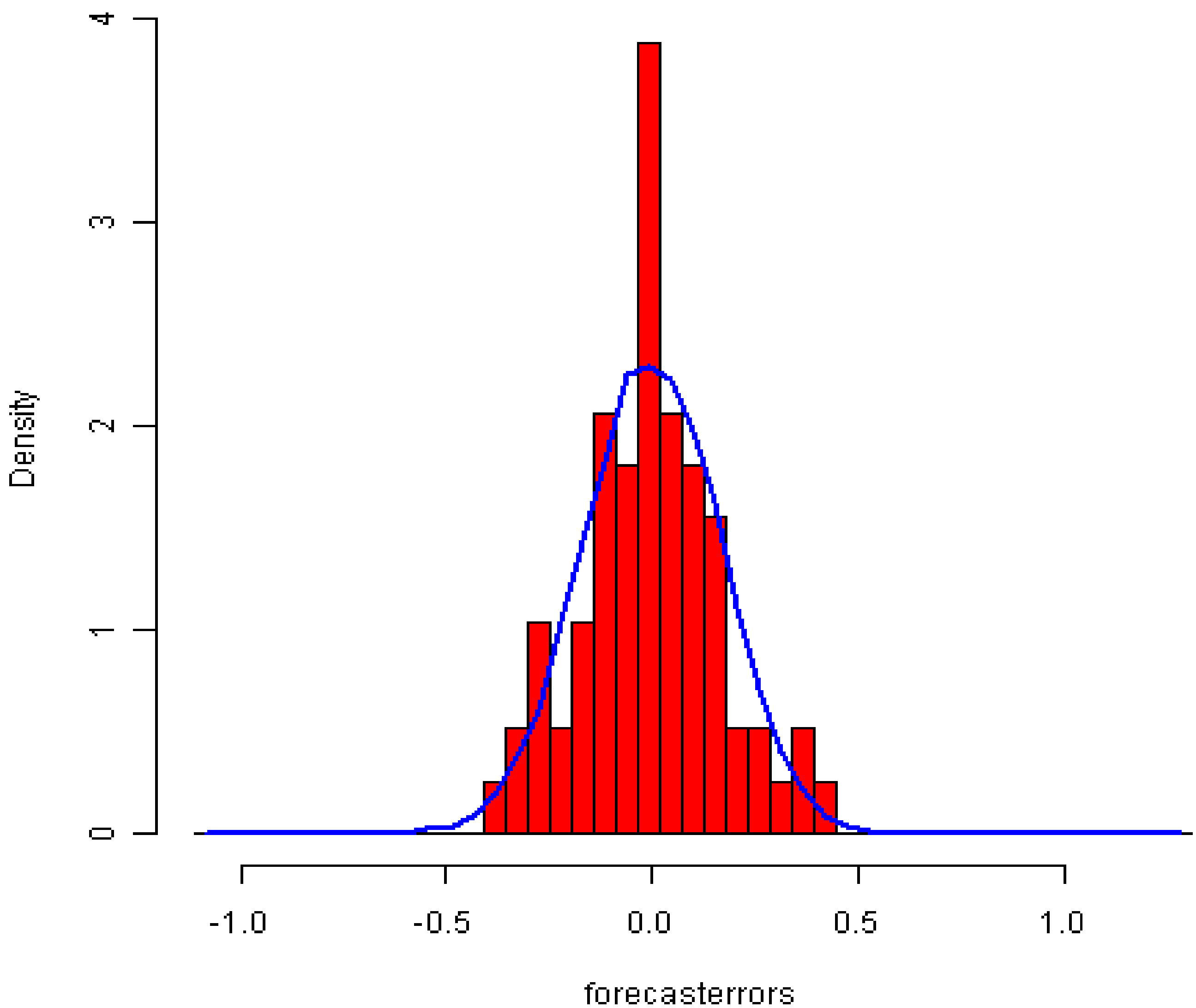
We can check whether the forecast errors have constant variance over time, and are normally distributed with mean zero, by making a time plot of the forecast errors and a histogram (with overlaid normal curve):




```
plot.ts(souvenirtimeseriesforecasts2$residuals) # make time series plot

souvenirtimeseriesforecasts2$residuals <- souvenirtimeseriesforecasts2$residuals
[!is.na(souvenirtimeseriesforecasts2$residuals)]

plotForecastErrors(skirtsseriesforecasts2$residuals) # make a histogram
```




From the time plot, it appears plausible that the forecast errors have constant variance over time. From the histogram of forecast errors, it seems plausible that the forecast errors are normally distributed with mean zero.

Thus,there is little evidence of autocorrelation at lags 1-20 for the forecast errors, and the forecast errors appear to be normally distributed with mean zero and constant variance over time. This suggests that Holt-Winters exponential smoothing provides an adequate predictive model of the log of sales at the souvenir shop, which probably cannot be improved upon. Furthermore, the assumptions upon which the prediction intervals were based are probably valid.

## 2.6 Links and Further Reading

Here are some links for further reading.

For a more in-depth introduction to R, a good online tutorial is available on the "Kickstarting R" website, cran.r-project.org/doc/contrib/Lemon-kickstart.

There is another nice (slightly more in-depth) tutorial to R available on the "Introduction to R" website, cran.r- project.org/doc/manuals/R-intro.html.

CHAPTER 5

You can find a list of R packages for analysing time series data on the CRAN Time Series Task View webpage.

To learn about time series analysis, I would highly recommend the book "Time series" (product code M249/02) by the Open University, available from the Open University Shop.

There are two books available in the "Use R!" series on using R for time series analyses, the first is Introductory Time Series with R by Cowpertwait and Metcalfe, and the second is Analysis of Integrated and Cointegrated Time Series with R by Pfaff.

## 2.7 Acknowledgements

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Many of the examples in this booklet are inspired by examples in the excellent Open University book, "Time series" (product code M249/02), available from the Open University Shop.

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## 2.8 Contact

I will be grateful if you will send me (Avril Coghlan) corrections or suggestions for improvements to my email address alc@sanger.ac.uk

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