
A Little Book of R For Time Series

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This is a simple introduction to time series analysis using the R statistics software.

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/>.

Contents:

Introduction to R

This little booklet has some information on how to use R for time series analysis.

R (www.r-project.org) is a commonly used free Statistics software. R allows you to carry out statistical analyses in an interactive mode, as well as allowing simple programming.

Installing R

To use R, you first need to install the R program on your computer.

How to check if R is installed on a Windows PC

Before you install R on your computer, the first thing to do is to check whether R is already installed on your computer (for example, by a previous user).

These instructions will focus on installing R on a Windows PC. However, I will also briefly mention how to install R on a Macintosh or Linux computer (see below).

If you are using a Windows PC, there are two ways you can check whether R is already installed on your computer:

1. Check if there is an “R” icon on the desktop of the computer that you are using. If so, double-click on the “R” icon to start R. If you cannot find an “R” icon, try step 2 instead.
2. Click on the “Start” menu at the bottom left of your Windows desktop, and then move your mouse over “All Programs” in the menu that pops up. See if “R” appears in the list of programs that pops up. If it does, it means that R is already installed on your computer, and you can start R by selecting “R” (or R X.X.X, where X.X.X gives the version of R, eg. R 2.10.0) from the list.

If either (1) or (2) above does succeed in starting R, it means that R is already installed on the computer that you are using. (If neither succeeds, R is not installed yet). If there is an old version of R installed on the Windows PC that you are using, it is worth installing the latest version of R, to make sure that you have all the latest R functions available to you to use.

Finding out what is the latest version of R

To find out what is the latest version of R, you can look at the CRAN (Comprehensive R Network) website, <http://cran.r-project.org/>.

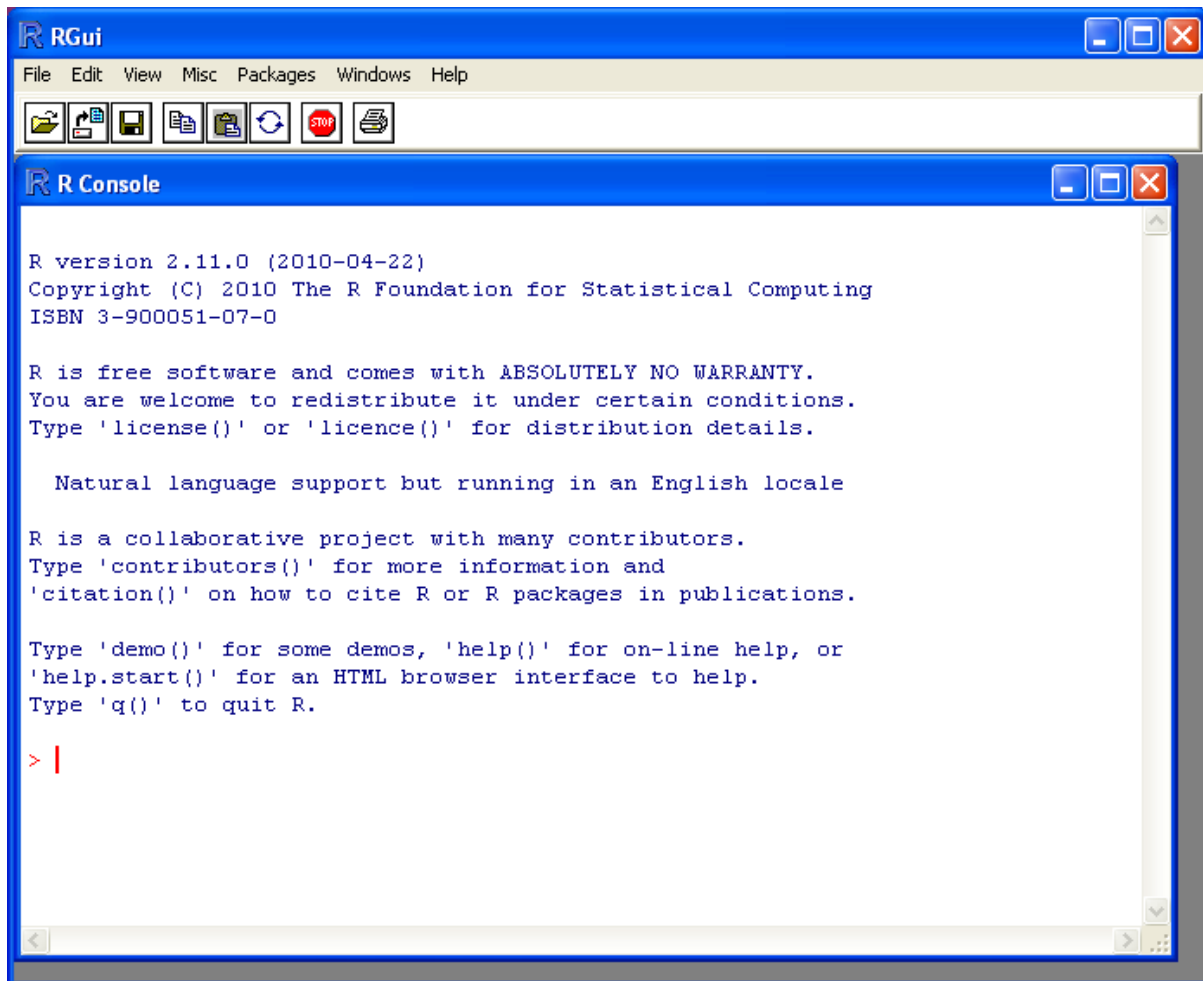
Beside “The latest release” (about half way down the page), it will say something like “R-X.X.X.tar.gz” (eg. “R-2.12.1.tar.gz”). This means that the latest release of R is X.X.X (for example, 2.12.1).

New releases of R are made very regularly (approximately once a month), as R is actively being improved all the time. It is worthwhile installing new versions of R regularly, to make sure that you have a recent version of R (to ensure compatibility with all the latest versions of the R packages that you have downloaded).

Installing R on a Windows PC

To install R on your Windows computer, follow these steps:

1. Go to <http://ftp.heanet.ie/mirrors/cran.r-project.org>.
2. Under “Download and Install R”, click on the “Windows” link.
3. Under “Subdirectories”, click on the “base” link.
4. On the next page, you should see a link saying something like “Download R 2.10.1 for Windows” (or R X.X.X, where X.X.X gives the version of R, eg. R 2.11.1). Click on this link.
5. You may be asked if you want to save or run a file “R-2.10.1-win32.exe”. Choose “Save” and save the file on the Desktop. Then double-click on the icon for the file to run it.
6. You will be asked what language to install it in - choose English.
7. The R Setup Wizard will appear in a window. Click “Next” at the bottom of the R Setup wizard window.
8. The next page says “Information” at the top. Click “Next” again.
9. The next page says “Information” at the top. Click “Next” again.
10. The next page says “Select Destination Location” at the top. By default, it will suggest to install R in “C:\Program Files” on your computer.
11. Click “Next” at the bottom of the R Setup wizard window.
12. The next page says “Select components” at the top. Click “Next” again.
13. The next page says “Startup options” at the top. Click “Next” again.
14. The next page says “Select start menu folder” at the top. Click “Next” again.
15. The next page says “Select additional tasks” at the top. Click “Next” again.
16. R should now be installed. This will take about a minute. When R has finished, you will see “Completing the R for Windows Setup Wizard” appear. Click “Finish”.
17. To start R, you can either follow step 18, or 19:
18. Check if there is an “R” icon on the desktop of the computer that you are using. If so, double-click on the “R” icon to start R. If you cannot find an “R” icon, try step 19 instead.
19. Click on the “Start” button at the bottom left of your computer screen, and then choose “All programs”, and start R by selecting “R” (or R X.X.X, where X.X.X gives the version of R, eg. R 2.10.0) from the menu of programs.
20. The R console (a rectangle) should pop up:



How to install R on non-Windows computers (eg. Macintosh or Linux computers)

The instructions above are for installing R on a Windows PC. If you want to install R on a computer that has a non-Windows operating system (for example, a Macintosh or computer running Linux, you should download the appropriate R installer for that operating system at <http://ftp.heanet.ie/mirrors/cran.r-project.org> and follow the R installation instructions for the appropriate operating system at http://ftp.heanet.ie/mirrors/cran.r-project.org/doc/FAQ/R-FAQ.html#How-can-R-be-installed_003f).

Installing R packages

R comes with some standard packages that are installed when you install R. However, in this booklet I will also tell you how to use some additional R packages that are useful, for example, the “rmeta” package. These additional packages do not come with the standard installation of R, so you need to install them yourself.

How to install an R package

Once you have installed R on a Windows computer (following the steps above), you can install an additional package by following the steps below:

1. To start R, follow either step 2 or 3:
2. Check if there is an “R” icon on the desktop of the computer that you are using. If so, double-click on the “R” icon to start R. If you cannot find an “R” icon, try step 3 instead.

3. Click on the “Start” button at the bottom left of your computer screen, and then choose “All programs”, and start R by selecting “R” (or R X.X.X, where X.X.X gives the version of R, eg. R 2.10.0) from the menu of programs.
4. The R console (a rectangle) should pop up.
5. Once you have started R, you can now install an R package (eg. the “rmeta” package) by choosing “Install package(s)” from the “Packages” menu at the top of the R console. This will ask you what website you want to download the package from, you should choose “Ireland” (or another country, if you prefer). It will also bring up a list of available packages that you can install, and you should choose the package that you want to install from that list (eg. “rmeta”).
6. This will install the “rmeta” package.
7. The “rmeta” package is now installed. Whenever you want to use the “rmeta” package after this, after starting R, you first have to load the package by typing into the R console:

```
> library("rmeta")
```

Note that there are some additional R packages for bioinformatics that are part of a special set of R packages called Bioconductor (www.bioconductor.org) such as the “yeastExpData” R package, the “Biostrings” R package, etc.). These Bioconductor packages need to be installed using a different, Bioconductor-specific procedure (see *How to install a Bioconductor R package* below).

How to install a Bioconductor R package

The procedure above can be used to install the majority of R packages. However, the Bioconductor set of bioinformatics R packages need to be installed by a special procedure. Bioconductor (www.bioconductor.org) is a group of R packages that have been developed for bioinformatics. This includes R packages such as “yeastExpData”, “Biostrings”, etc.

To install the Bioconductor packages, follow these steps:

1. To start R, follow either step 2 or 3:
2. Check if there is an “R” icon on the desktop of the computer that you are using. If so, double-click on the “R” icon to start R. If you cannot find an “R” icon, try step 3 instead.
3. Click on the “Start” button at the bottom left of your computer screen, and then choose “All programs”, and start R by selecting “R” (or R X.X.X, where X.X.X gives the version of R, eg. R 2.10.0) from the menu of programs.
4. The R console (a rectangle) should pop up.
5. Once you have started R, now type in the R console:

```
> source("http://bioconductor.org/biocLite.R")
> biocLite()
```

6. This will install a core set of Bioconductor packages (“affy”, “affydata”, “affyPLM”, “annaffy”, “annotate”, “Biobase”, “Biostrings”, “DynDoc”, “gcrma”, “genefilter”, “geneplotter”, “hgu95av2.db”, “limma”, “mar-ray”, “matchprobes”, “multtest”, “ROC”, “vsn”, “xtable”, “affyQCReport”). This takes a few minutes (eg. 10 minutes).
7. At a later date, you may wish to install some extra Bioconductor packages that do not belong to the core set of Bioconductor packages. For example, to install the Bioconductor package called “yeastExpData”, start R and type in the R console:

```
> source("http://bioconductor.org/biocLite.R")
> biocLite("yeastExpData")
```

8. Whenever you want to use a package after installing it, you need to load it into R by typing:

```
> library("yeastExpData")
```

Running R

To use R, you first need to start the R program on your computer. You should have already installed R on your computer (see above).

To start R, you can either follow step 1 or 2: 1. Check if there is an “R” icon on the desktop of the computer that you are using.

If so, double-click on the “R” icon to start R. If you cannot find an “R” icon, try step 2 instead.

2. Click on the “Start” button at the bottom left of your computer screen, and then choose “All programs”, and start R by selecting “R” (or R X.X.X, where X.X.X gives the version of R, eg. R 2.10.0) from the menu of programs.

This should bring up a new window, which is the *R console*.

A brief introduction to R

You will type R commands into the R console in order to carry out analyses in R. In the R console you will see:

```
>
```

This is the R prompt. We type the commands needed for a particular task after this prompt. The command is carried out after you hit the Return key.

Once you have started R, you can start typing in commands, and the results will be calculated immediately, for example:

```
> 2*3
[1] 6
> 10-3
[1] 7
```

All variables (scalars, vectors, matrices, etc.) created by R are called *objects*. In R, we assign values to variables using an arrow. For example, we can assign the value $2*3$ to the variable x using the command:

```
> x <- 2*3
```

To view the contents of any R object, just type its name, and the contents of that R object will be displayed:

```
> x
[1] 6
```

There are several possible different types of objects in R, including scalars, vectors, matrices, arrays, data frames, tables, and lists. The scalar variable x above is one example of an R object. While a scalar variable such as x has just one element, a vector consists of several elements. The elements in a vector are all of the same type (eg. numeric or characters), while lists may include elements such as characters as well as numeric quantities.

To create a vector, we can use the `c()` (combine) function. For example, to create a vector called *myvector* that has elements with values 8, 6, 9, 10, and 5, we type:

```
> myvector <- c(8, 6, 9, 10, 5)
```

To see the contents of the variable *myvector*, we can just type its name:

```
> myvector
[1] 8 6 9 10 5
```

The [1] is the index of the first element in the vector. We can extract any element of the vector by typing the vector name with the index of that element given in square brackets. For example, to get the value of the 4th element in the vector *myvector*, we type:

```
> myvector[4]
[1] 10
```

In contrast to a vector, a list can contain elements of different types, for example, both numeric and character elements. A list can also include other variables such as a vector. The `list()` function is used to create a list. For example, we could create a list *mylist* by typing:

```
> mylist <- list(name="Fred", wife="Mary", myvector)
```

We can then print out the contents of the list *mylist* by typing its name:

```
> mylist
$name
[1] "Fred"

$wife
[1] "Mary"

[[3]]
[1] 8 6 9 10 5
```

The elements in a list are numbered, and can be referred to using indices. We can extract an element of a list by typing the list name with the index of the element given in double square brackets (in contrast to a vector, where we only use single square brackets). Thus, we can extract the second and third elements from *mylist* by typing:

```
> mylist[[2]]
[1] "Mary"
> mylist[[3]]
[1] 8 6 9 10 5
```

Elements of lists may also be named, and in this case the elements may be referred to by giving the list name, followed by "\$", followed by the element name. For example, *mylist\$name* is the same as *mylist[[1]]* and *mylist\$wife* is the same as *mylist[[2]]*:

```
> mylist$wife
[1] "Mary"
```

We can find out the names of the named elements in a list by using the `attributes()` function, for example:

```
> attributes(mylist)
$name
[1] "name" "wife" ""
```

When you use the `attributes()` function to find the named elements of a list variable, the named elements are always listed under a heading "\$names". Therefore, we see that the named elements of the list variable *mylist* are called "name" and "wife", and we can retrieve their values by typing *mylist\$name* and *mylist\$wife*, respectively.

Another type of object that you will encounter in R is a *table* variable. For example, if we made a vector variable *mynames* containing the names of children in a class, we can use the `table()` function to produce a table variable that contains the number of children with each possible name:

```
> mynames <- c("Mary", "John", "Ann", "Sinead", "Joe", "Mary", "Jim", "John",
  ↪ "Simon")
> table(mynames)
mynames
  Ann   Jim   Joe  John  Mary  Simon Sinead
   1    1    1    2    2    1    1
```

We can store the table variable produced by the function `table()`, and call the stored table “mytable”, by typing:

```
> mytable <- table(mynames)
```

To access elements in a table variable, you need to use double square brackets, just like accessing elements in a list. For example, to access the fourth element in the table `mytable` (the number of children called “John”), we type:

```
> mytable[[4]]
[1] 2
```

Alternatively, you can use the name of the fourth element in the table (“John”) to find the value of that table element:

```
> mytable[["John"]]
[1] 2
```

Functions in R usually require *arguments*, which are input variables (ie. objects) that are passed to them, which they then carry out some operation on. For example, the `log10()` function is passed a number, and it then calculates the log to the base 10 of that number:

```
> log10(100)
2
```

In R, you can get help about a particular function by using the `help()` function. For example, if you want help about the `log10()` function, you can type:

```
> help("log10")
```

When you use the `help()` function, a box or webpage will pop up with information about the function that you asked for help with.

If you are not sure of the name of a function, but think you know part of its name, you can search for the function name using the `help.search()` and `RSiteSearch()` functions. The `help.search()` function searches to see if you already have a function installed (from one of the R packages that you have installed) that may be related to some topic you’re interested in. The `RSiteSearch()` function searches all R functions (including those in packages that you haven’t yet installed) for functions related to the topic you are interested in.

For example, if you want to know if there is a function to calculate the standard deviation of a set of numbers, you can search for the names of all installed functions containing the word “deviation” in their description by typing:

```
> help.search("deviation")
Help files with alias or concept or title matching
'deviation' using fuzzy matching:

genefilter::rowSds          Row variance and standard deviation of
                           a numeric array
nlme::pooledSD             Extract Pooled Standard Deviation
stats::mad                 Median Absolute Deviation
stats::sd                  Standard Deviation
vsn::meanSdPlot           Plot row standard deviations versus row
```

Among the functions that were found, is the function `sd()` in the “stats” package (an R package that comes with the standard R installation), which is used for calculating the standard deviation.

In the example above, the `help.search()` function found a relevant function (`sd()` here). However, if you did not find what you were looking for with `help.search()`, you could then use the `RSiteSearch()` function to see if a search of all functions described on the R website may find something relevant to the topic that you’re interested in:

```
> RSiteSearch("deviation")
```

The results of the `RSiteSearch()` function will be hits to descriptions of R functions, as well as to R mailing list discussions of those functions.

We can perform computations with R using objects such as scalars and vectors. For example, to calculate the average of the values in the vector *myvector* (ie. the average of 8, 6, 9, 10 and 5), we can use the `mean()` function:

```
> mean(myvector)
[1] 7.6
```

We have been using built-in R functions such as `mean()`, `length()`, `print()`, `plot()`, etc. We can also create our own functions in R to do calculations that you want to carry out very often on different input data sets. For example, we can create a function to calculate the value of 20 plus square of some input number:

```
> myfunction <- function(x) { return(20 + (x*x)) }
```

This function will calculate the square of a number (x), and then add 20 to that value. The `return()` statement returns the calculated value. Once you have typed in this function, the function is then available for use. For example, we can use the function for different input numbers (eg. 10, 25):

```
> myfunction(10)
[1] 120
> myfunction(25)
[1] 645
```

To quit R, type:

```
> q()
```

Links and Further Reading

Some links are included here 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.

Acknowledgements

For very helpful comments and suggestions for improvements on the installation instructions, thank you very much to Friedrich Leisch and Phil Spector.

Contact

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

License

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Using R for Time Series Analysis

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 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/>.

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.

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)
  Read 42 items
> 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
```

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")
  Read 168 items
> 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

```

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")
Read 84 items
> 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

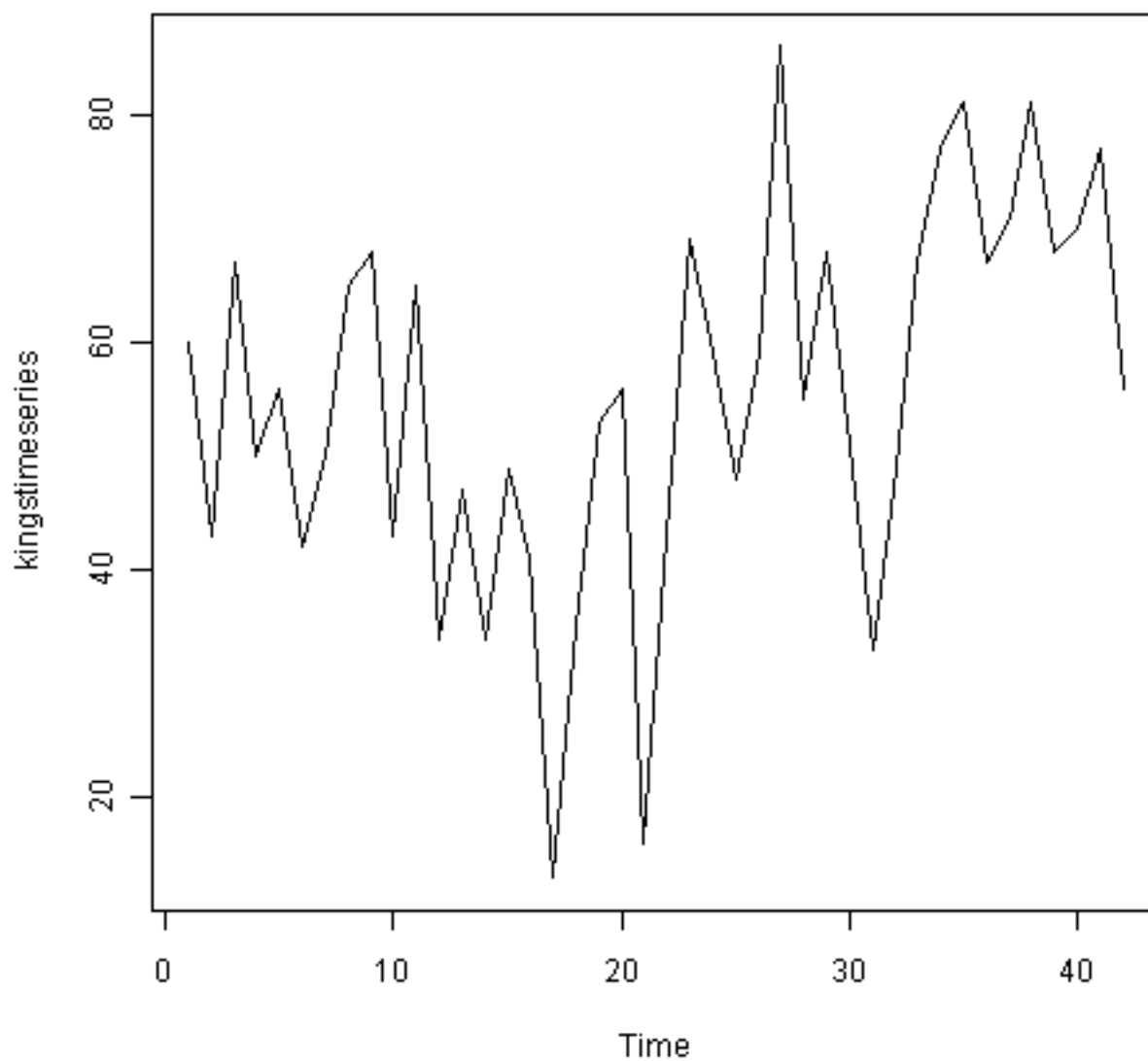
```

Plotting Time Series

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:

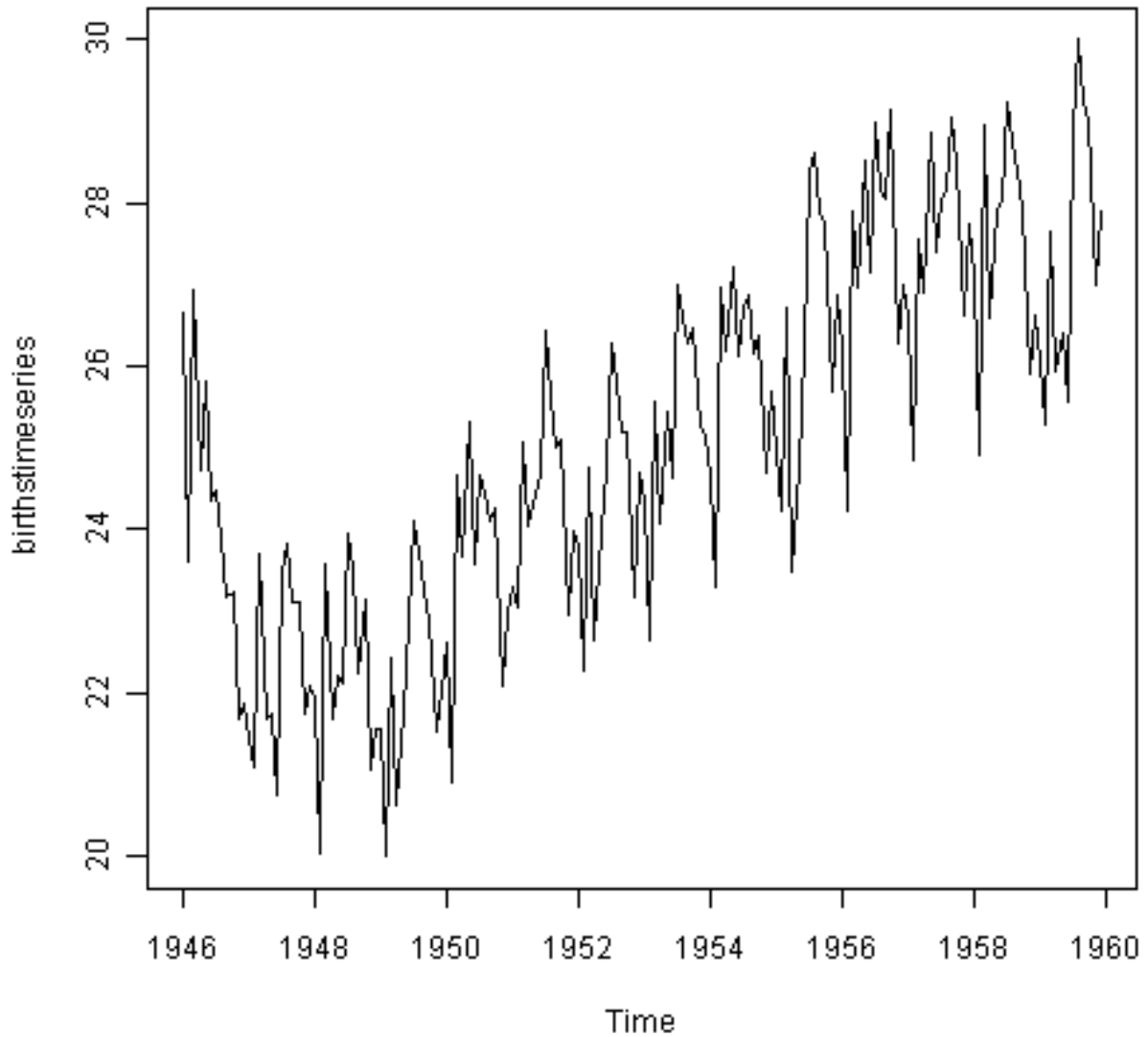
```
> plot.ts(kingstimeseries)
```



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:

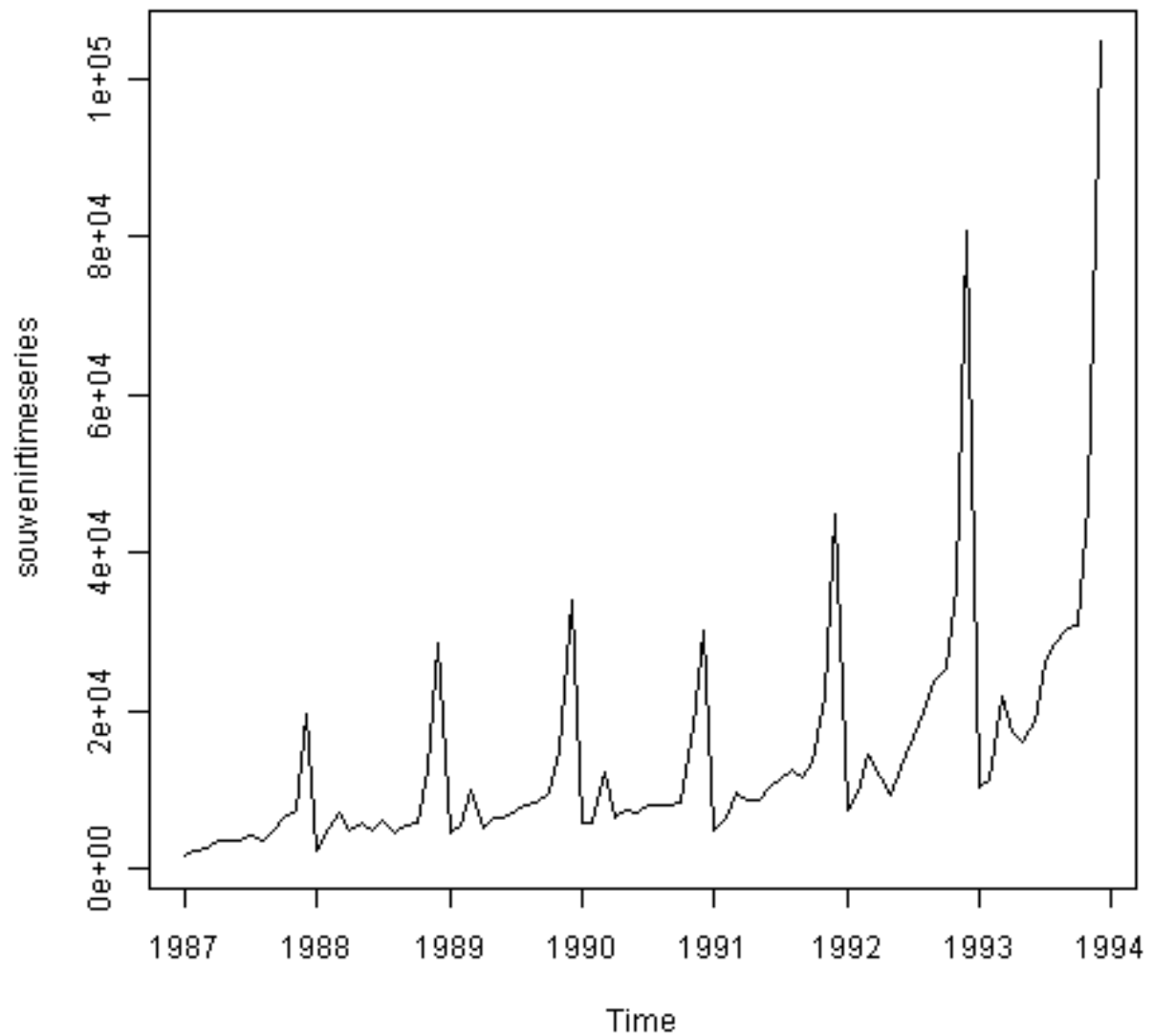
```
> plot.ts(birthstimeseries)
```



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.

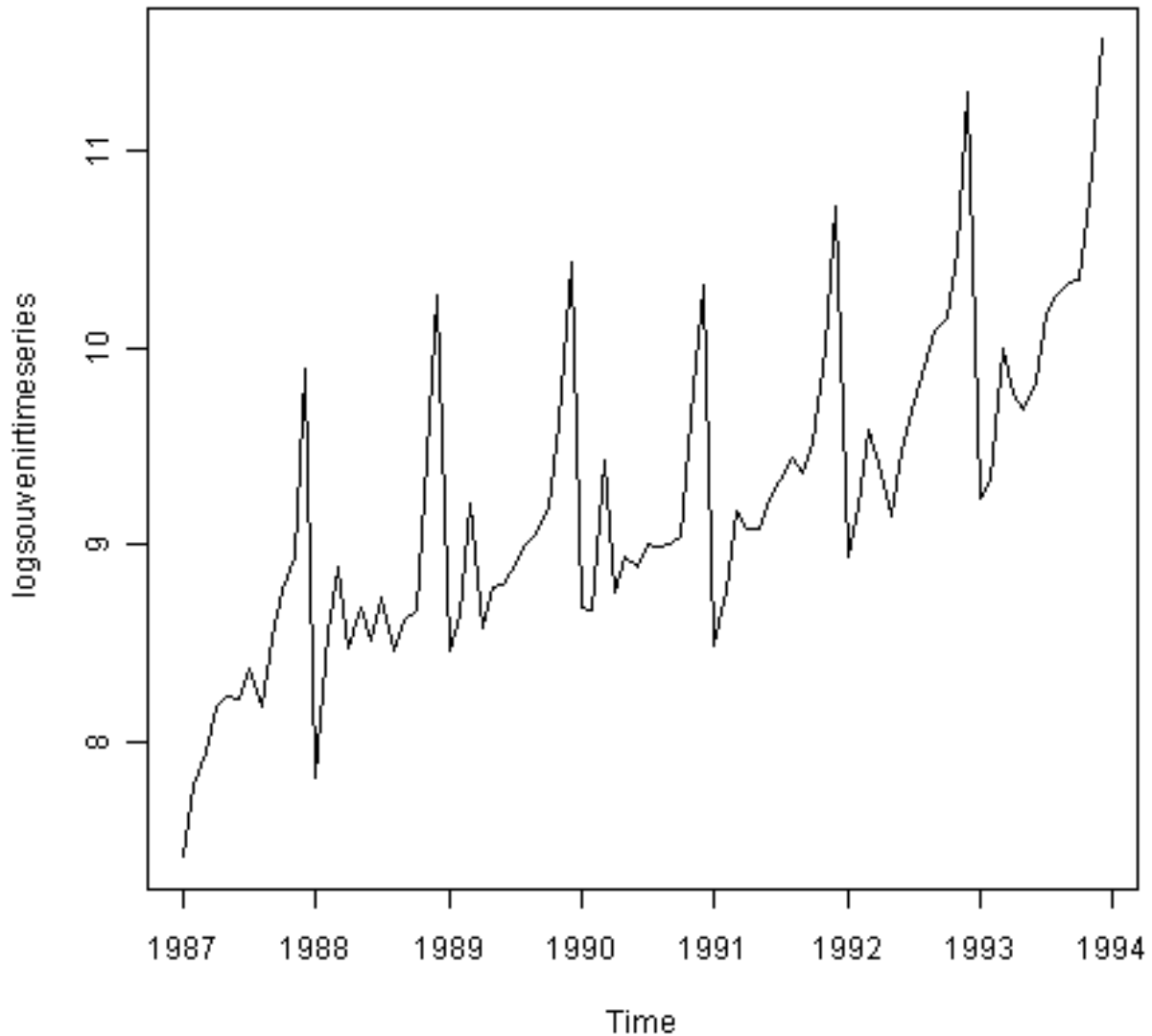
Similarly, to plot the time series of the monthly sales for the souvenir shop at a beach resort town in Queensland, Australia, we type:

```
> 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

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.

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 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.

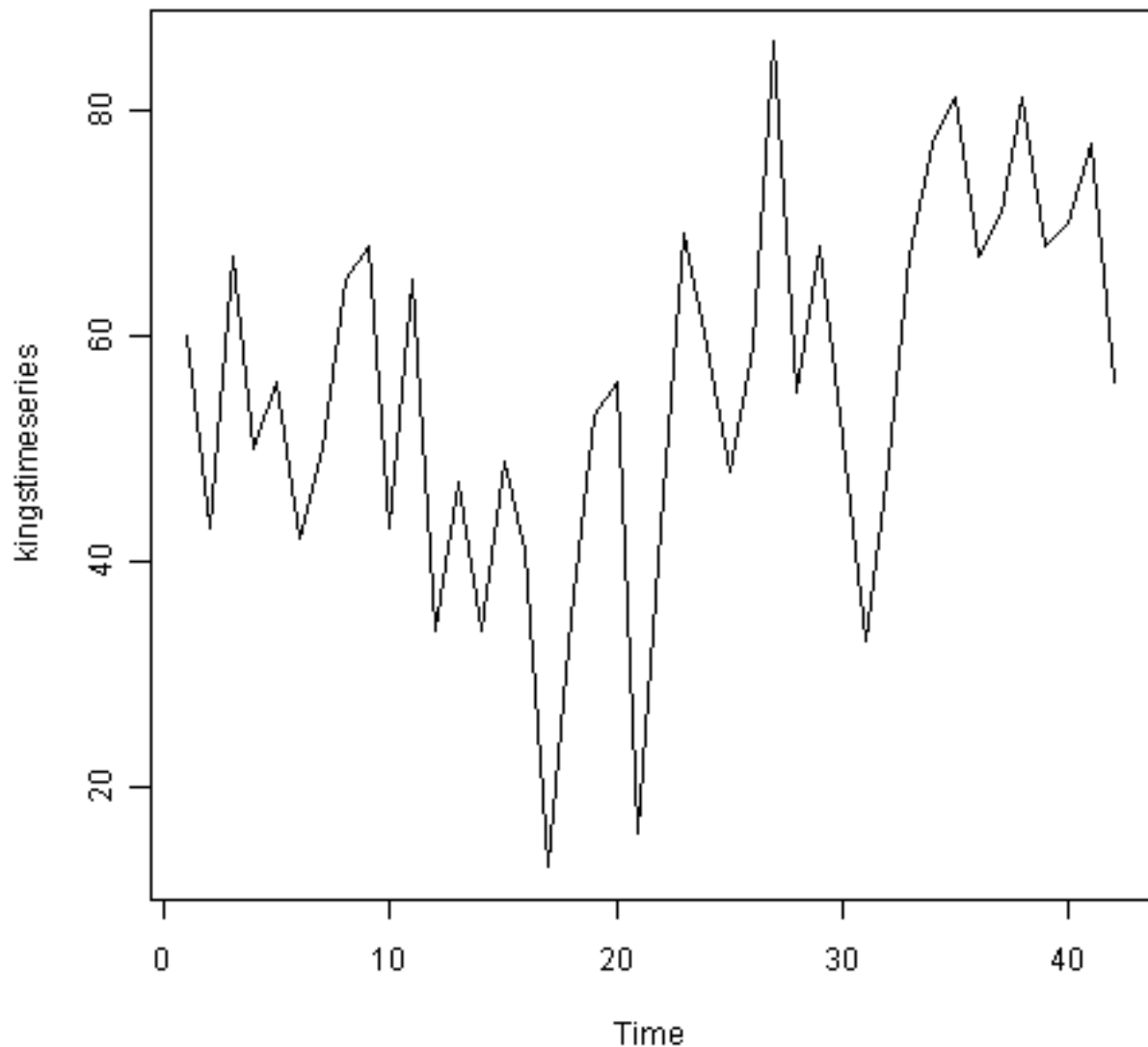
The `SMA()` function in the “TTR” R package can be used to smooth time series data using a simple moving average. To use this function, we first need to install the “TTR” R package (for instructions on how to install an

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")
```

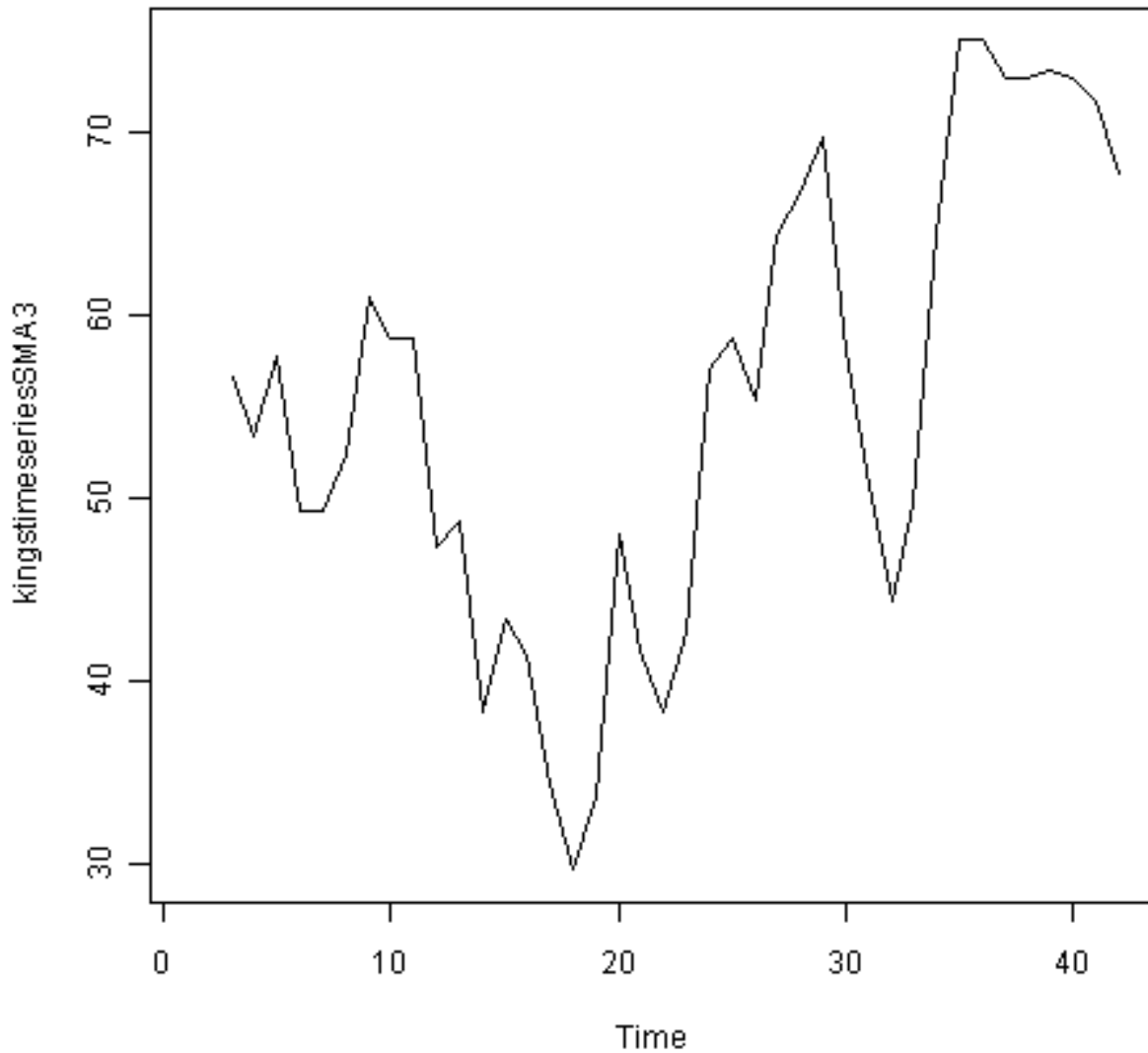
You can then use the “SMA()” function to smooth time series data. To use the SMA() function, you need to specify the order (span) of the simple moving average, using the parameter “n”. For example, to calculate a simple moving average of order 5, we set n=5 in the SMA() function.

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:



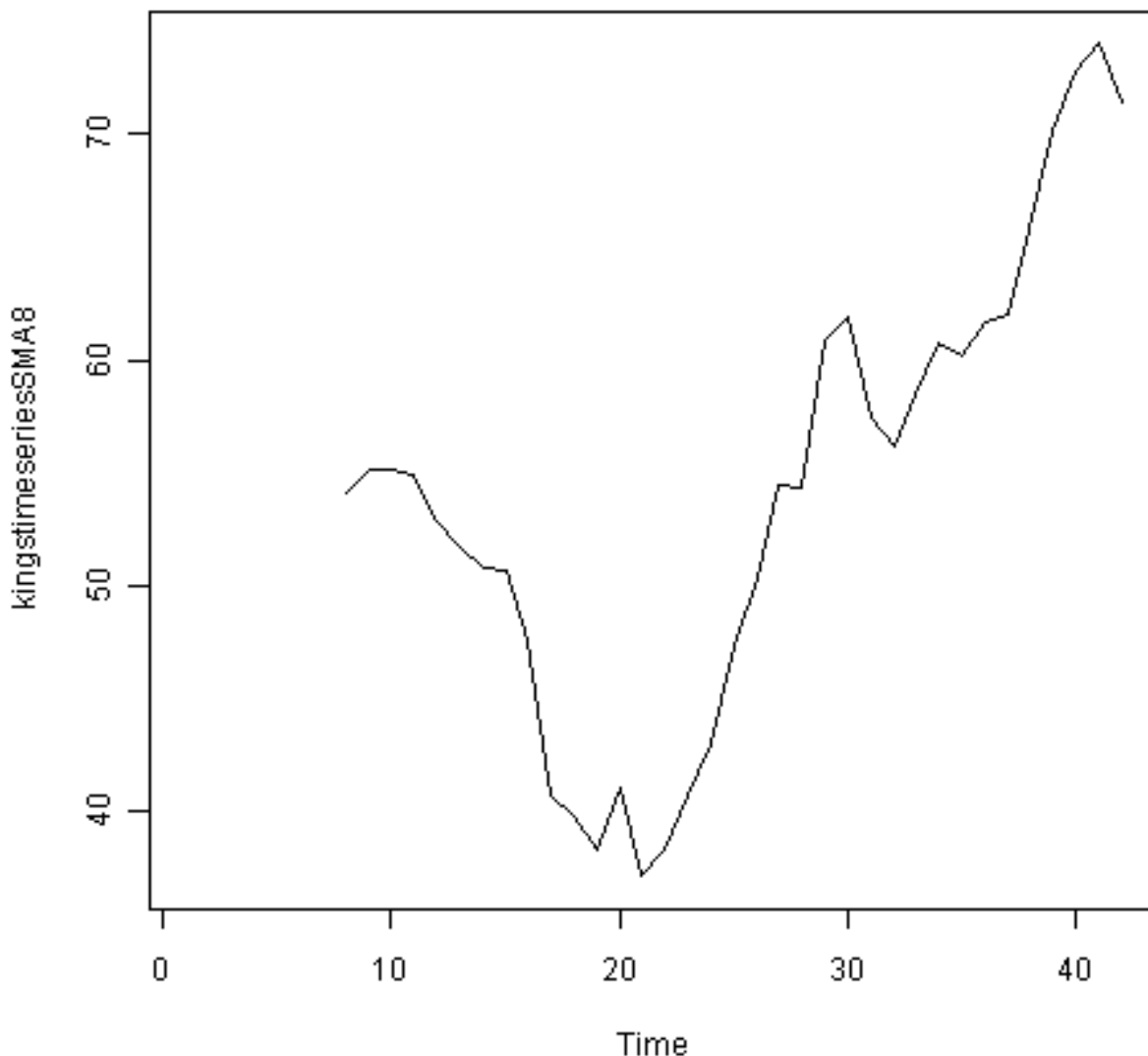
Thus, we can try to estimate the trend component of this time series by smoothing using a simple moving average. To smooth the time series using a simple moving average of order 3, and plot the smoothed time series data, we type:

```
> 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.

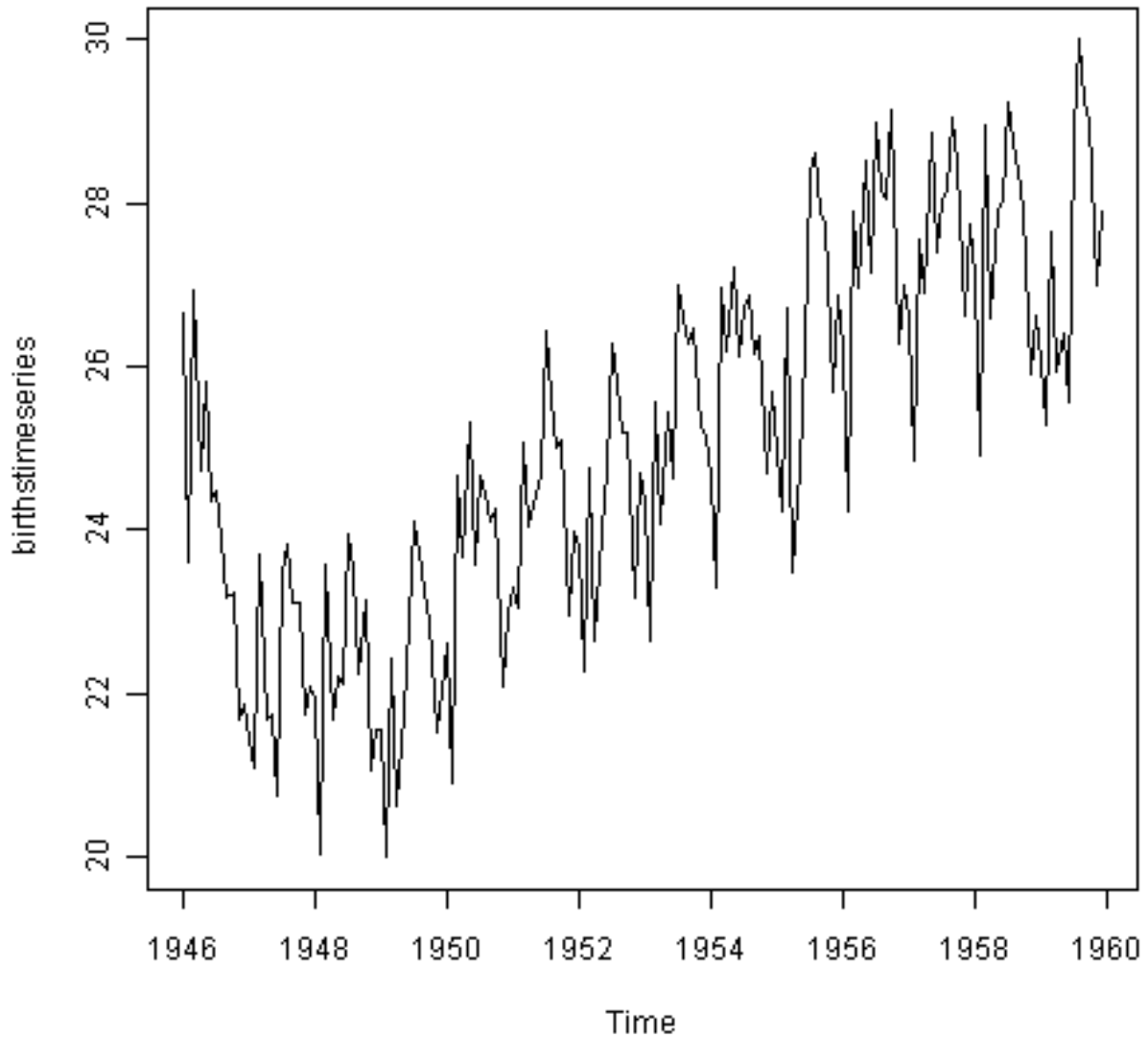
Decomposing Seasonal Data

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
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
```

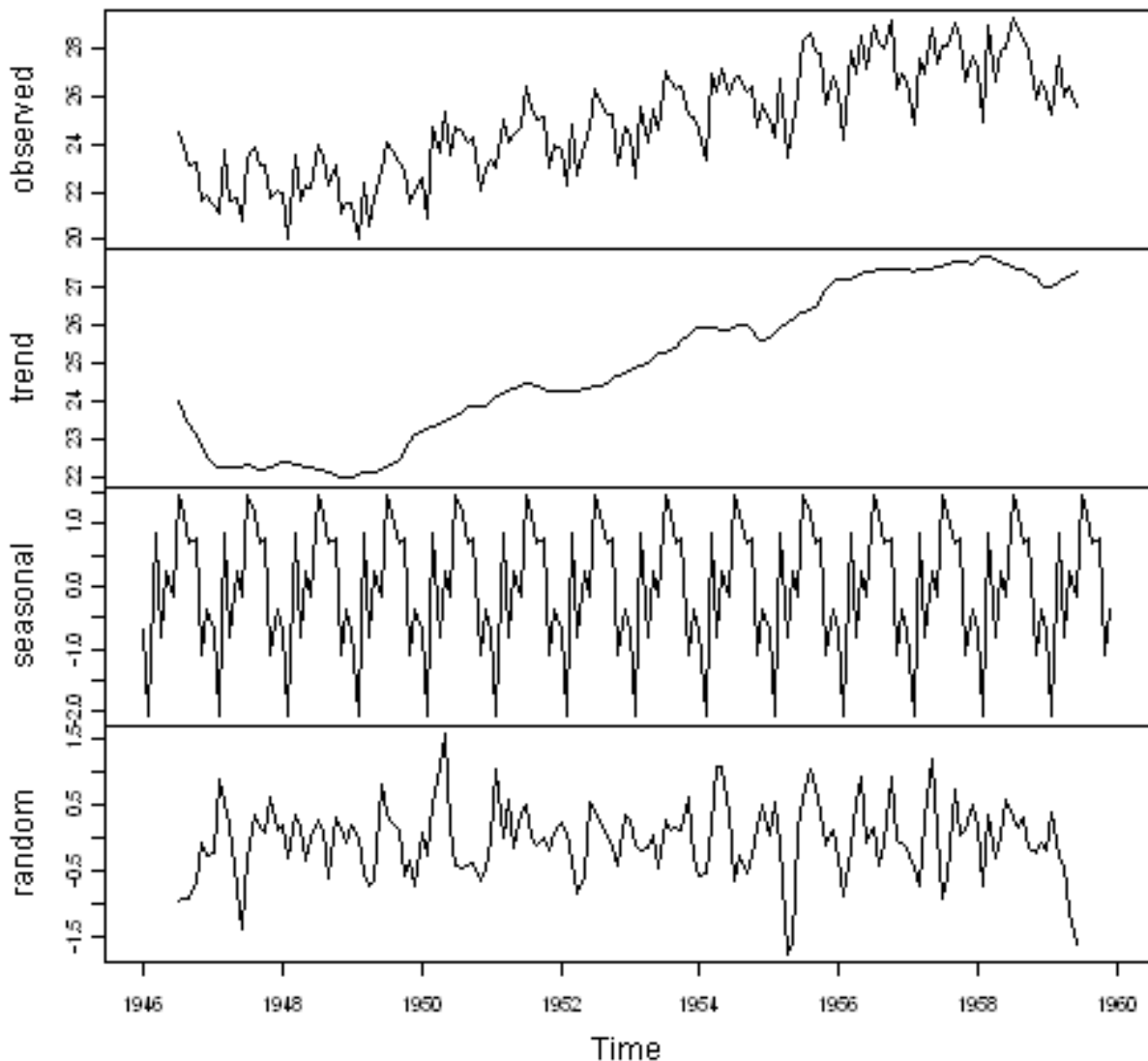
```
1952 -0.6771947 -2.0829607 0.8625232 -0.8016787 0.2516514 -0.1532556 1.4560457
↪ 1.1645938 0.6916162 0.7752444 -1.1097652 -0.3768197
1953 -0.6771947 -2.0829607 0.8625232 -0.8016787 0.2516514 -0.1532556 1.4560457
↪ 1.1645938 0.6916162 0.7752444 -1.1097652 -0.3768197
1954 -0.6771947 -2.0829607 0.8625232 -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)
```

Decomposition of additive time series



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.

Seasonally Adjusting

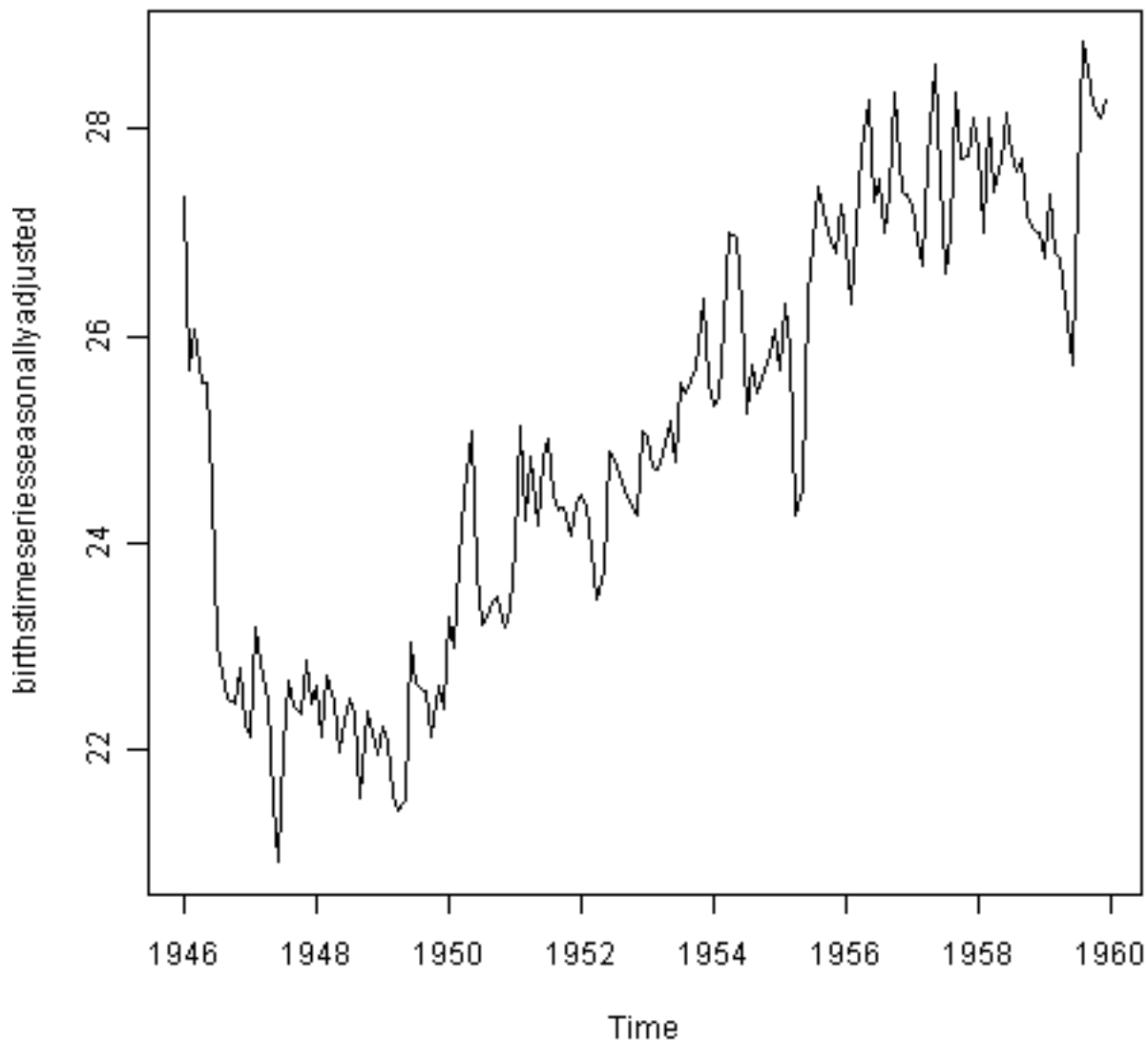
If you have a seasonal time series that can be described using an additive model, you can seasonally adjust the time series by estimating the seasonal component, and subtracting the estimated seasonal component from the original time series. We can do this using the estimate of the seasonal component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

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

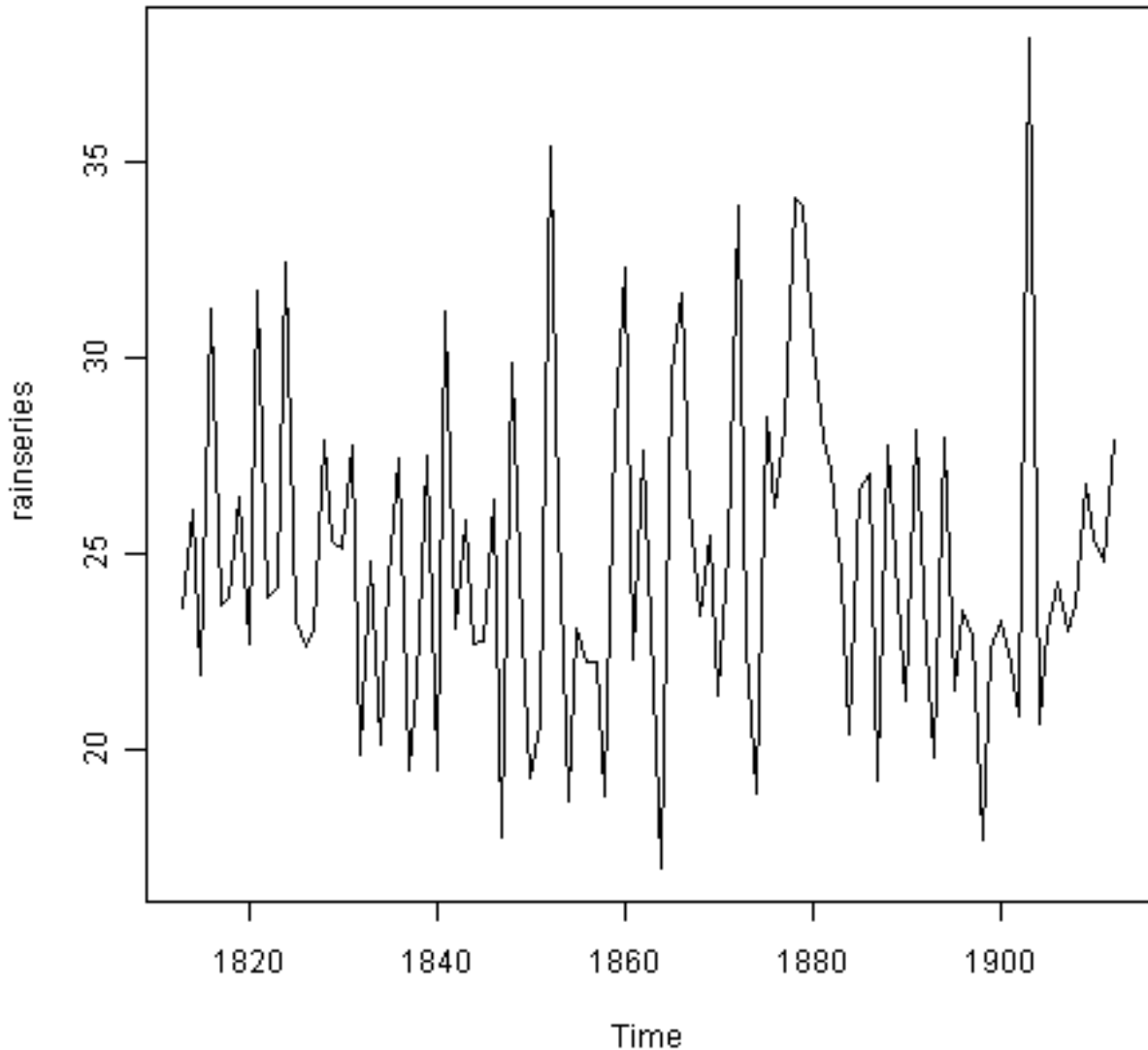
Simple Exponential Smoothing

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)
  Read 100 items
> 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).

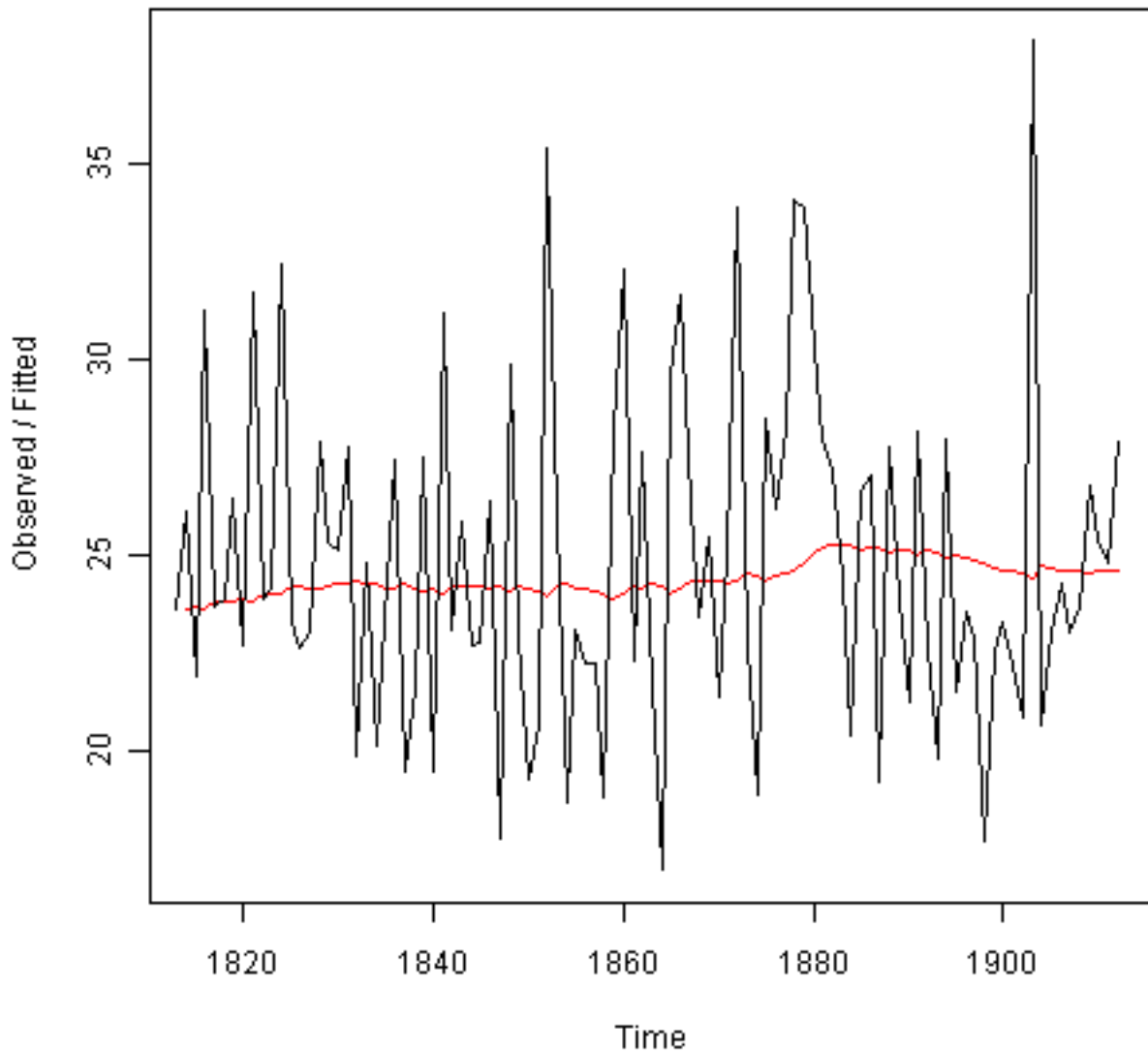
By default, `HoltWinters()` just makes forecasts for the same time period covered by our original time series. In this case, our original time series included rainfall for London from 1813-1912, so the forecasts are also for 1813-1912.

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.HoltWinters()`” function in the R “forecast” package. To use the `forecast.HoltWinters()` function, we first need to install the “forecast” R package (for instructions on how to install an R package, see [How to install an R](#)

package).

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

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

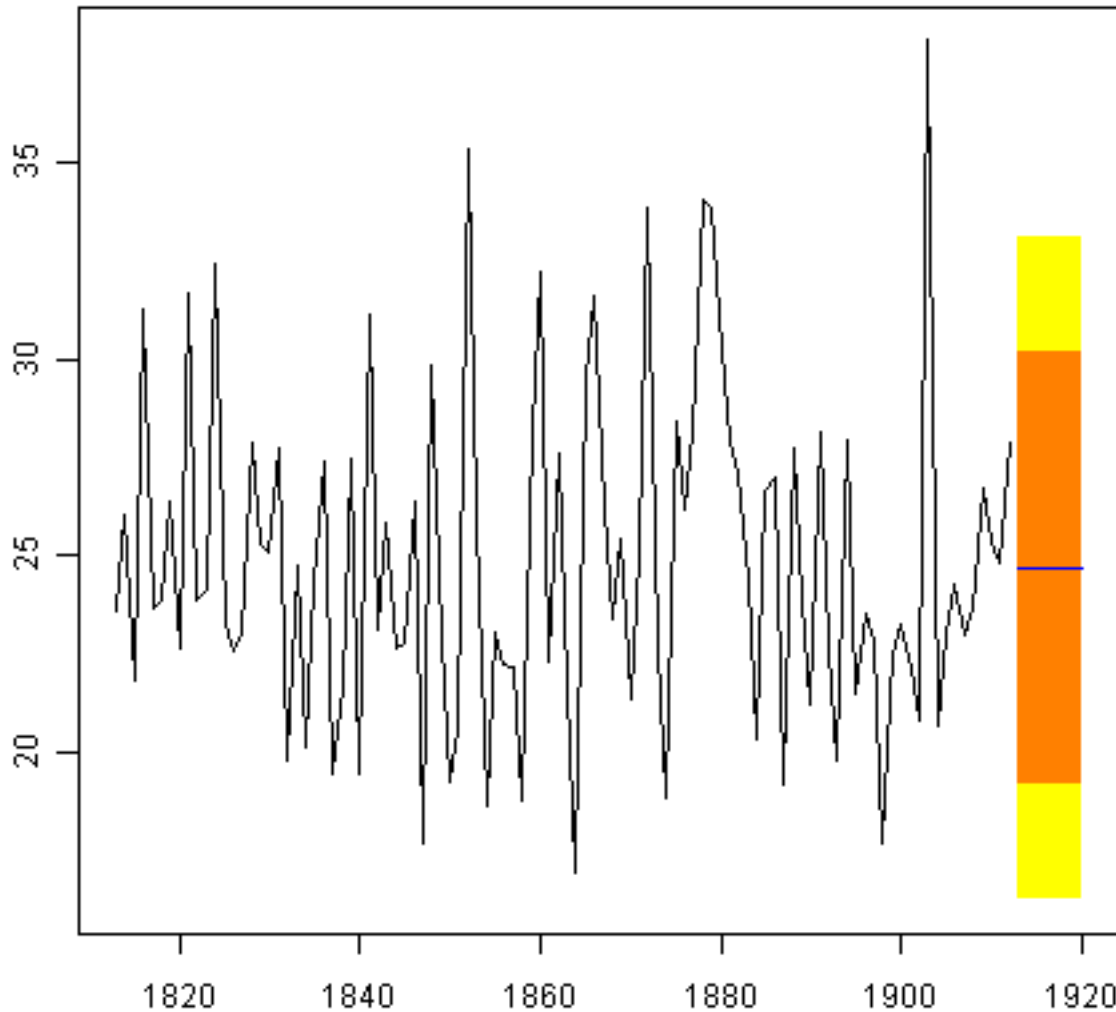
When using the `forecast.HoltWinters()` function, as its first argument (input), you pass it the predictive model that you have already fitted using the `HoltWinters()` function. For example, in the case of the rainfall time series, we stored the predictive model made using `HoltWinters()` in the variable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

```
> rainseriesforecasts2 <- forecast.HoltWinters(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.HoltWinters()` 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.HoltWinters()`, we can use the “`plot.forecast()`” function:

```
> plot.forecast(rainseriesforecasts2)
```

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

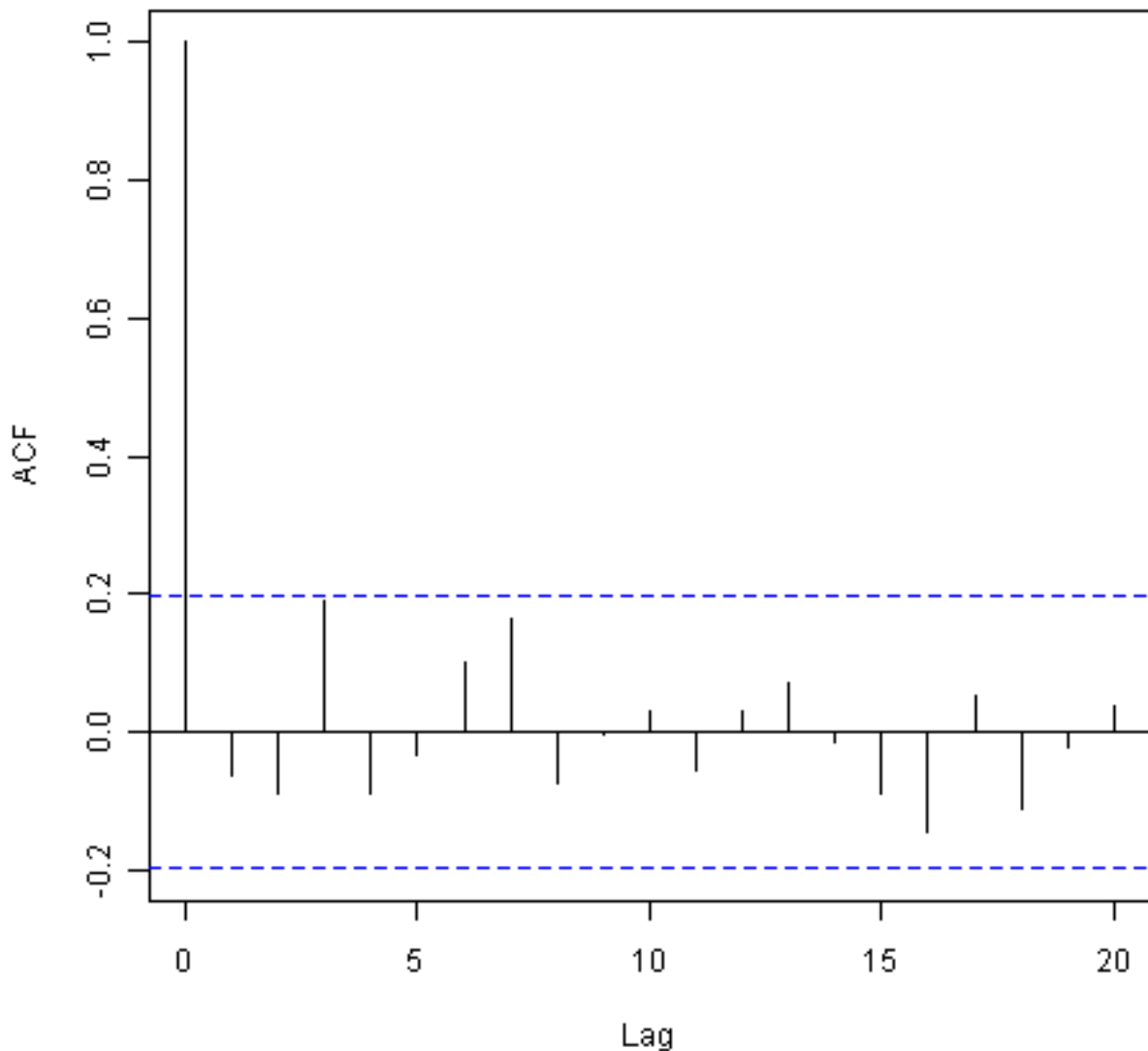
The ‘forecast errors’ are calculated as the observed values minus predicted values, for each time point. We can only calculate the forecast errors for the time period covered by our original time series, which is 1813-1912 for the rainfall data. As mentioned above, one measure of the accuracy of the 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.HoltWinters()`. 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)
```



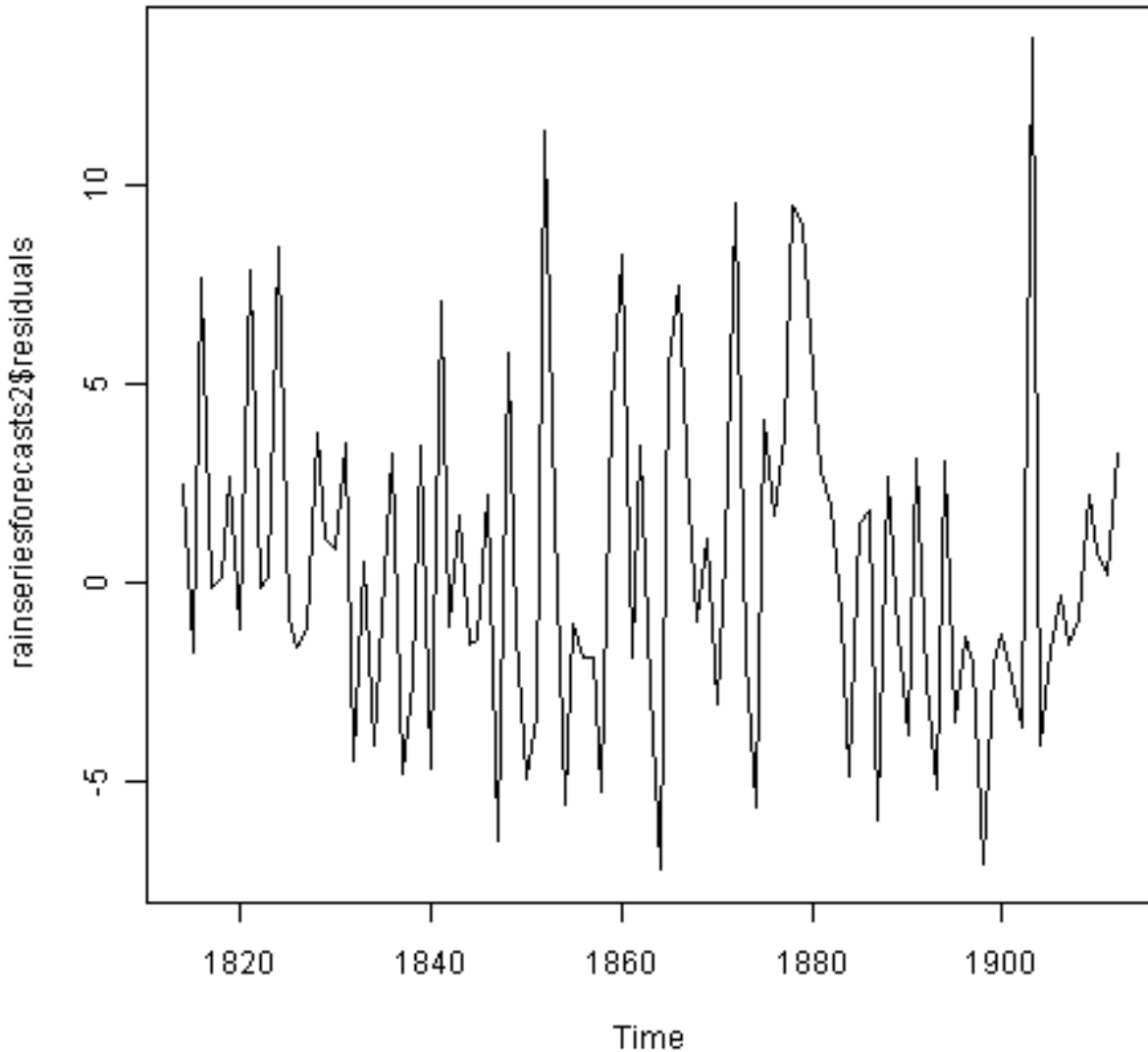
You can see from the sample correlogram that the autocorrelation at lag 3 is just touching the significance bounds. To test whether there is significant evidence for non-zero correlations at lags 1-20, we can carry out a Ljung-Box test. This can be done in R using the “Box.test()”, function. The maximum 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()”, below:

```
> 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)
```

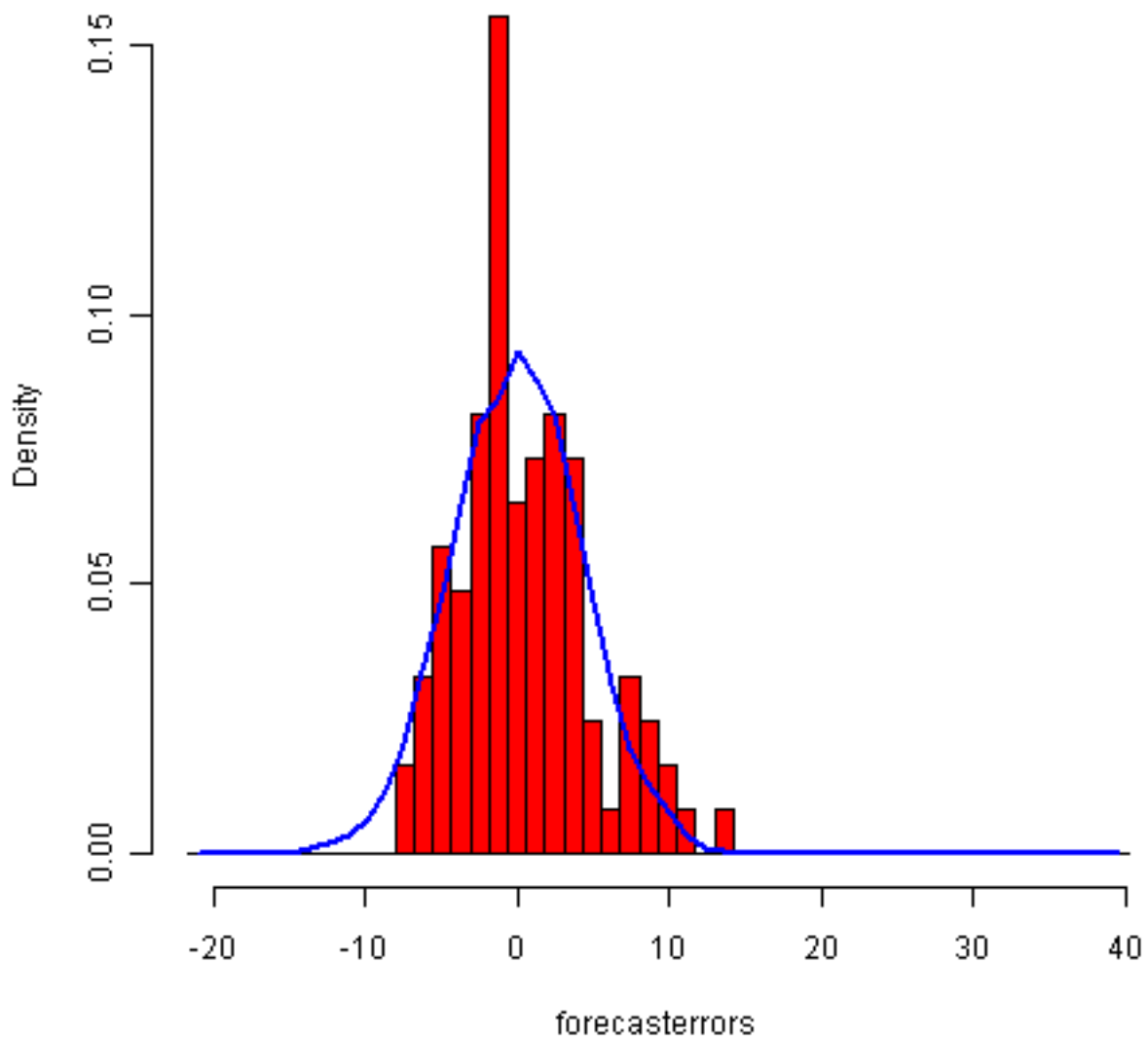
```

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:

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



The plot shows that the distribution of forecast errors is roughly centred 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.

Holt's Exponential Smoothing

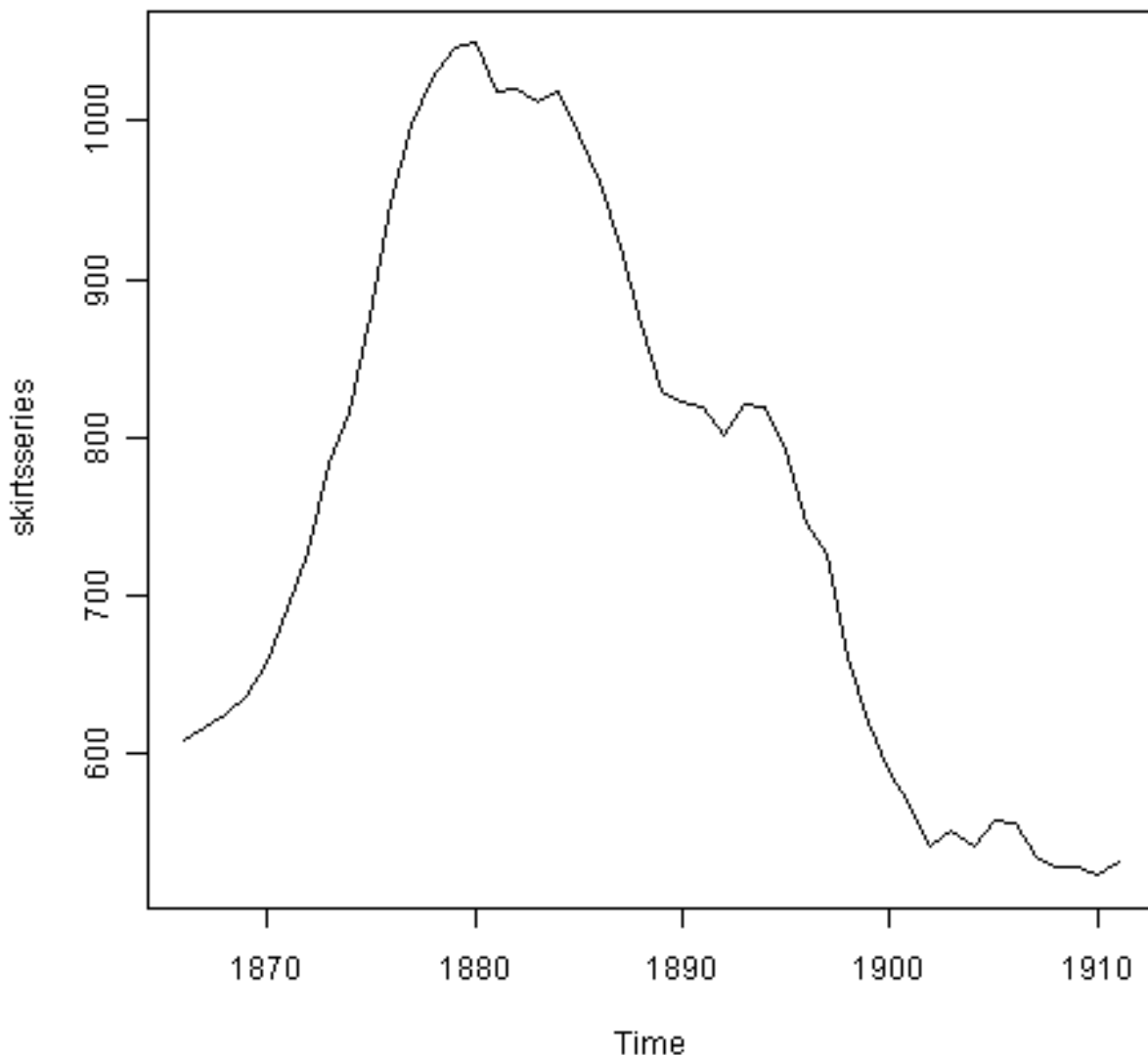
If you have a time series that can be described using an additive model with increasing or decreasing trend and no seasonality, you can use Holt's exponential smoothing to make short-term forecasts.

Holt's exponential smoothing estimates the level and slope at the current time point. Smoothing is controlled by two parameters, α , for the estimate of the level at the current time point, and β for the estimate of the slope b of the trend component at the current time point. As with simple exponential smoothing, the parameters α and β 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)
  Read 46 items
> 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).

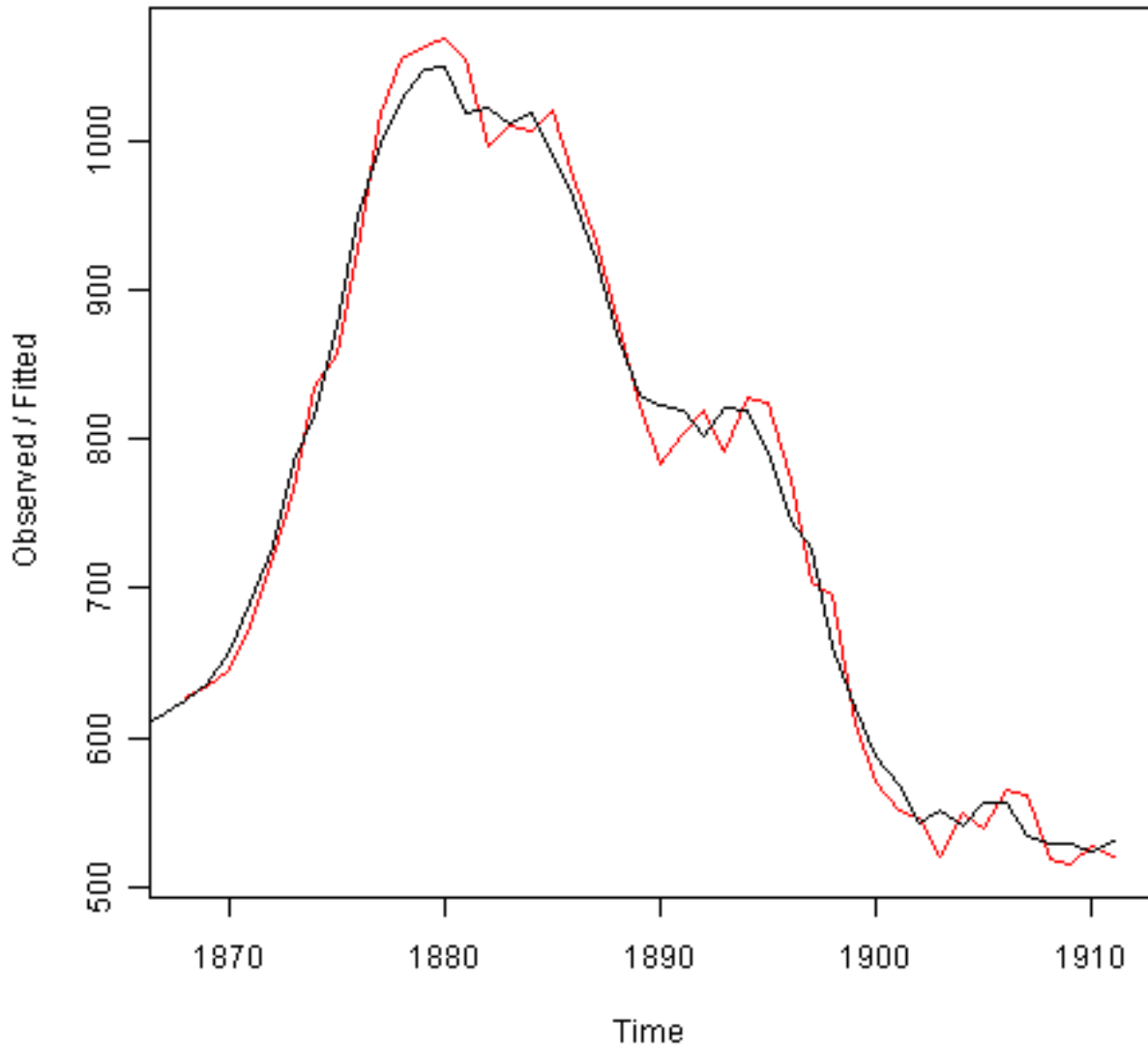
For example, to use Holt's exponential smoothing to fit a predictive model for skirt hem diameter, we type:

```
> 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)
```



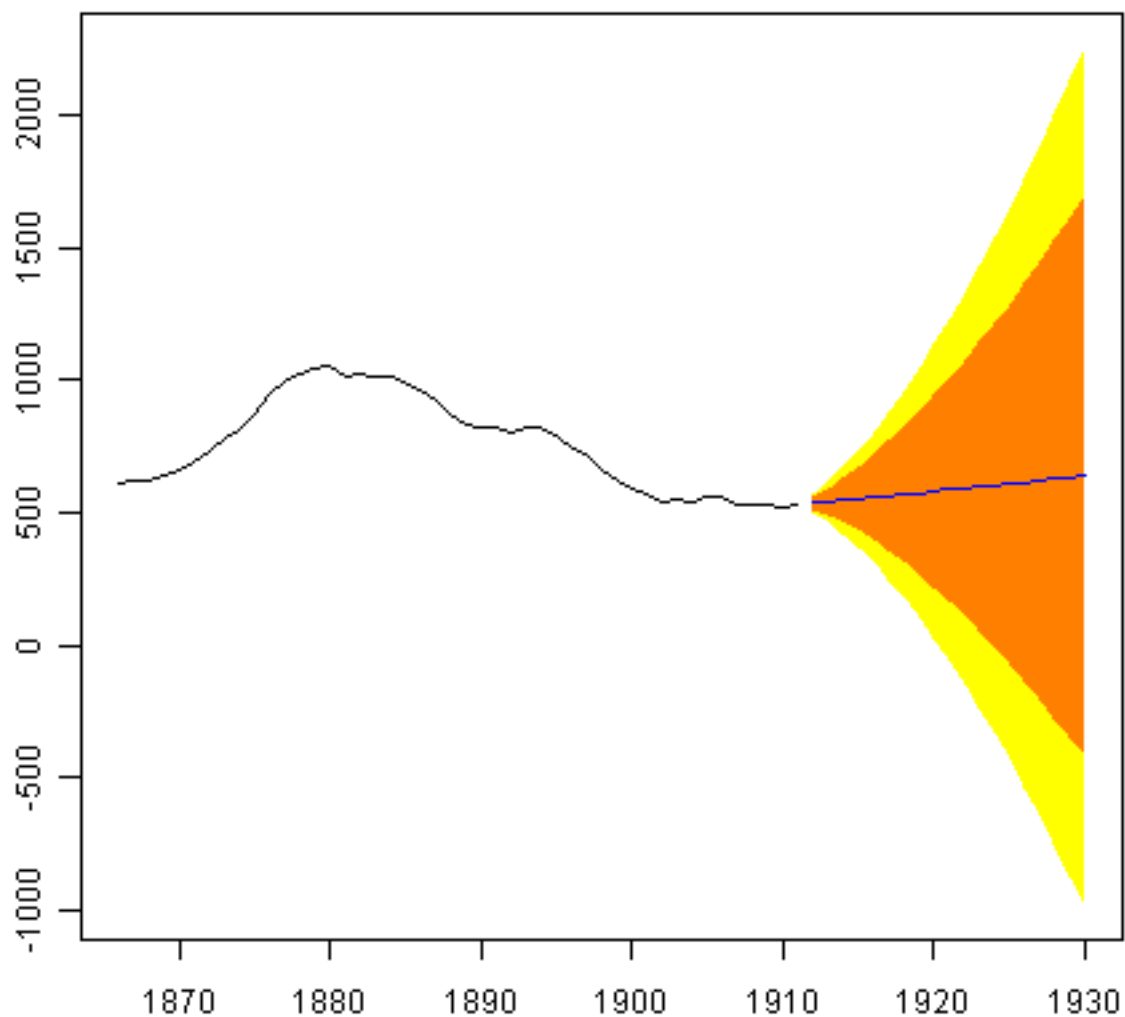
We can see from the picture that the in-sample forecasts agree pretty well with the observed values, although they tend to lag behind the observed values a little bit.

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.HoltWinters()` 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:

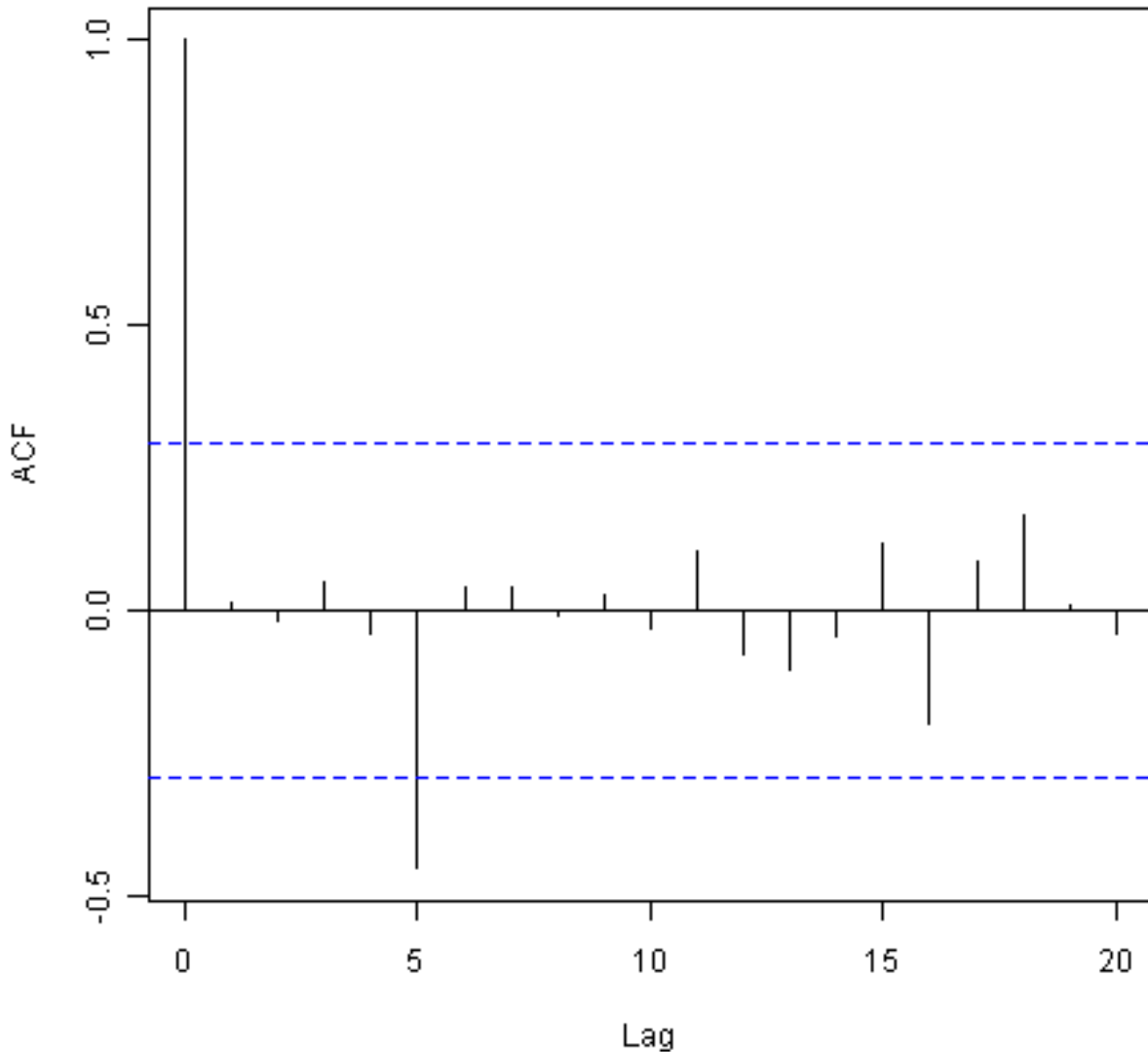
```
> skirtsseriesforecasts2 <- forecast.HoltWinters(skirtsseriesforecasts, h=19)
> plot.forecast(skirtsseriesforecasts2)
```



The forecasts are shown as a blue line, with the 80% prediction intervals as an orange shaded area, and the 95% prediction intervals as a yellow 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:

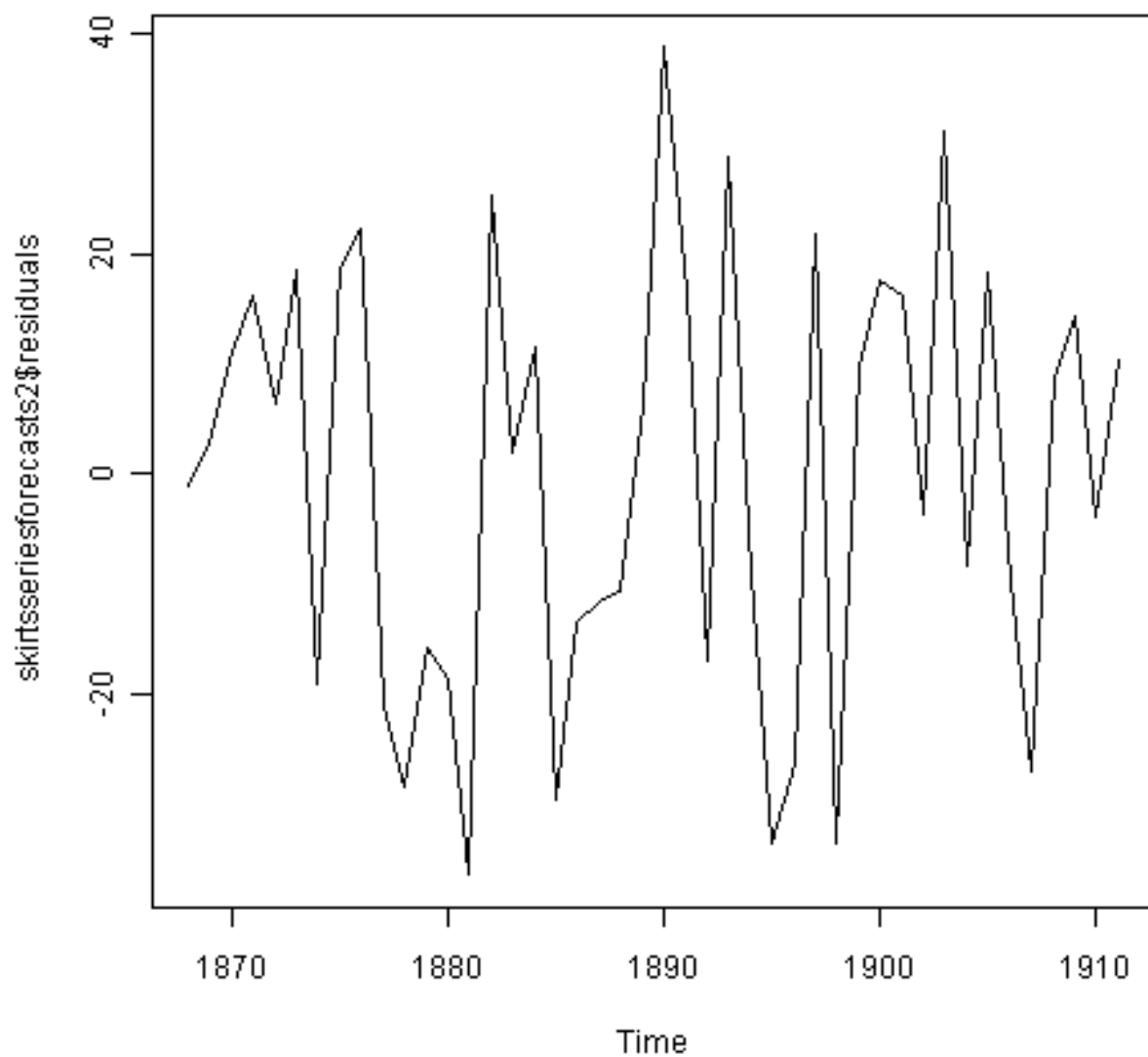
```
> acf(skirtseriesforecasts2$residuals, lag.max=20)
> Box.test(skirtseriesforecasts2$residuals, lag=20, type="Ljung-Box")
  Box-Ljung test
data:  skirtseriesforecasts2$residuals
X-squared = 19.7312, df = 20, p-value = 0.4749
```

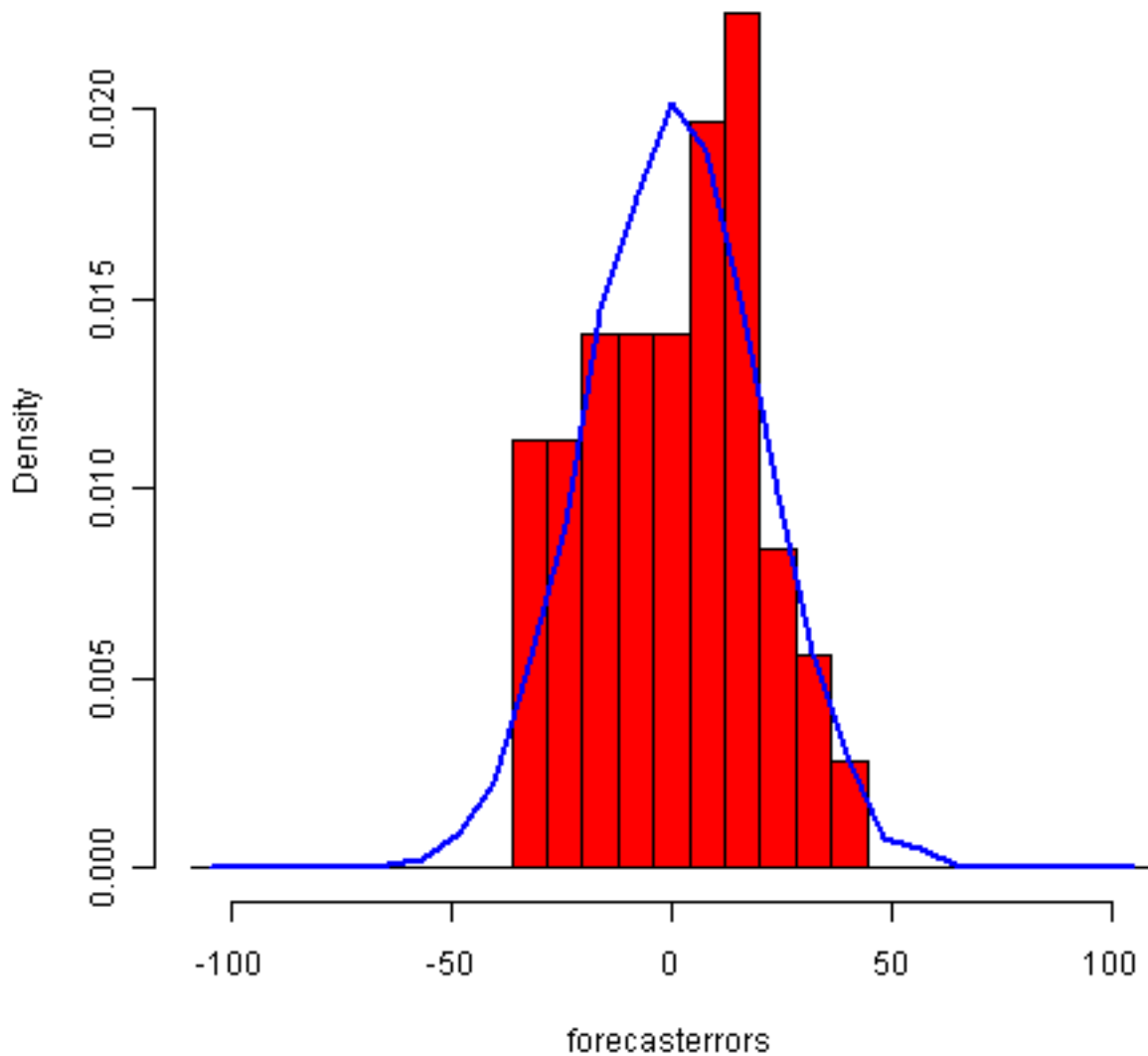



Here the correlogram shows that the sample autocorrelation for the in-sample forecast errors at lag 5 exceeds the significance bounds. However, we would expect one in 20 of the autocorrelations for the first twenty lags to exceed the 95% significance bounds by chance alone. Indeed, when we carry out 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(skitrseriesforecasts2$residuals)           # make a time plot
> plotForecastErrors(skitrseriesforecasts2$residuals) # make a histogram
```





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.

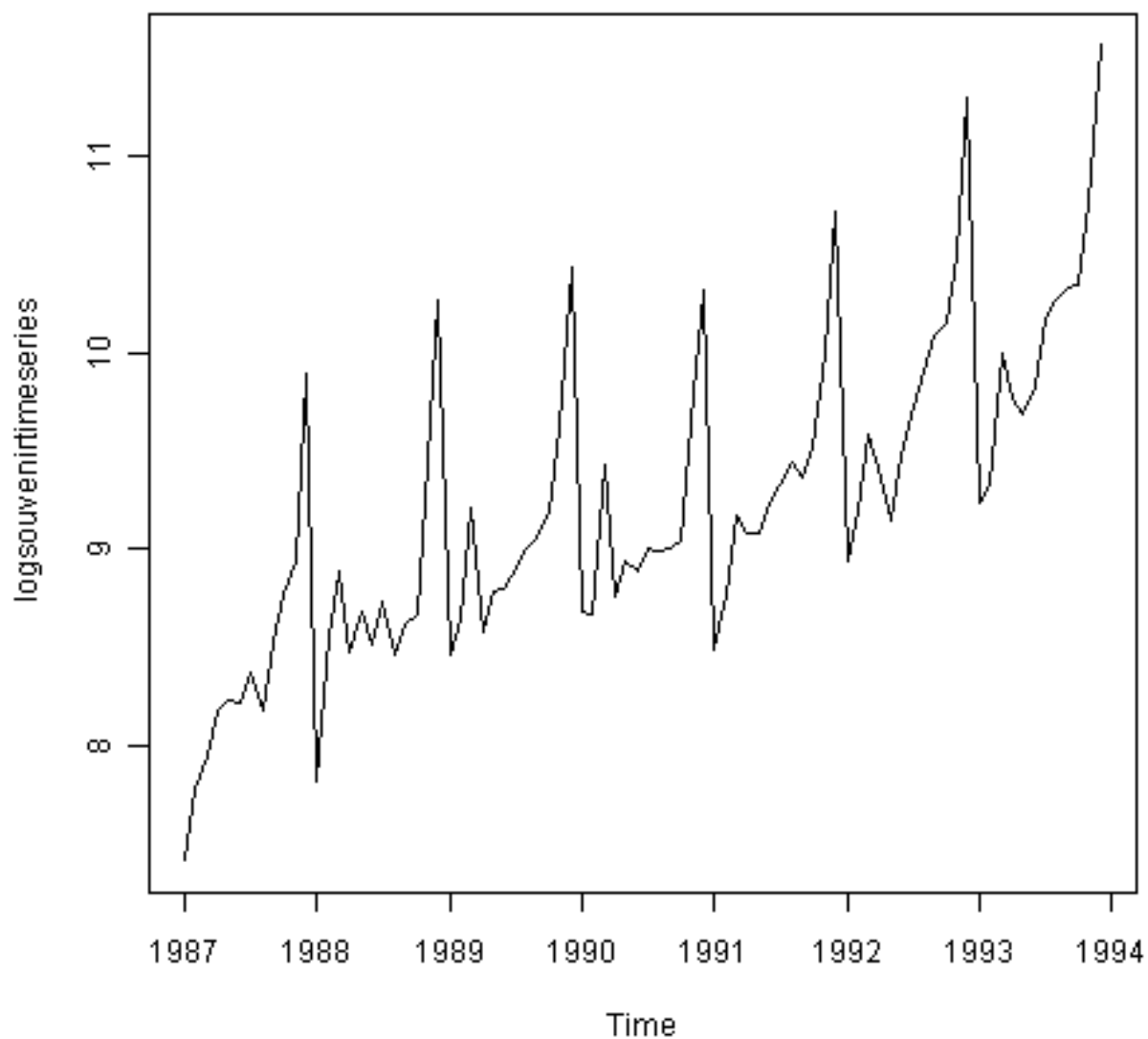
Thus, the Ljung-Box test shows that there is little evidence of autocorrelations in the forecast errors, while the time plot and histogram of forecast errors show that it is plausible that the forecast errors are normally distributed with mean zero and constant variance. Therefore, we can conclude that 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.

Holt-Winters Exponential Smoothing

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
```

```

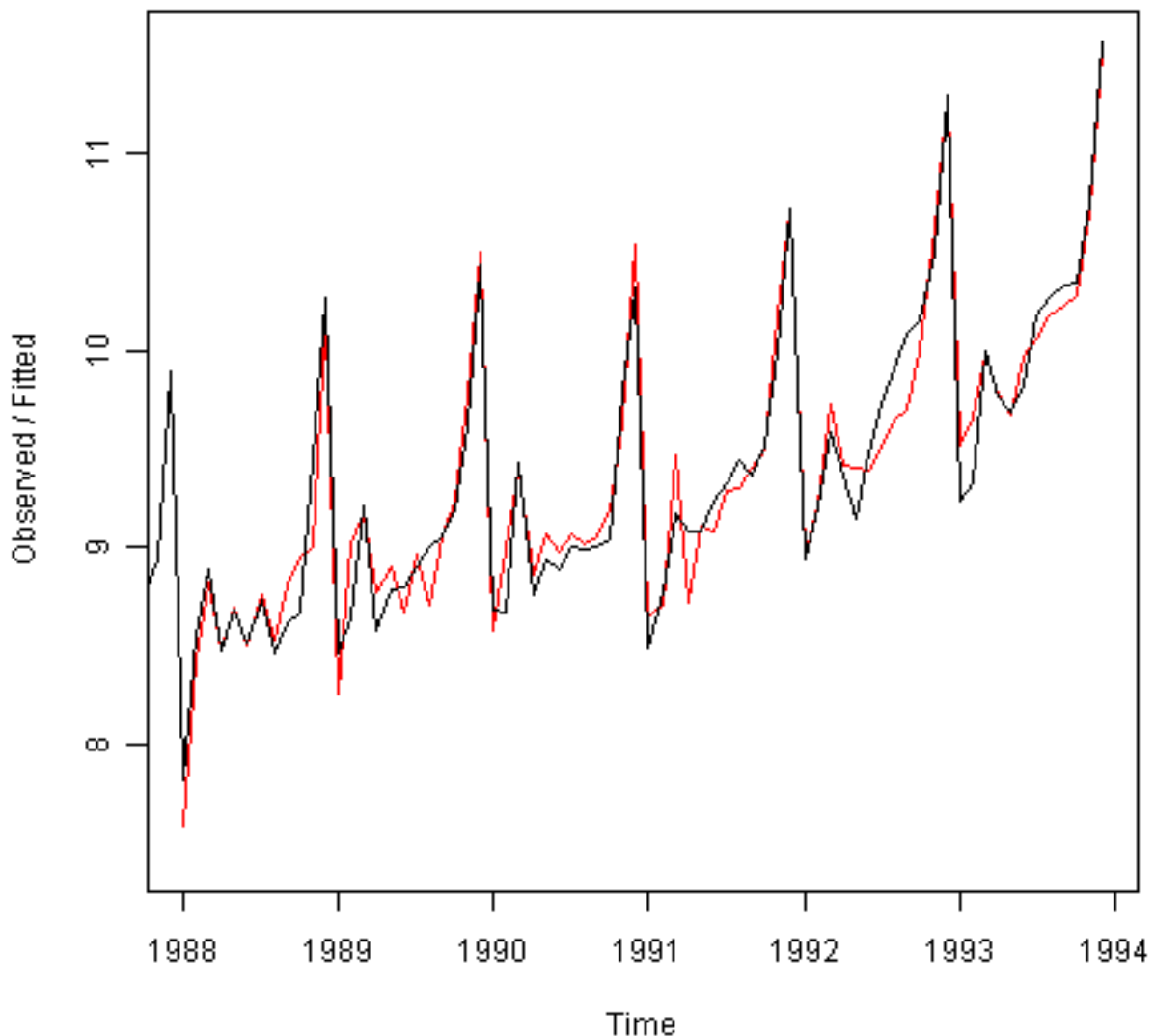
s10  0.05197826
s11  0.41793637
s12  1.18088423
> souvenirtimeseriesforecasts$SSE
2.011491

```

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)
```

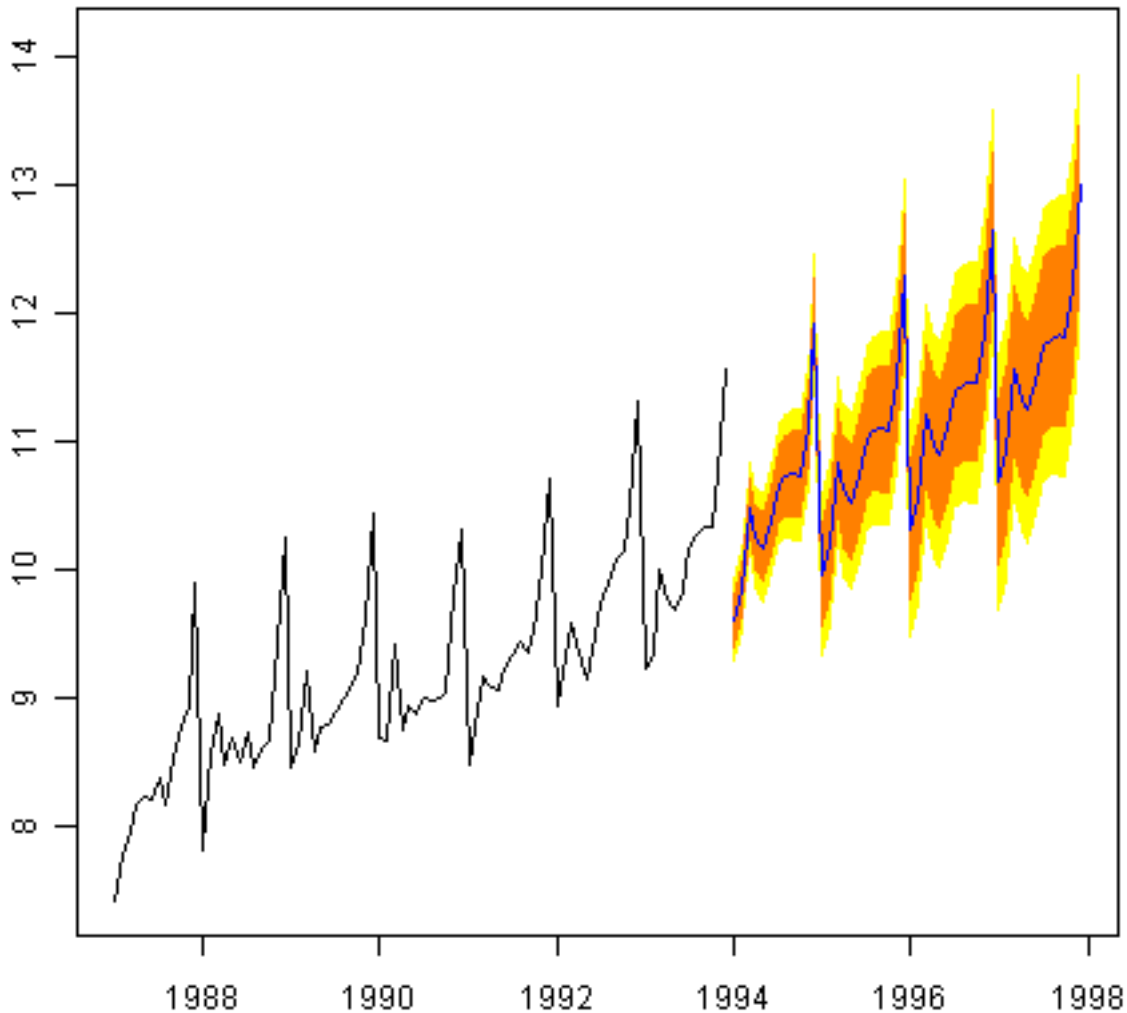


We see from the plot that the Holt-Winters exponential method is very successful in predicting the seasonal peaks, which occur roughly in November every year.

To make forecasts for future times not included in the original time series, we use the “`forecast.HoltWinters()`” 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:

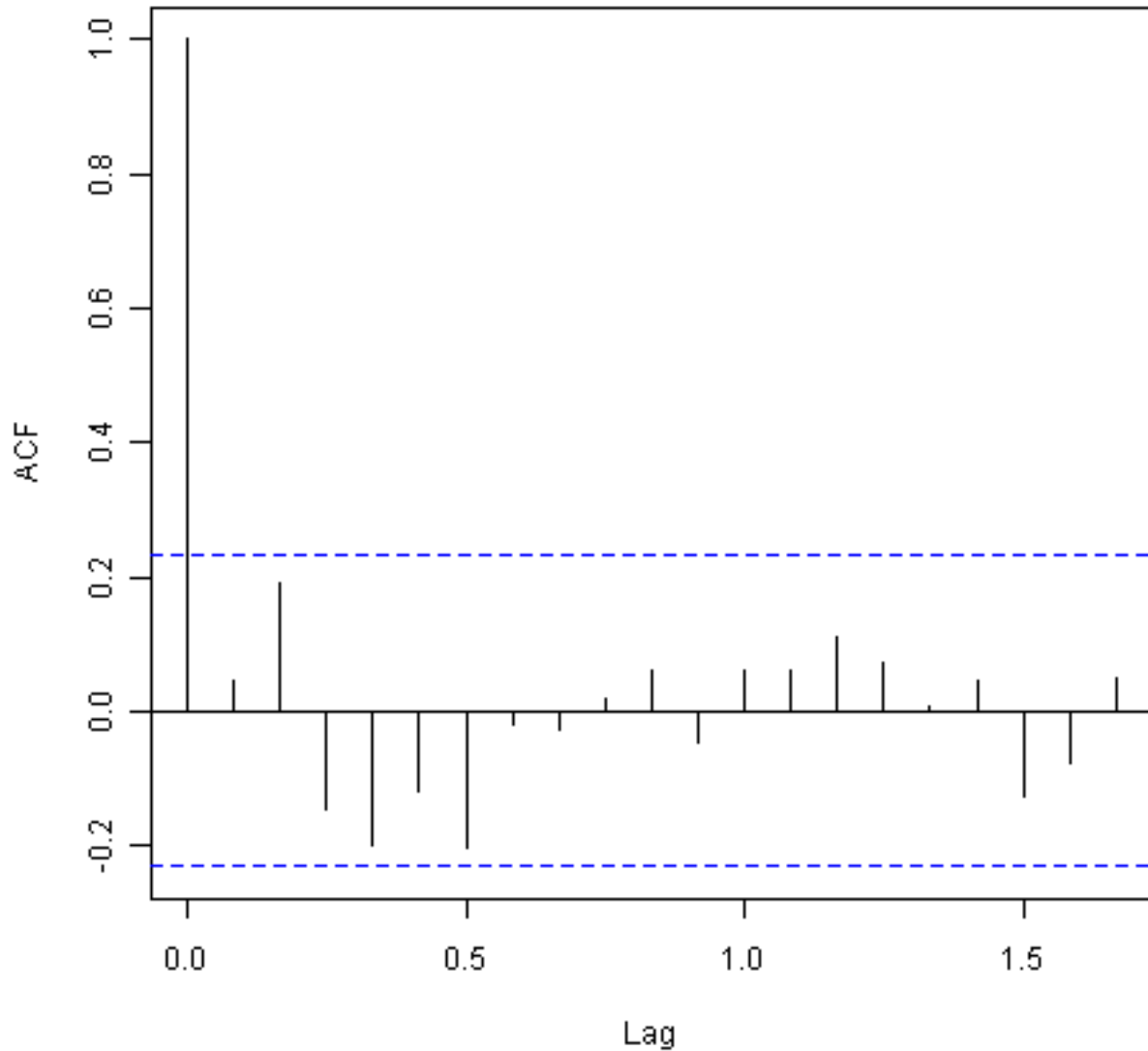
```
> souvenirtimeseriesforecasts2 <- forecast.HoltWinters(souvenirtimeseriesforecasts,  
+ h=48)  
> plot.forecast(souvenirtimeseriesforecasts2)
```



The forecasts are shown as a blue line, and the orange and yellow 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:

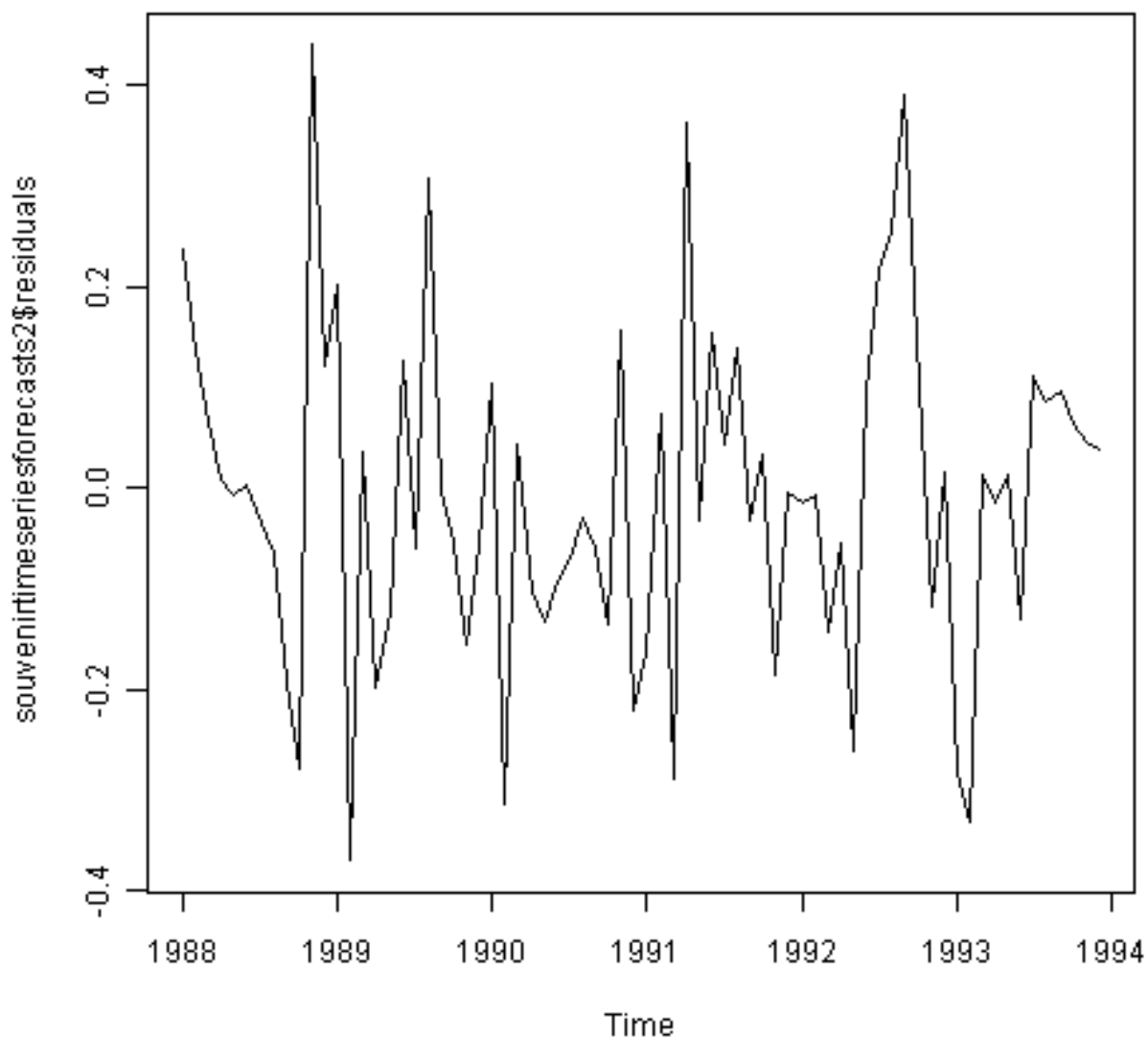
```
> acf(souvenirtimeseriesforecasts2$residuals, lag.max=20)  
> Box.test(souvenirtimeseriesforecasts2$residuals, lag=20, type="Ljung-Box")  
Box-Ljung test  
data: souvenirtimeseriesforecasts2$residuals  
X-squared = 17.5304, df = 20, p-value = 0.6183
```

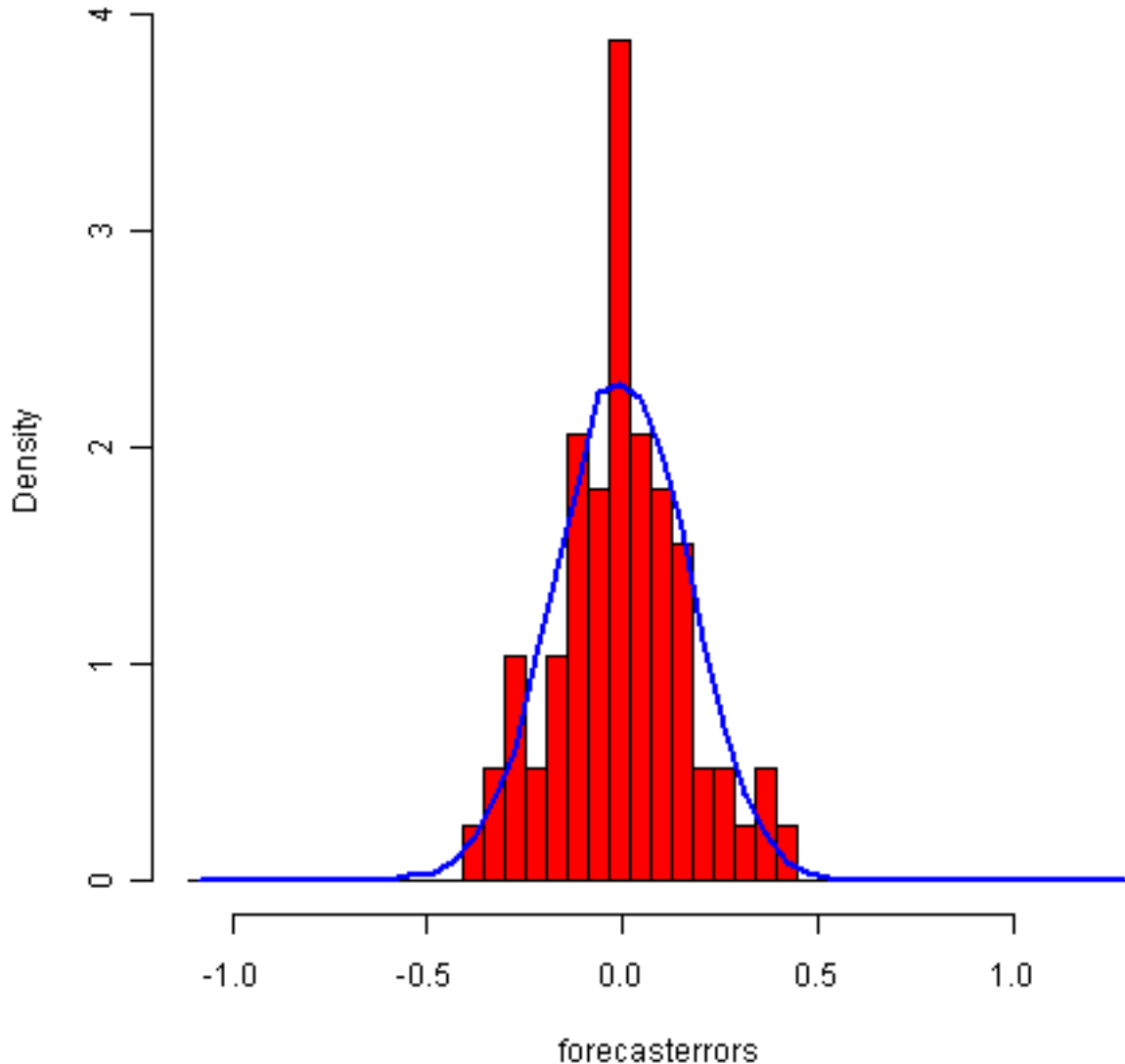


The correlogram shows that the autocorrelations for the in-sample forecast errors do not exceed the significance bounds for lags 1-20. Furthermore, the p-value for Ljung-Box test is 0.6, indicating that there is little evidence of non-zero autocorrelations at lags 1-20.

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$residuals) # make a time plot
> plotForecastErrors(souvenirtimeseriesforecasts2$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.

ARIMA Models

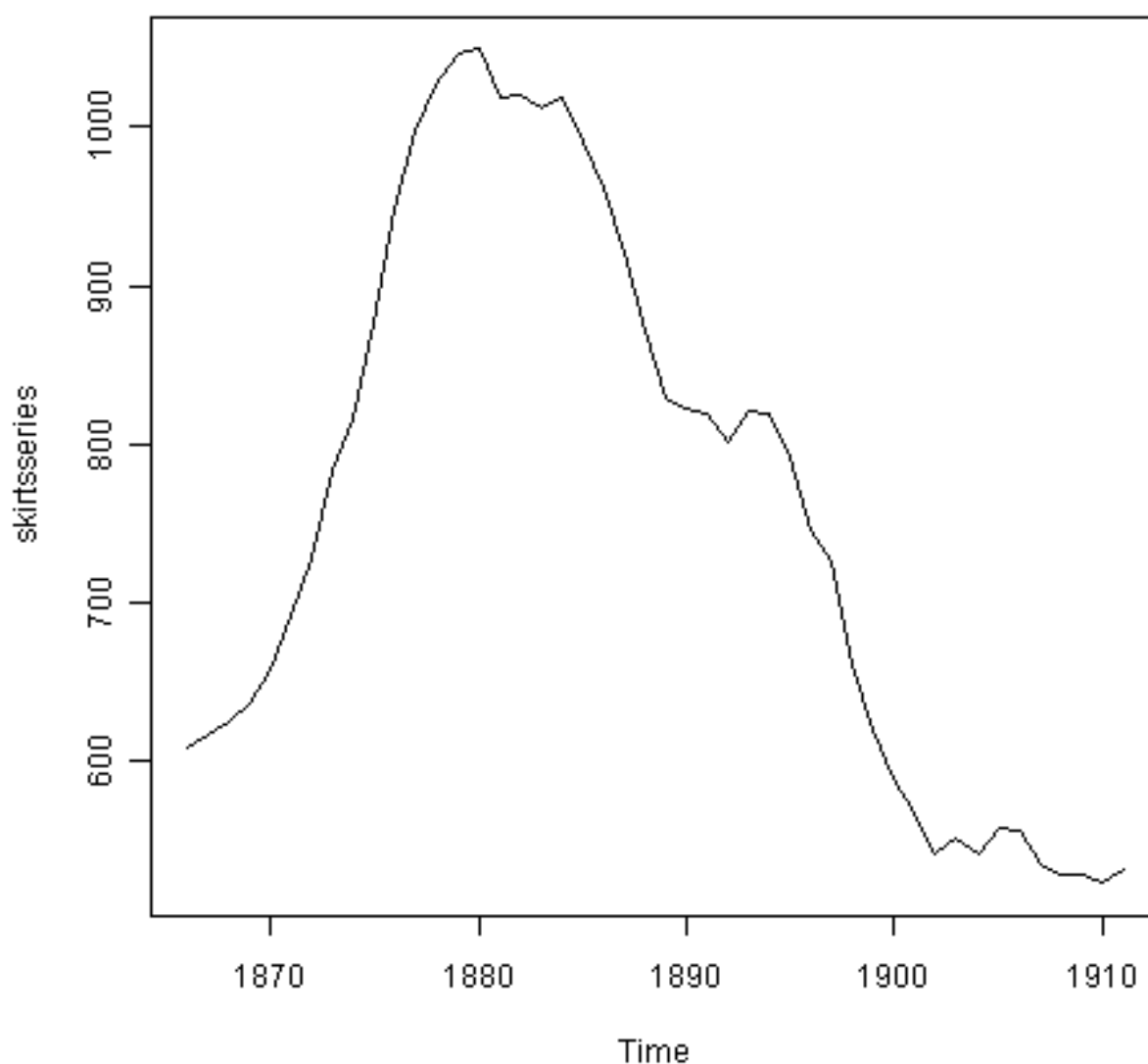
Exponential smoothing methods are useful for making forecasts, and make no assumptions about the correlations between successive values of the time series. However, if you want to make prediction intervals for forecasts made using exponential smoothing methods, the prediction intervals require that the forecast errors are uncorrelated and are normally distributed with mean zero and constant variance.

While exponential smoothing methods do not make any assumptions about correlations between successive values of the time series, in some cases you can make a better predictive model by taking correlations in the data into account. Autoregressive Integrated Moving Average (ARIMA) models include an explicit statistical model for the irregular component of a time series, that allows for non-zero autocorrelations in the irregular component.

Differencing a Time Series

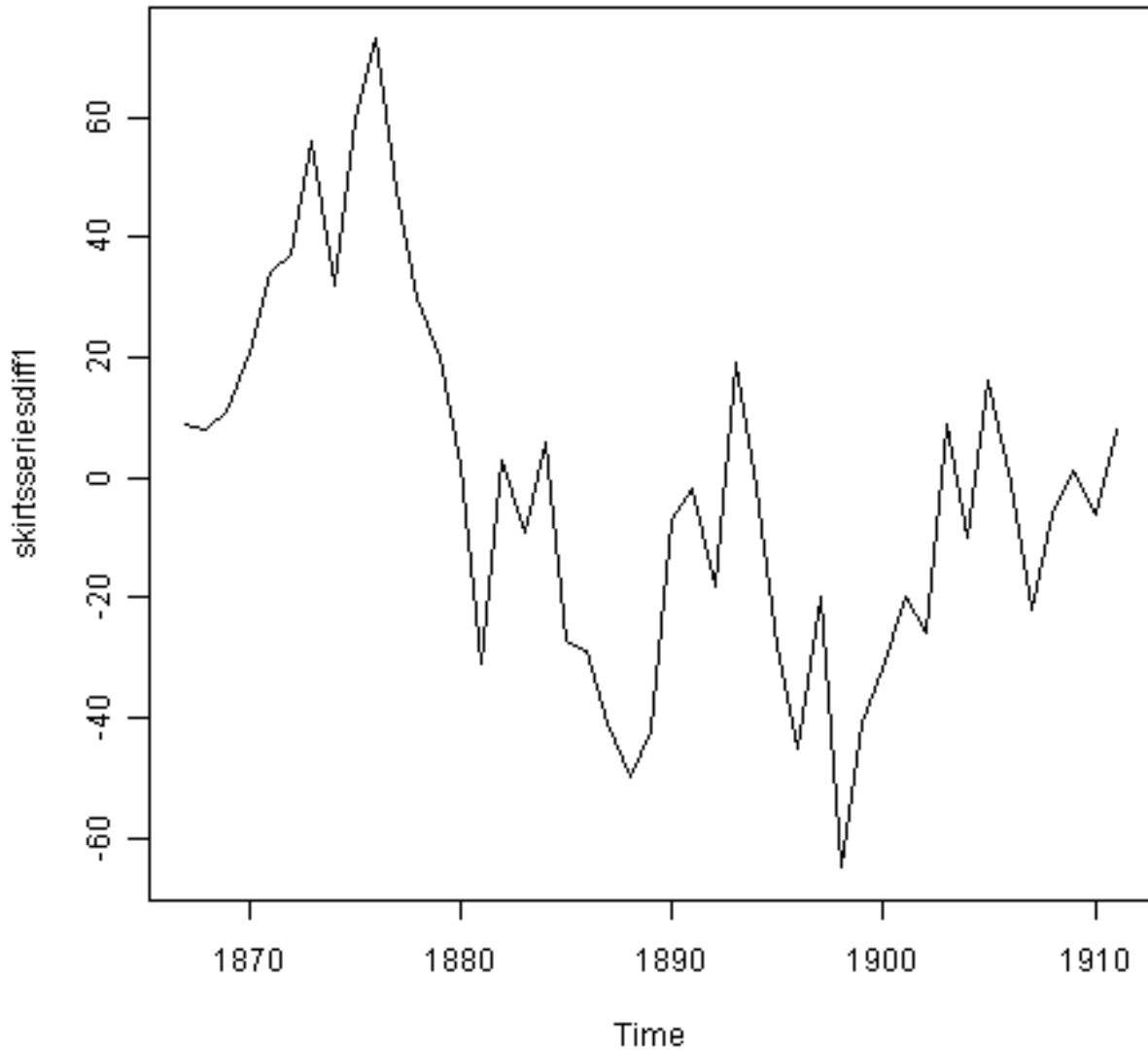
ARIMA models are defined for stationary time series. Therefore, if you start off with a non-stationary time series, you will first need to ‘difference’ the time series until you obtain a stationary time series. If you have to difference the time series d times to obtain a stationary series, then you have an ARIMA(p,d,q) model, where d is the order of differencing used.

You can difference a time series using the “diff()” function in R. For example, the time series of the annual diameter of women’s skirts at the hem, from 1866 to 1911 is not stationary in mean, as the level changes a lot over time:



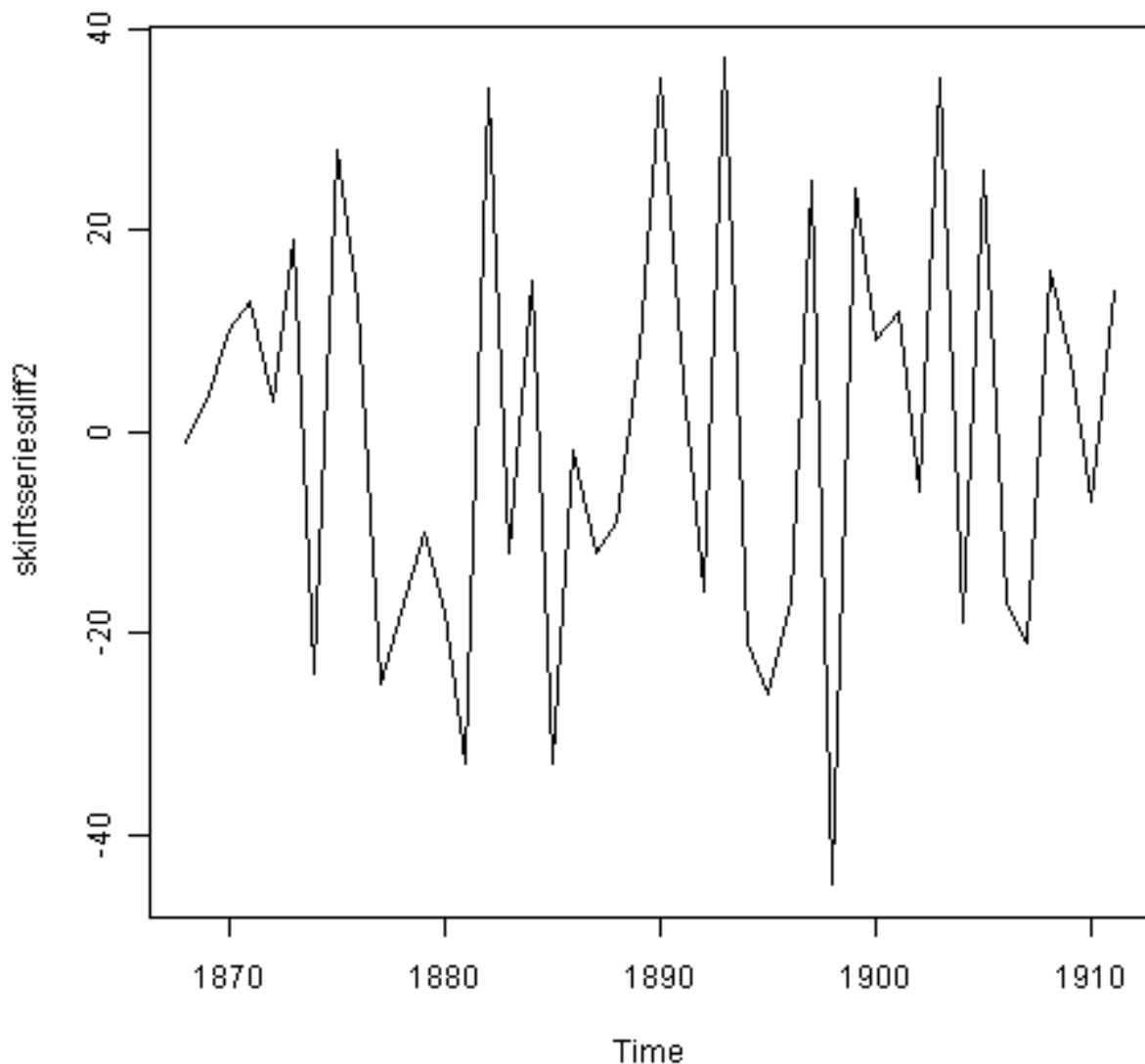
We can difference the time series (which we stored in “skirtseries”, see above) once, and plot the differenced series, by typing:

```
> skirtseriesdiff1 <- diff(skirtseries, differences=1)
> plot.ts(skirtseriesdiff1)
```



The resulting time series of first differences (above) does not appear to be stationary in mean. Therefore, we can difference the time series twice, to see if that gives us a stationary time series:

```
> skirtsseriesdiff2 <- diff(skirtsseries, differences=2)
> plot.ts(skirtsseriesdiff2)
```

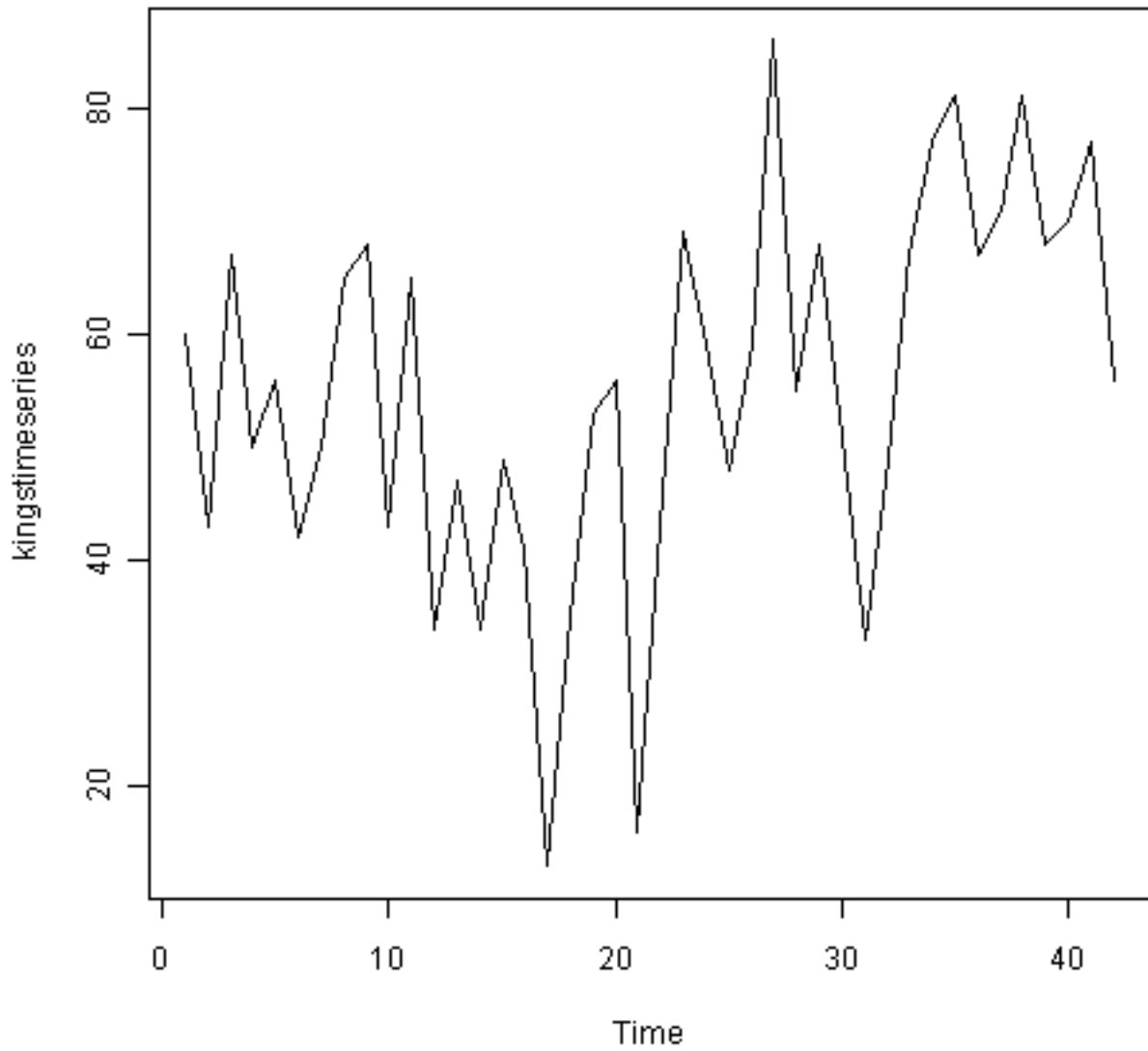
**Formal tests for stationarity**

Formal tests for stationarity called “unit root tests” are available in the `fUnitRoots` package, available on CRAN, but will not be discussed here.

The time series of second differences (above) does appear to be stationary in mean and variance, as the level of the series stays roughly constant over time, and the variance of the series appears roughly constant over time. Thus, it appears that we need to difference the time series of the diameter of skirts twice in order to achieve a stationary series.

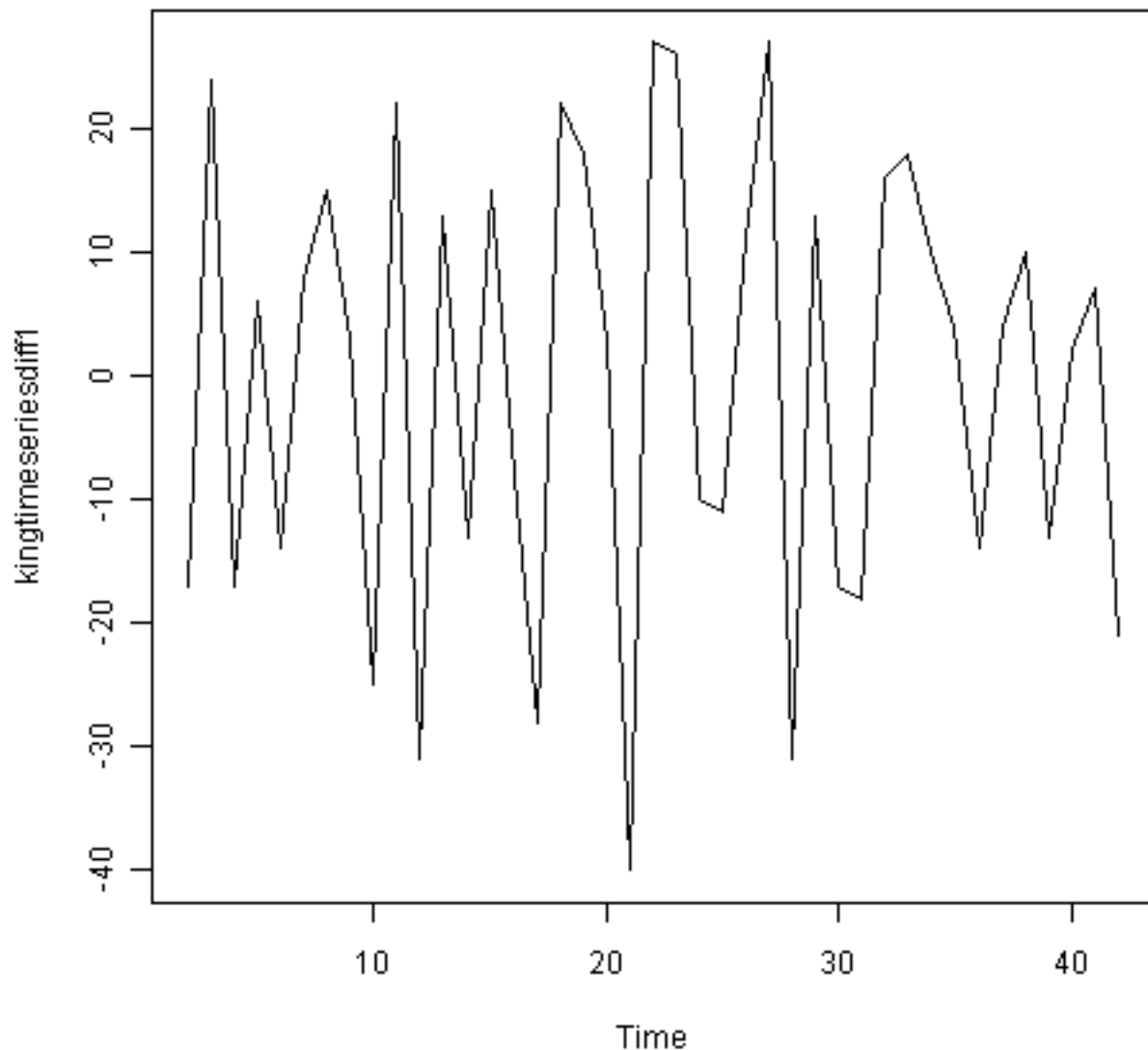
If you need to difference your original time series data d times in order to obtain a stationary time series, this means that you can use an $ARIMA(p,d,q)$ model for your time series, where d is the order of differencing used. For example, for the time series of the diameter of women’s skirts, we had to difference the time series twice, and so the order of differencing (d) is 2. This means that you can use an $ARIMA(p,2,q)$ model for your time series. The next step is to figure out the values of p and q for the $ARIMA$ model.

Another example is the time series of the age of death of the successive kings of England (see above):



From the time plot (above), we can see that the time series is not stationary in mean. To calculate the time series of first differences, and plot it, we type:

```
> kingtimeseriesdiff1 <- diff(kingstimeseries, differences=1)
> plot.ts(kingtimeseriesdiff1)
```



The time series of first differences appears to be stationary in mean and variance, and so an $ARIMA(p,1,q)$ model is probably appropriate for the time series of the age of death of the kings of England. By taking the time series of first differences, we have removed the trend component of the time series of the ages at death of the kings, and are left with an irregular component. We can now examine whether there are correlations between successive terms of this irregular component; if so, this could help us to make a predictive model for the ages at death of the kings.

Selecting a Candidate ARIMA Model

If your time series is stationary, or if you have transformed it to a stationary time series by differencing d times, the next step is to select the appropriate ARIMA model, which means finding the values of most appropriate values of p and q for an $ARIMA(p,d,q)$ model. To do this, you usually need to examine the correlogram and partial correlogram of the stationary time series.

To plot a correlogram and partial correlogram, we can use the “`acf()`” and “`pacf()`” functions in R, respectively. To get the actual values of the autocorrelations and partial autocorrelations, we set “`plot=FALSE`” in the “`acf()`” and “`pacf()`” functions.

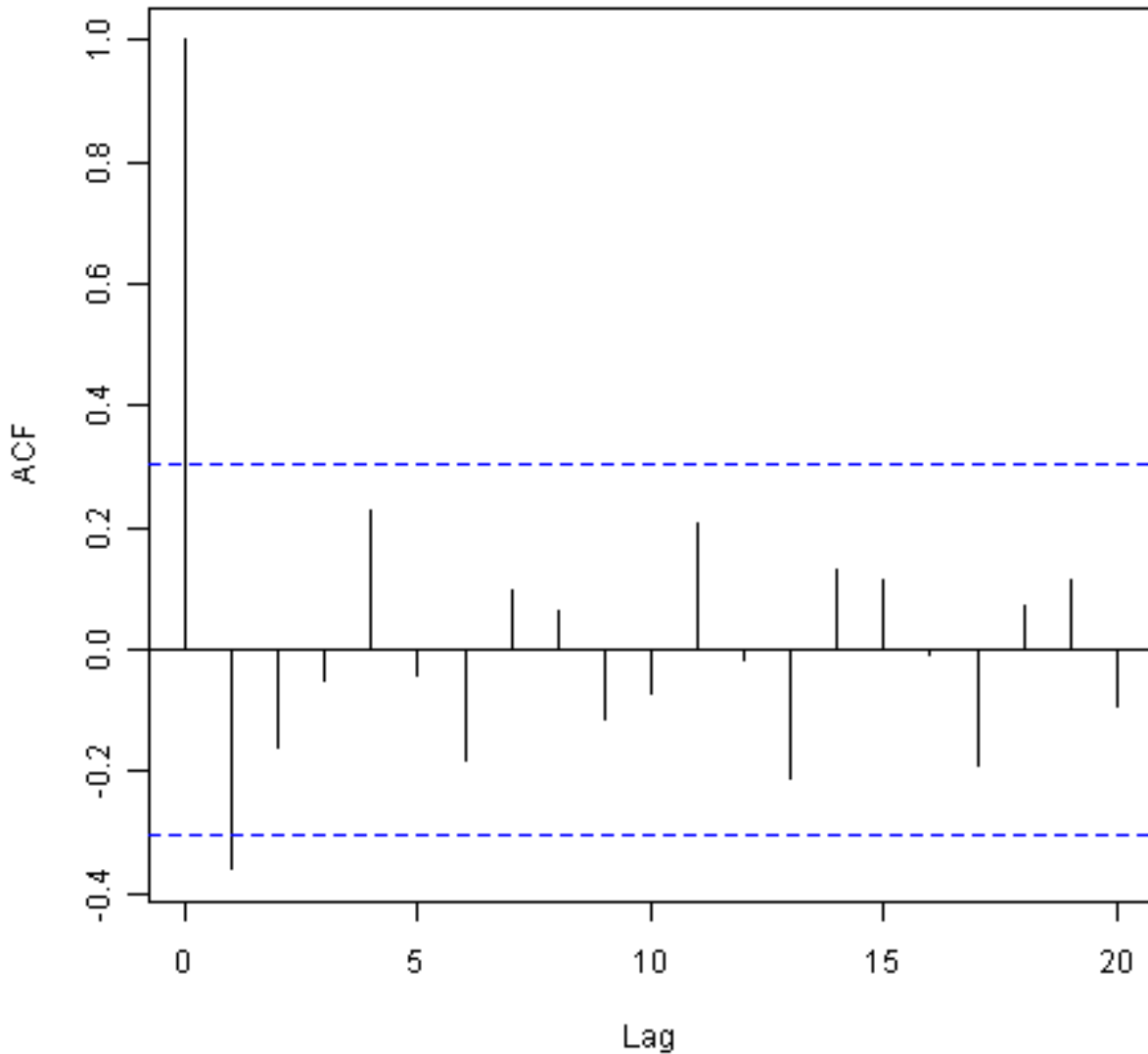
Example of the Ages at Death of the Kings of England

For example, to plot the correlogram for lags 1-20 of the once differenced time series of the ages at death of the kings of England, and to get the values of the autocorrelations, we type:

```

> acf(kingtimeseriesdiff1, lag.max=20) # plot a correlogram
> acf(kingtimeseriesdiff1, lag.max=20, plot=FALSE) # get the autocorrelation values
Autocorrelations of series 'kingtimeseriesdiff1', by lag
  0      1      2      3      4      5      6      7      8      9     10
1.000 -0.360 -0.162 -0.050  0.227 -0.042 -0.181  0.095  0.064 -0.116 -0.071
 11     12     13     14     15     16     17     18     19     20
0.206 -0.017 -0.212  0.130  0.114 -0.009 -0.192  0.072  0.113 -0.093

```



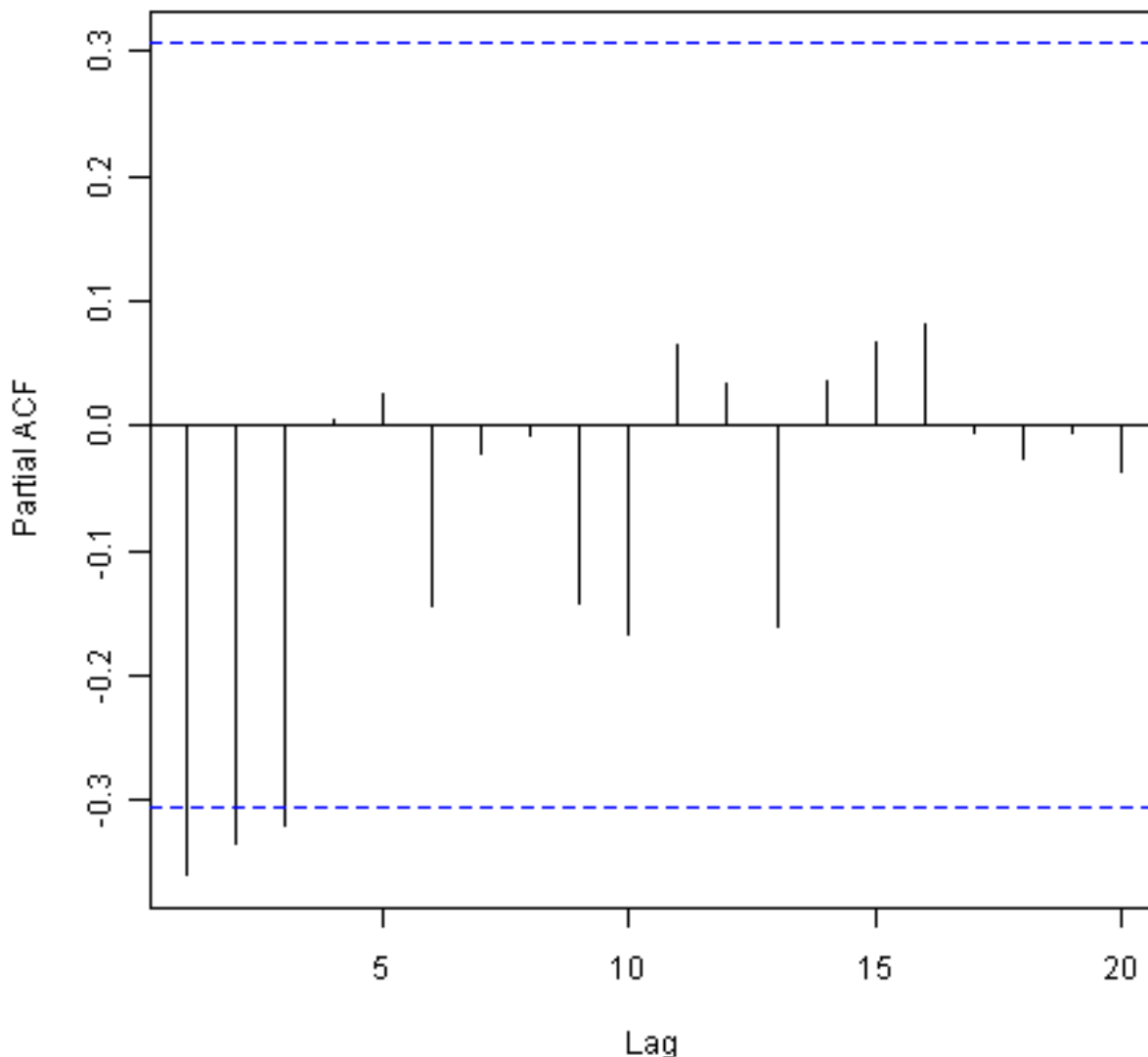
We see from the correlogram that the autocorrelation at lag 1 (-0.360) exceeds the significance bounds, but all other autocorrelations between lags 1-20 do not exceed the significance bounds.

To plot the partial correlogram for lags 1-20 for the once differenced time series of the ages at death of the English kings, and get the values of the partial autocorrelations, we use the “pacf()” function, by typing:

```

> pacf(kingtimeseriesdiff1, lag.max=20) # plot a partial correlogram
> pacf(kingtimeseriesdiff1, lag.max=20, plot=FALSE) # get the partial_
↪ autocorrelation values
Partial autocorrelations of series 'kingtimeseriesdiff1', by lag
  1      2      3      4      5      6      7      8      9     10     11
-0.360 -0.335 -0.321  0.005  0.025 -0.144 -0.022 -0.007 -0.143 -0.167  0.065
 12     13     14     15     16     17     18     19     20
 0.034 -0.161  0.036  0.066  0.081 -0.005 -0.027 -0.006 -0.037

```



The partial correlogram shows that the partial autocorrelations at lags 1, 2 and 3 exceed the significance bounds, are negative, and are slowly decreasing in magnitude with increasing lag (lag 1: -0.360, lag 2: -0.335, lag 3: -0.321). The partial autocorrelations tail off to zero after lag 3.

Since the correlogram is zero after lag 1, and the partial correlogram tails off to zero after lag 3, this means that the following ARMA (autoregressive moving average) models are possible for the time series of first differences:

- an ARMA(3,0) model, that is, an autoregressive model of order $p=3$, since the partial autocorrelogram is zero after lag 3, and the autocorrelogram tails off to zero (although perhaps too abruptly for this model to be appropriate)
- an ARMA(0,1) model, that is, a moving average model of order $q=1$, since the autocorrelogram is zero after lag 1 and the partial autocorrelogram tails off to zero
- an ARMA(p,q) model, that is, a mixed model with p and q greater than 0, since the autocorrelogram and partial correlogram tail off to zero (although the correlogram probably tails off to zero too abruptly for this model to be appropriate)

We use the principle of parsimony to decide which model is best: that is, we assume that the model with the fewest parameters is best. The ARMA(3,0) model has 3 parameters, the ARMA(0,1) model has 1 parameter, and the ARMA(p,q) model has at least 2 parameters. Therefore, the ARMA(0,1) model is taken as the best model.

An ARMA(0,1) model is a moving average model of order 1, or MA(1) model. This model can be written as: $X_t - \mu = Z_t - (\theta * Z_{t-1})$, where X_t is the stationary time series we are studying (the first differenced series of ages at death of English kings), μ is the mean of time series X_t , Z_t is white noise with mean zero and constant variance, and θ is a parameter that can be estimated.

A MA (moving average) model is usually used to model a time series that shows short-term dependencies between successive observations. Intuitively, it makes good sense that a MA model can be used to describe the irregular component in the time series of ages at death of English kings, as we might expect the age at death of a particular English king to have some effect on the ages at death of the next king or two, but not much effect on the ages at death of kings that reign much longer after that.

Shortcut: the `auto.arima()` function

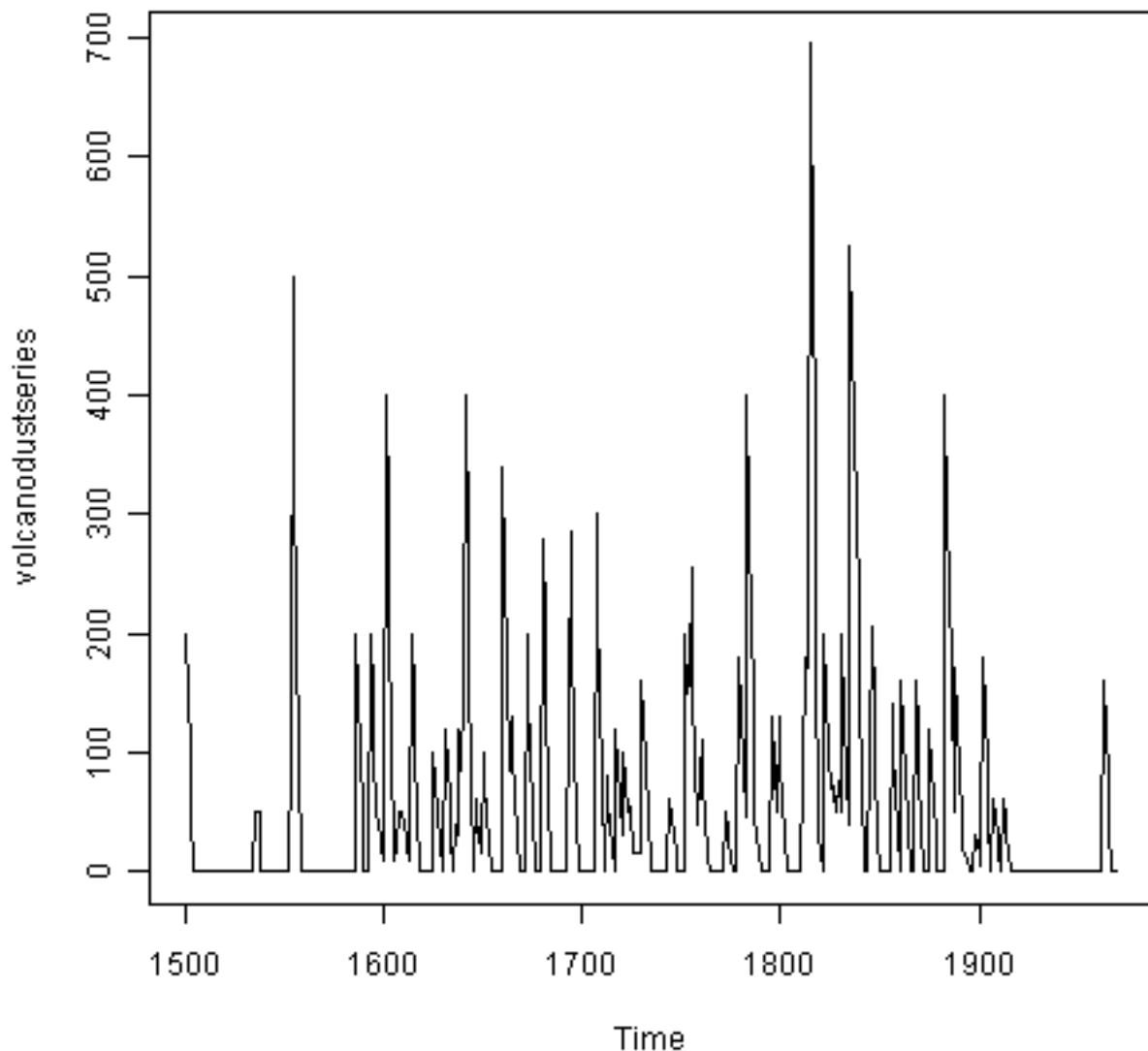
The `auto.arima()` function can be used to find the appropriate ARIMA model, eg., type “`library(forecast)`”, then “`auto.arima(kings)`”. The output says an appropriate model is ARIMA(0,1,1).

Since an ARMA(0,1) model (with $p=0$, $q=1$) is taken to be the best candidate model for the time series of first differences of the ages at death of English kings, then the original time series of the ages of death can be modelled using an ARIMA(0,1,1) model (with $p=0$, $d=1$, $q=1$, where d is the order of differencing required).

Example of the Volcanic Dust Veil in the Northern Hemisphere

Let’s take another example of selecting an appropriate ARIMA model. The file <http://robjhyndman.com/tsdldata/annual/dvi.dat> contains data on the volcanic dust veil index in the northern hemisphere, from 1500-1969 (original data from Hipel and McLeod, 1994). This is a measure of the impact of volcanic eruptions’ release of dust and aerosols into the environment. We can read it into R and make a time plot by typing:

```
> volcanodust <- scan("http://robjhyndman.com/tsdldata/annual/dvi.dat", skip=1)
  Read 470 items
> volcanodustseries <- ts(volcanodust, start=c(1500))
> plot.ts(volcanodustseries)
```

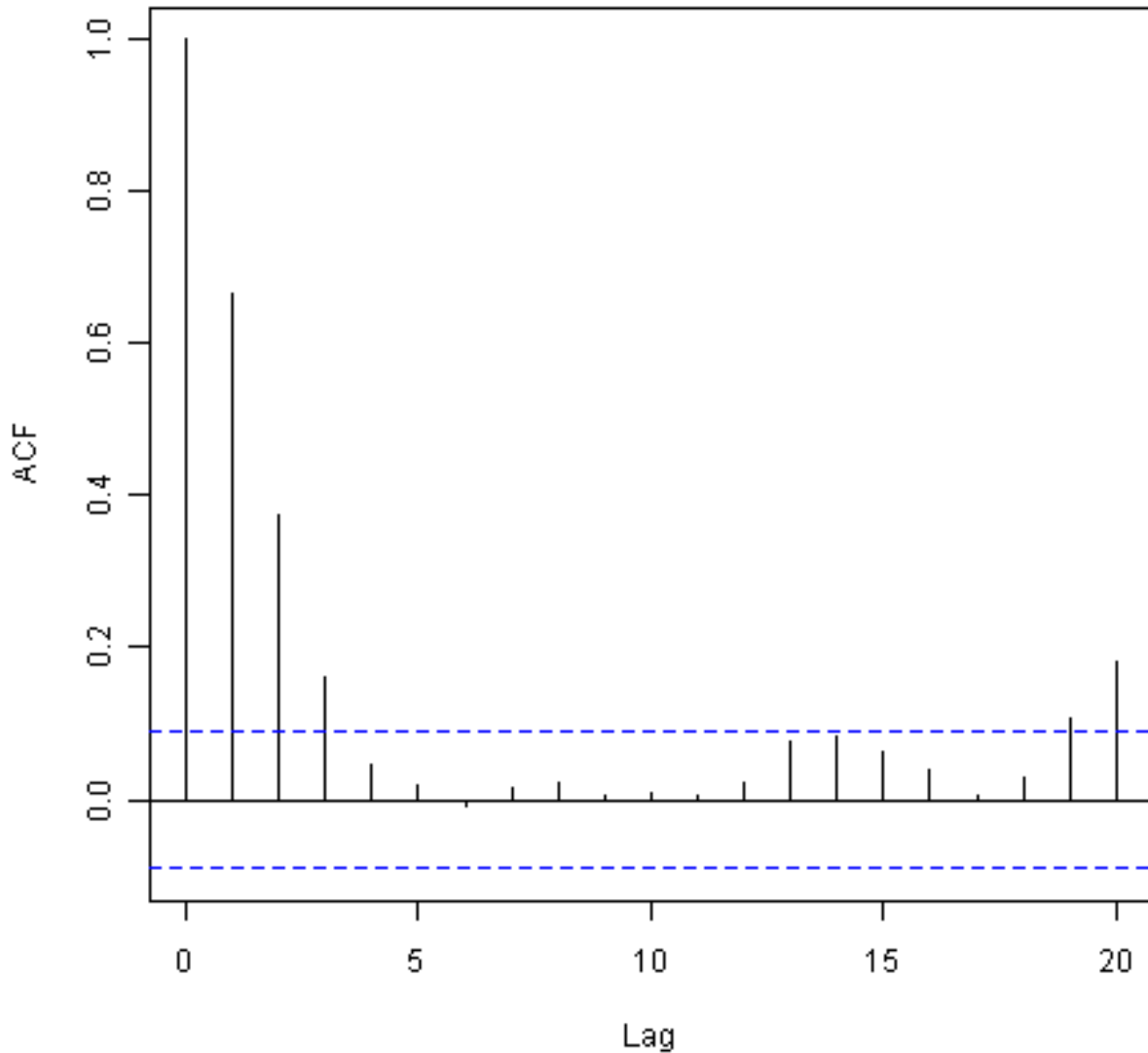


From the time plot, it appears that the random fluctuations in the time series are roughly constant in size over time, so an additive model is probably appropriate for describing this time series.

Furthermore, the time series appears to be stationary in mean and variance, as its level and variance appear to be roughly constant over time. Therefore, we do not need to difference this series in order to fit an ARIMA model, but can fit an ARIMA model to the original series (the order of differencing required, d , is zero here).

We can now plot a correlogram and partial correlogram for lags 1-20 to investigate what ARIMA model to use:

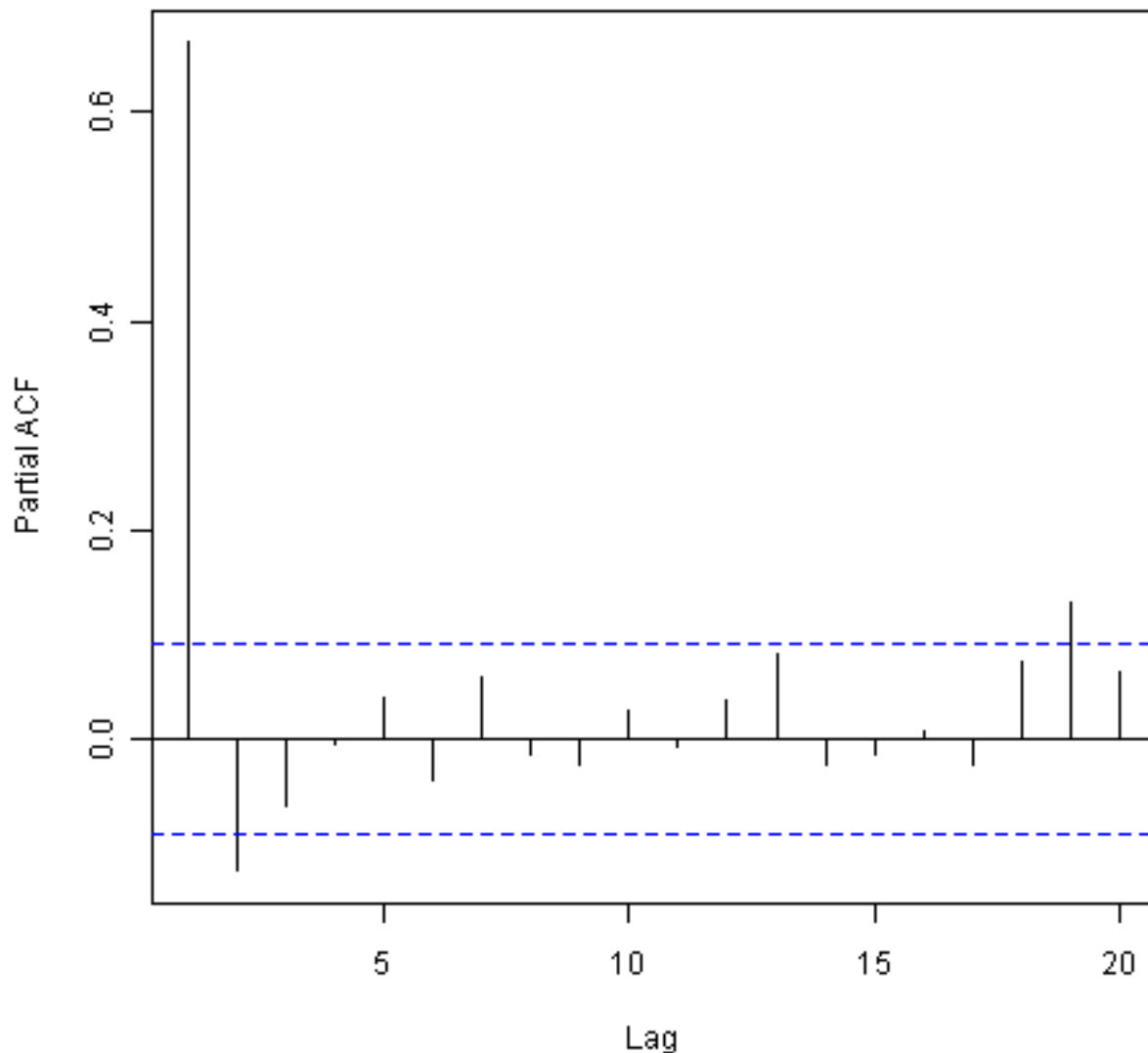
```
> acf(volcanodustseries, lag.max=20) # plot a correlogram
> acf(volcanodustseries, lag.max=20, plot=FALSE) # get the values of the
↪ autocorrelations
Autocorrelations of series 'volcanodustseries', by lag
  0    1    2    3    4    5    6    7    8    9   10
1.000 0.666 0.374 0.162 0.046 0.017 -0.007 0.016 0.021 0.006 0.010
 11   12   13   14   15   16   17   18   19   20
0.004 0.024 0.075 0.082 0.064 0.039 0.005 0.028 0.108 0.182
```



We see from the correlogram that the autocorrelations for lags 1, 2 and 3 exceed the significance bounds, and that the autocorrelations tail off to zero after lag 3. The autocorrelations for lags 1, 2, 3 are positive, and decrease in magnitude with increasing lag (lag 1: 0.666, lag 2: 0.374, lag 3: 0.162).

The autocorrelation for lags 19 and 20 exceed the significance bounds too, but it is likely that this is due to chance, since they just exceed the significance bounds (especially for lag 19), the autocorrelations for lags 4-18 do not exceed the significance bounds, and we would expect 1 in 20 lags to exceed the 95% significance bounds by chance alone.

```
> pacf(volcanodustseries, lag.max=20)
> pacf(volcanodustseries, lag.max=20, plot=FALSE)
Partial autocorrelations of series 'volcanodustseries', by lag
  1      2      3      4      5      6      7      8      9     10     11
0.666 -0.126 -0.064 -0.005  0.040 -0.039  0.058 -0.016 -0.025  0.028 -0.008
 12     13     14     15     16     17     18     19     20
0.036  0.082 -0.025 -0.014  0.008 -0.025  0.073  0.131  0.063
```



From the partial autocorrelogram, we see that the partial autocorrelation at lag 1 is positive and exceeds the significance bounds (0.666), while the partial autocorrelation at lag 2 is negative and also exceeds the significance bounds (-0.126). The partial autocorrelations tail off to zero after lag 2.

Since the correlogram tails off to zero after lag 3, and the partial correlogram is zero after lag 2, the following ARMA models are possible for the time series:

- an ARMA(2,0) model, since the partial autocorrelogram is zero after lag 2, and the correlogram tails off to zero after lag 3, and the partial correlogram is zero after lag 2
- an ARMA(0,3) model, since the autocorrelogram is zero after lag 3, and the partial correlogram tails off to zero (although perhaps too abruptly for this model to be appropriate)
- an ARMA(p,q) mixed model, since the correlogram and partial correlogram tail off to zero (although the partial correlogram perhaps tails off too abruptly for this model to be appropriate)

Shortcut: the `auto.arima()` function

Again, we can use `auto.arima()` to find an appropriate model, by typing `“auto.arima(volcanodust)”`, which gives us ARIMA(1,0,2), which has 3 parameters. However, different criteria can be used to select a model (see `auto.arima()` help page). If we use the “bic” criterion, which penalises the number of parameters, we get ARIMA(2,0,0), which is ARMA(2,0): `“auto.arima(volcanodust,ic=“bic”)`”.

The ARMA(2,0) model has 2 parameters, the ARMA(0,3) model has 3 parameters, and the ARMA(p,q) model

has at least 2 parameters. Therefore, using the principle of parsimony, the ARMA(2,0) model and ARMA(p,q) model are equally good candidate models.

An ARMA(2,0) model is an autoregressive model of order 2, or AR(2) model. This model can be written as: $X_t - \mu = (\text{Beta1} * (X_{t-1} - \mu)) + (\text{Beta2} * (X_{t-2} - \mu)) + Z_t$, where X_t is the stationary time series we are studying (the time series of volcanic dust veil index), μ is the mean of time series X_t , Beta1 and Beta2 are parameters to be estimated, and Z_t is white noise with mean zero and constant variance.

An AR (autoregressive) model is usually used to model a time series which shows longer term dependencies between successive observations. Intuitively, it makes sense that an AR model could be used to describe the time series of volcanic dust veil index, as we would expect volcanic dust and aerosol levels in one year to affect those in much later years, since the dust and aerosols are unlikely to disappear quickly.

If an ARMA(2,0) model (with $p=2$, $q=0$) is used to model the time series of volcanic dust veil index, it would mean that an ARIMA(2,0,0) model can be used (with $p=2$, $d=0$, $q=0$, where d is the order of differencing required). Similarly, if an ARMA(p,q) mixed model is used, where p and q are both greater than zero, than an ARIMA(p,0,q) model can be used.

Forecasting Using an ARIMA Model

Once you have selected the best candidate ARIMA(p,d,q) model for your time series data, you can estimate the parameters of that ARIMA model, and use that as a predictive model for making forecasts for future values of your time series.

You can estimate the parameters of an ARIMA(p,d,q) model using the “arima()” function in R.

Example of the Ages at Death of the Kings of England

For example, we discussed above that an ARIMA(0,1,1) model seems a plausible model for the ages at deaths of the kings of England. You can specify the values of p , d and q in the ARIMA model by using the “order” argument of the “arima()” function in R. To fit an ARIMA(p,d,q) model to this time series (which we stored in the variable “kingstimeseries”, see above), we type:

```
> kingstimeseriesarima <- arima(kingstimeseries, order=c(0,1,1)) # fit an ARIMA(0,
↪1,1) model
> kingstimeseriesarima
ARIMA(0,1,1)
Coefficients:
      ma1
      -0.7218
s.e.      0.1208
sigma^2 estimated as 230.4:  log likelihood = -170.06
AIC = 344.13   AICc = 344.44   BIC = 347.56
```

As mentioned above, if we are fitting an ARIMA(0,1,1) model to our time series, it means we are fitting an ARMA(0,1) model to the time series of first differences. An ARMA(0,1) model can be written $X_t - \mu = Z_t - (\theta * Z_{t-1})$, where θ is a parameter to be estimated. From the output of the “arima()” R function (above), the estimated value of θ (given as ‘ma1’ in the R output) is -0.7218 in the case of the ARIMA(0,1,1) model fitted to the time series of ages at death of kings.

Specifying the confidence level for prediction intervals

You can specify the confidence level for prediction intervals in forecast.Arima() by using the “level” argument. For example, to get a 99.5% prediction interval, we would type “forecast.Arima(kingstimeseriesarima, h=5, level=c(99.5))”.

We can then use the ARIMA model to make forecasts for future values of the time series, using the “forecast.Arima()” function in the “forecast” R package. For example, to forecast the ages at death of the next five English kings, we type:

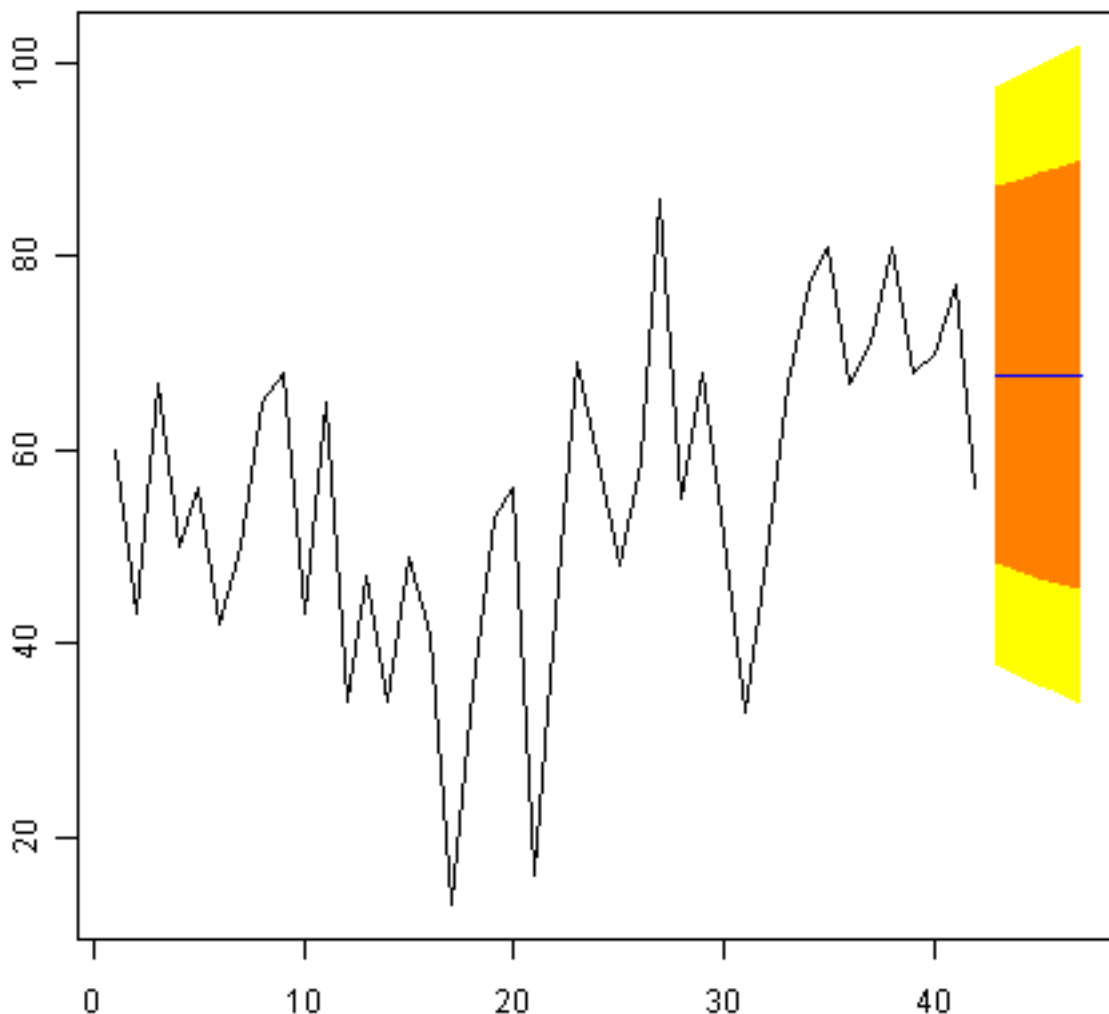
```
> library("forecast") # load the "forecast" R library
> kingstimeseriesforecasts <- forecast.Arima(kingstimeseriesarima, h=5)
> kingstimeseriesforecasts
  Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
43      67.75063 48.29647 87.20479 37.99806 97.50319
44      67.75063 47.55748 87.94377 36.86788 98.63338
45      67.75063 46.84460 88.65665 35.77762 99.72363
46      67.75063 46.15524 89.34601 34.72333 100.77792
47      67.75063 45.48722 90.01404 33.70168 101.79958
```

The original time series for the English kings includes the ages at death of 42 English kings. The forecast.Arima() function gives us a forecast of the age of death of the next five English kings (kings 43-47), as well as 80% and 95% prediction intervals for those predictions. The age of death of the 42nd English king was 56 years (the last observed value in our time series), and the ARIMA model gives the forecasted age at death of the next five kings as 67.8 years.

We can plot the observed ages of death for the first 42 kings, as well as the ages that would be predicted for these 42 kings and for the next 5 kings using our ARIMA(0,1,1) model, by typing:

```
> plot.forecast(kingstimeseriesforecasts)
```

Forecasts from ARIMA(0,1,1)

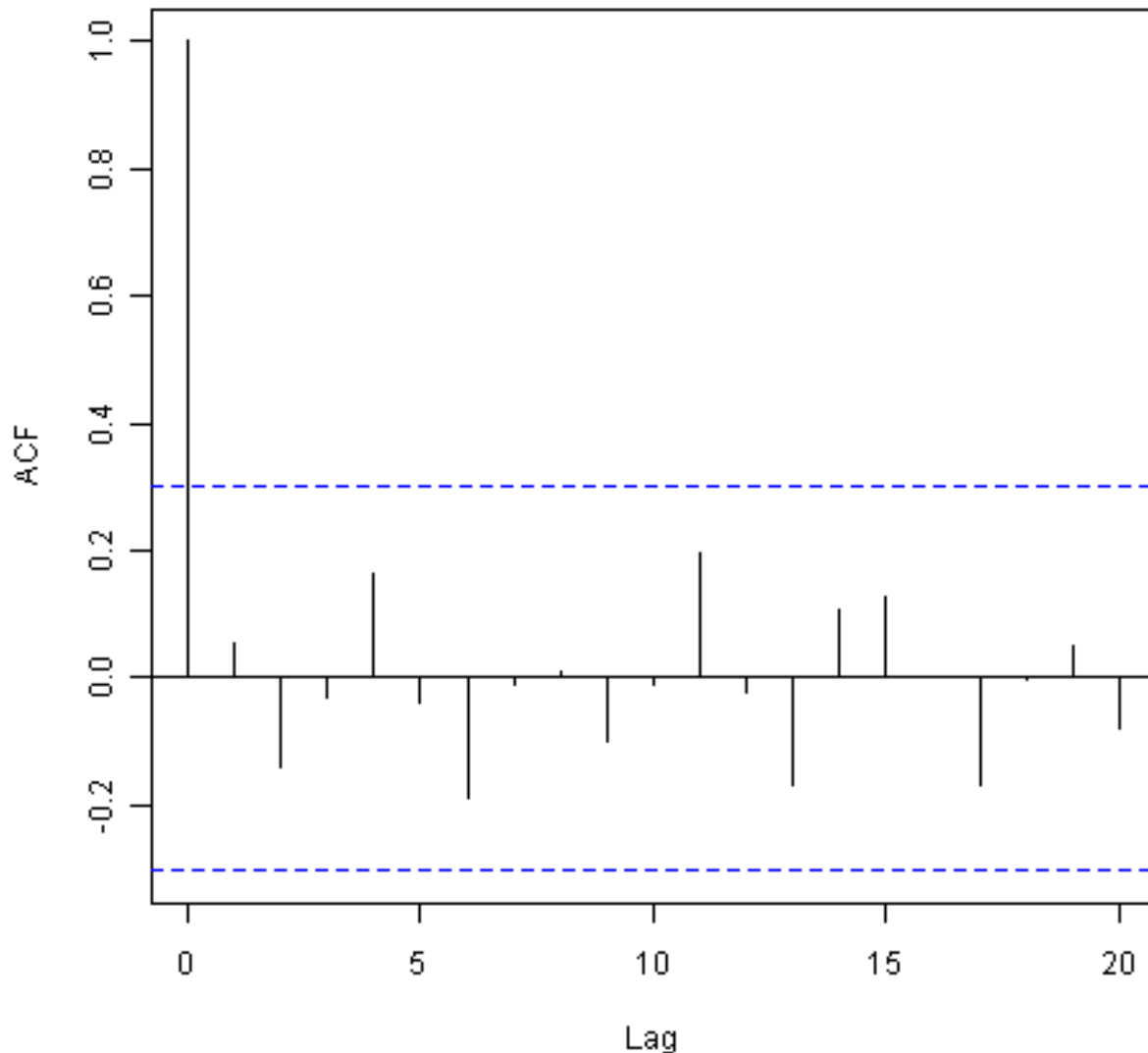


As in the case of exponential smoothing models, it is a good idea to investigate whether the forecast errors of an ARIMA model are normally distributed with mean zero and constant variance, and whether there are correlations

between successive forecast errors.

For example, we can make a correlogram of the forecast errors for our ARIMA(0,1,1) model for the ages at death of kings, and perform the Ljung-Box test for lags 1-20, by typing:

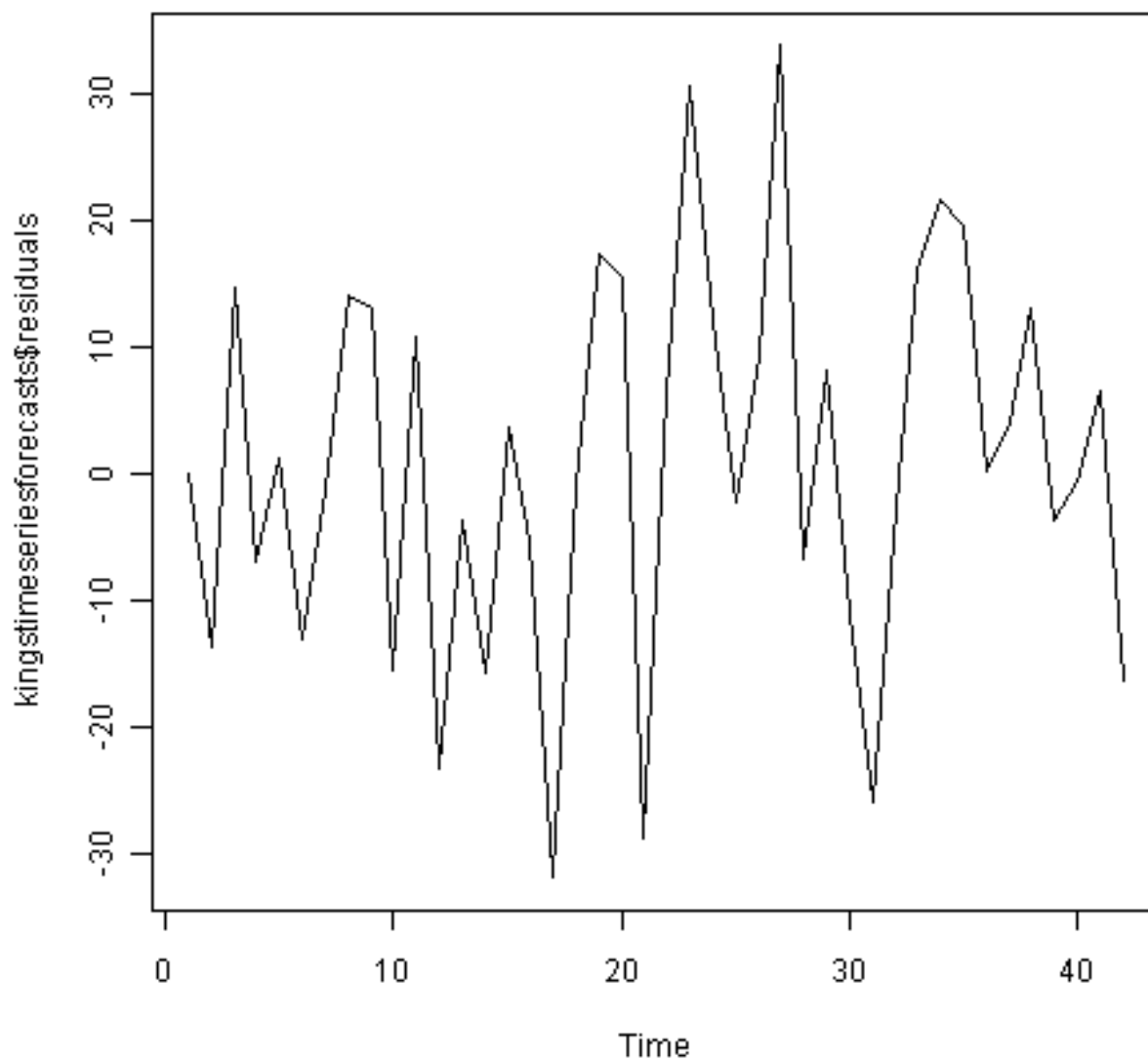
```
> acf(kingstimeseriesforecasts$residuals, lag.max=20)
> Box.test(kingstimeseriesforecasts$residuals, lag=20, type="Ljung-Box")
Box-Ljung test
data: kingstimeseriesforecasts$residuals
X-squared = 13.5844, df = 20, p-value = 0.851
```

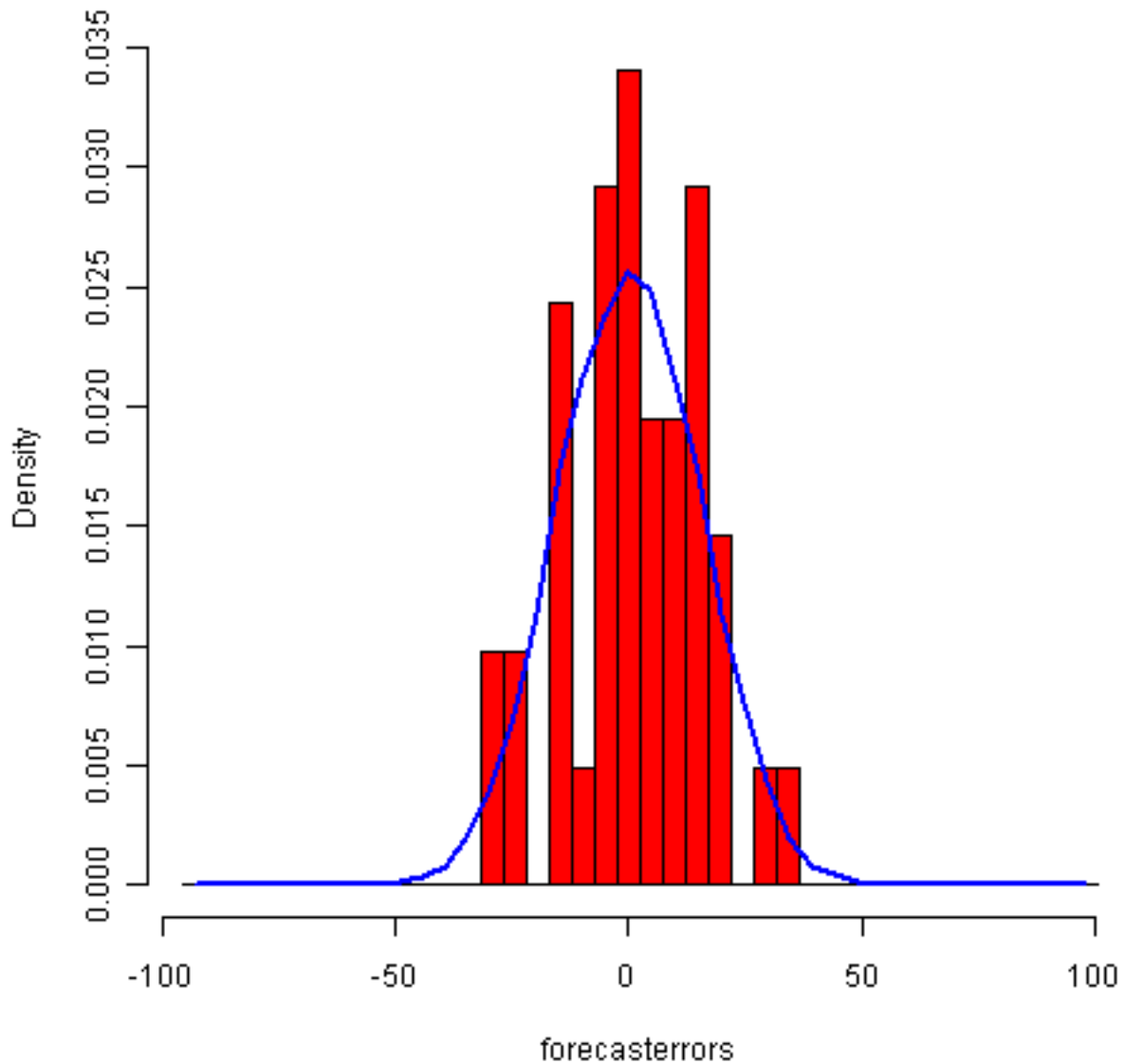


Since the correlogram shows that none of the sample autocorrelations for lags 1-20 exceed the significance bounds, and the p-value for the Ljung-Box test is 0.9, we can conclude that there is very little evidence for non-zero autocorrelations in the forecast errors at lags 1-20.

To investigate whether the forecast errors are normally distributed with mean zero and constant variance, we can make a time plot and histogram (with overlaid normal curve) of the forecast errors:

```
> plot.ts(kingstimeseriesforecasts$residuals) # make time plot of ↵
↵forecast errors
> plotForecastErrors(kingstimeseriesforecasts$residuals) # make a histogram
```





The time plot of the in-sample forecast errors shows that the variance of the forecast errors seems to be roughly constant over time (though perhaps there is slightly higher variance for the second half of the time series). The histogram of the time series shows that the forecast errors are roughly normally distributed and the mean seems to be close to zero. Therefore, it is plausible that the forecast errors are normally distributed with mean zero and constant variance.

Since successive forecast errors do not seem to be correlated, and the forecast errors seem to be normally distributed with mean zero and constant variance, the ARIMA(0,1,1) does seem to provide an adequate predictive model for the ages at death of English kings.

Example of the Volcanic Dust Veil in the Northern Hemisphere

We discussed above that an appropriate ARIMA model for the time series of volcanic dust veil index may be an ARIMA(2,0,0) model. To fit an ARIMA(2,0,0) model to this time series, we can type:

```
> volcanodustseriesarima <- arima(volcanodustseries, order=c(2,0,0))
> volcanodustseriesarima
ARIMA(2,0,0) with non-zero mean
Coefficients:
    ar1      ar2  intercept
 0.7533 -0.1268   57.5274
s.e.  0.0457  0.0458    8.5958
```

```
sigma^2 estimated as 4870: log likelihood = -2662.54
AIC = 5333.09 AICc = 5333.17 BIC = 5349.7
```

As mentioned above, an ARIMA(2,0,0) model can be written as: $X_t - \mu = (\text{Beta1} * (X_{t-1} - \mu)) + (\text{Beta2} * (X_{t-2} - \mu)) + Z_t$, where Beta1 and Beta2 are parameters to be estimated. The output of the arima() function tells us that Beta1 and Beta2 are estimated as 0.7533 and -0.1268 here (given as ar1 and ar2 in the output of arima()).

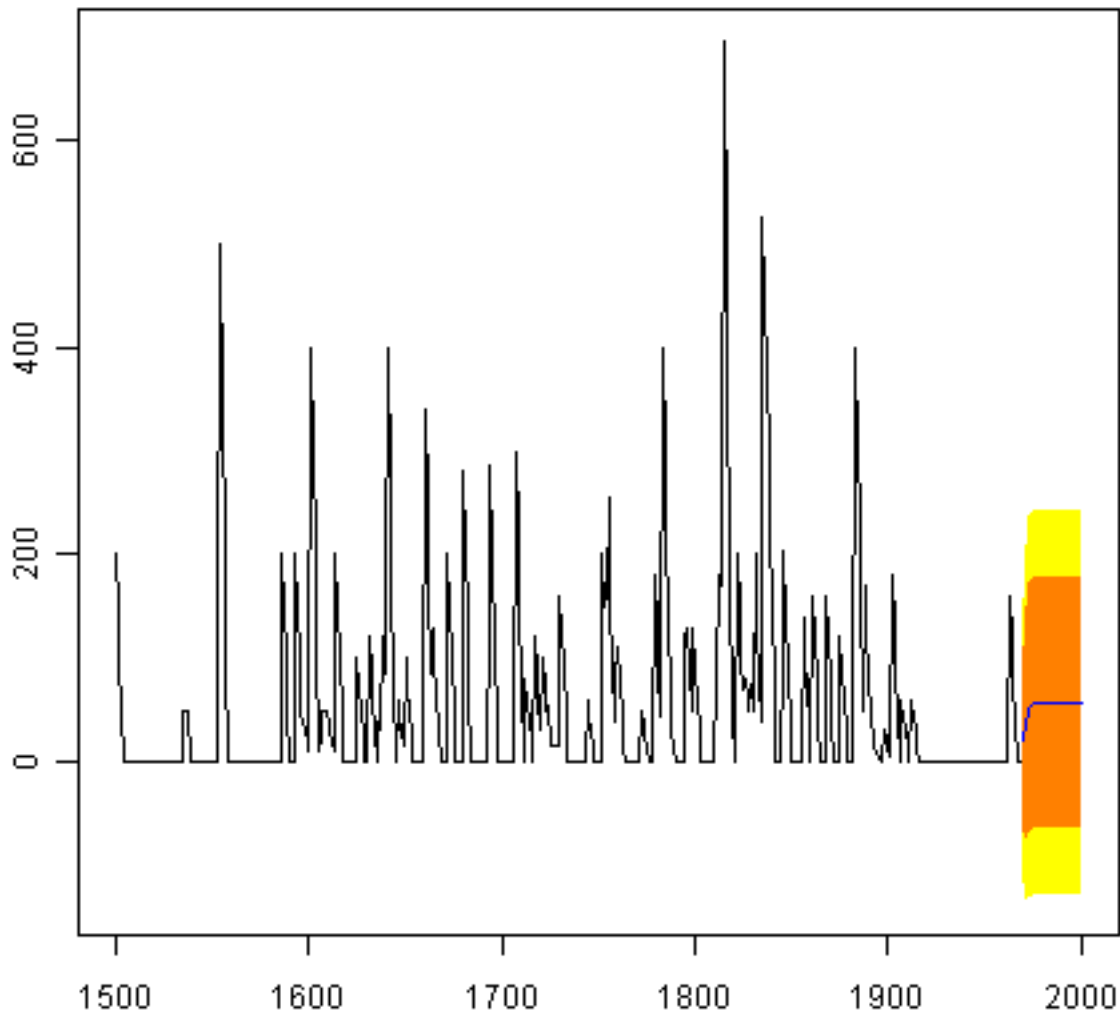
Now we have fitted the ARIMA(2,0,0) model, we can use the “forecast.ARIMA()” model to predict future values of the volcanic dust veil index. The original data includes the years 1500-1969. To make predictions for the years 1970-2000 (31 more years), we type:

```
> volcanodustseriesforecasts <- forecast.Arima(volcanodustseriesarima, h=31)
> volcanodustseriesforecasts
Point      Forecast      Lo 80      Hi 80      Lo 95      Hi 95
1970      21.48131     -67.94860    110.9112   -115.2899   158.2526
1971      37.66419     -74.30305    149.6314   -133.5749   208.9033
1972      47.13261     -71.57070    165.8359   -134.4084   228.6737
1973      52.21432     -68.35951    172.7881   -132.1874   236.6161
1974      54.84241     -66.22681    175.9116   -130.3170   240.0018
1975      56.17814     -65.01872    177.3750   -129.1765   241.5327
1976      56.85128     -64.37798    178.0805   -128.5529   242.2554
1977      57.18907     -64.04834    178.4265   -128.2276   242.6057
1978      57.35822     -63.88124    178.5977   -128.0615   242.7780
1979      57.44283     -63.79714    178.6828   -127.9777   242.8634
1980      57.48513     -63.75497    178.7252   -127.9356   242.9059
1981      57.50627     -63.73386    178.7464   -127.9145   242.9271
1982      57.51684     -63.72330    178.7570   -127.9040   242.9376
1983      57.52212     -63.71802    178.7623   -127.8987   242.9429
1984      57.52476     -63.71538    178.7649   -127.8960   242.9456
1985      57.52607     -63.71407    178.7662   -127.8947   242.9469
1986      57.52673     -63.71341    178.7669   -127.8941   242.9475
1987      57.52706     -63.71308    178.7672   -127.8937   242.9479
1988      57.52723     -63.71291    178.7674   -127.8936   242.9480
1989      57.52731     -63.71283    178.7674   -127.8935   242.9481
1990      57.52735     -63.71279    178.7675   -127.8934   242.9481
1991      57.52737     -63.71277    178.7675   -127.8934   242.9482
1992      57.52738     -63.71276    178.7675   -127.8934   242.9482
1993      57.52739     -63.71275    178.7675   -127.8934   242.9482
1994      57.52739     -63.71275    178.7675   -127.8934   242.9482
1995      57.52739     -63.71275    178.7675   -127.8934   242.9482
1996      57.52739     -63.71275    178.7675   -127.8934   242.9482
1997      57.52739     -63.71275    178.7675   -127.8934   242.9482
1998      57.52739     -63.71275    178.7675   -127.8934   242.9482
1999      57.52739     -63.71275    178.7675   -127.8934   242.9482
2000      57.52739     -63.71275    178.7675   -127.8934   242.9482
```

We can plot the original time series, and the forecasted values, by typing:

```
> plot.forecast(volcanodustseriesforecasts)
```

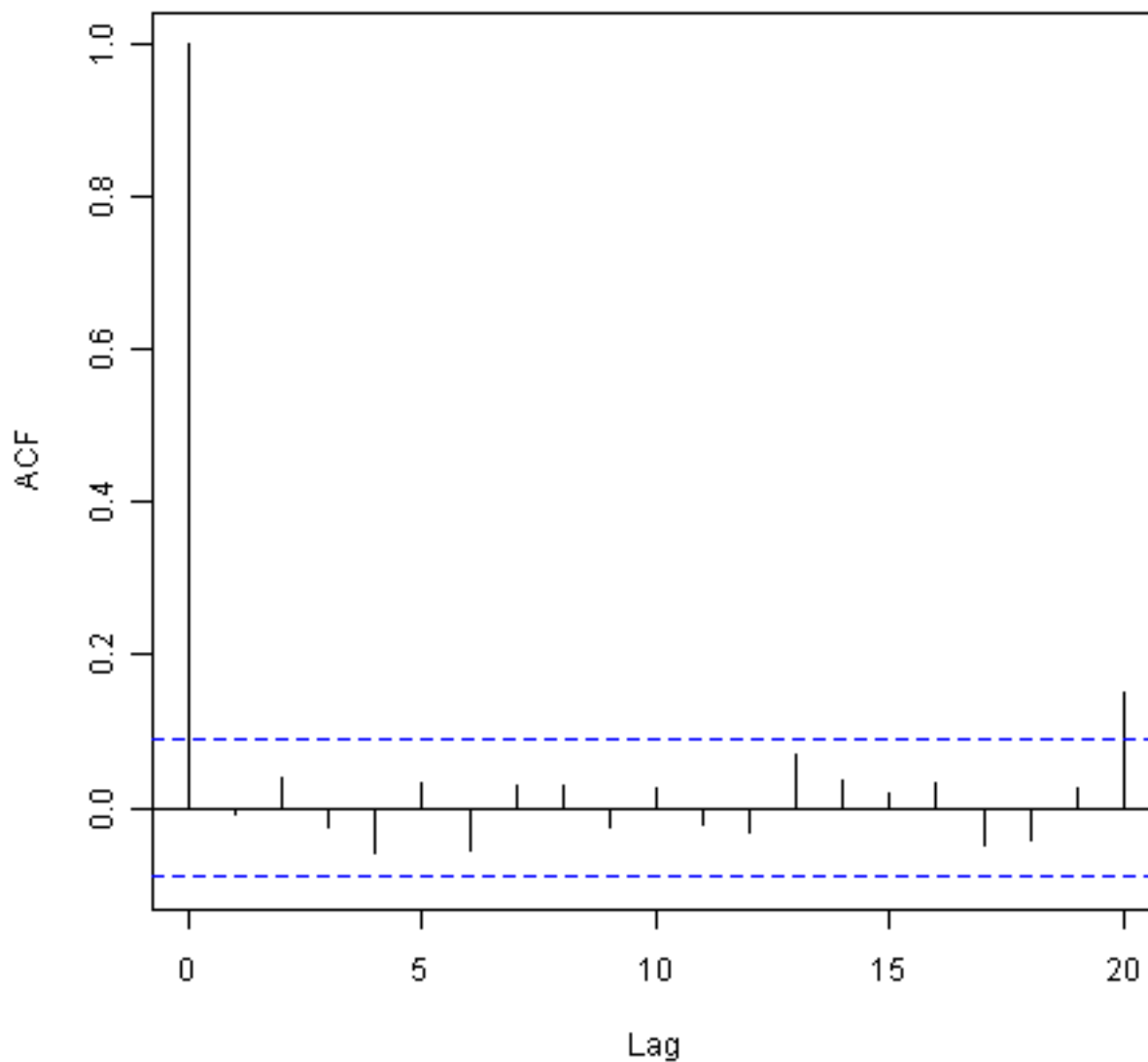
Forecasts from ARIMA(2,0,0) with non-zero mean



One worrying thing is that the model has predicted negative values for the volcanic dust veil index, but this variable can only have positive values! The reason is that the `arima()` and `forecast.Arima()` functions don't know that the variable can only take positive values. Clearly, this is not a very desirable feature of our current predictive model.

Again, we should investigate whether the forecast errors seem to be correlated, and whether they are normally distributed with mean zero and constant variance. To check for correlations between successive forecast errors, we can make a correlogram and use the Ljung-Box test:

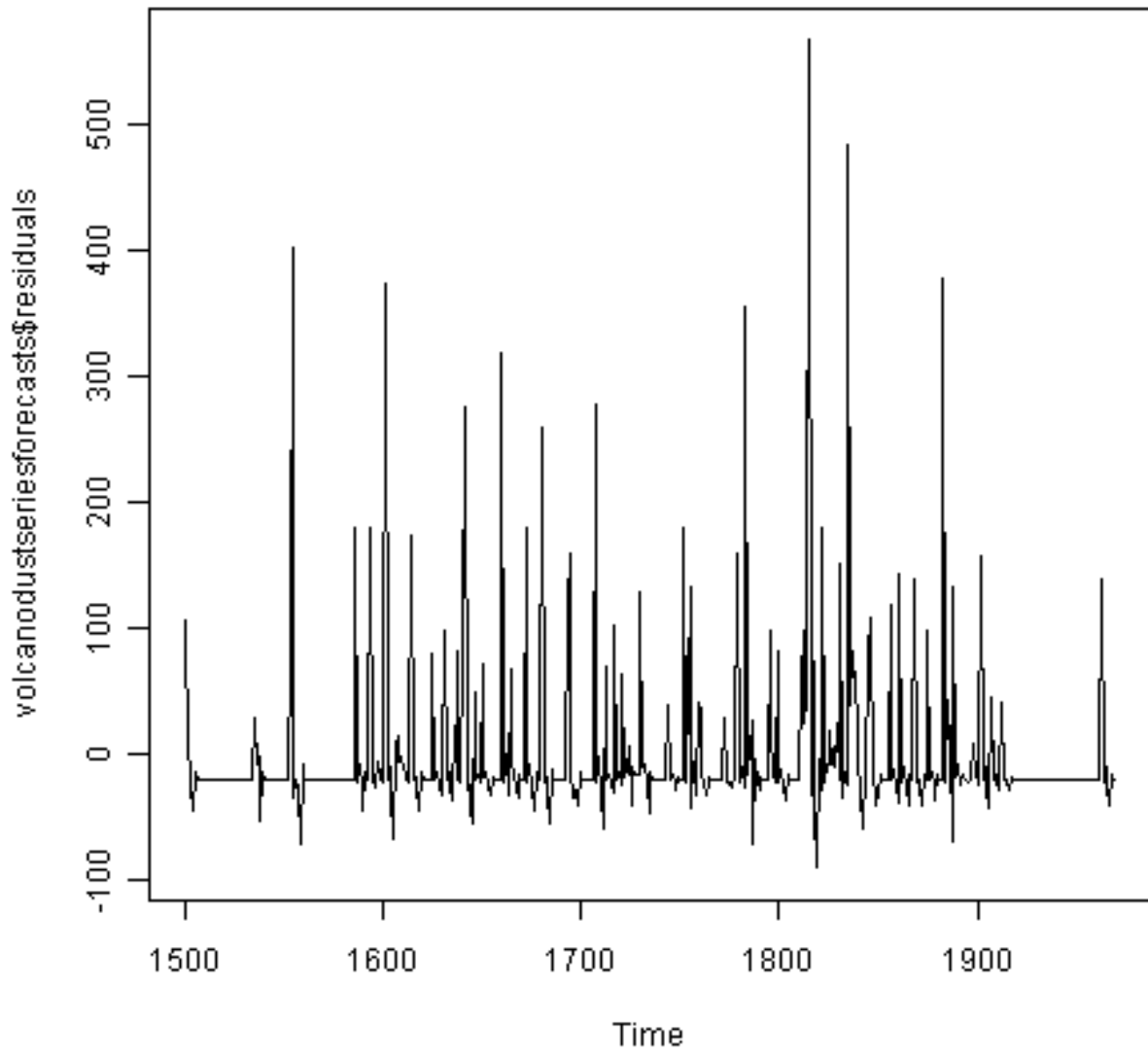
```
> acf(volcanodustseriesforecasts$residuals, lag.max=20)
> Box.test(volcanodustseriesforecasts$residuals, lag=20, type="Ljung-Box")
Box-Ljung test
data: volcanodustseriesforecasts$residuals
X-squared = 24.3642, df = 20, p-value = 0.2268
```

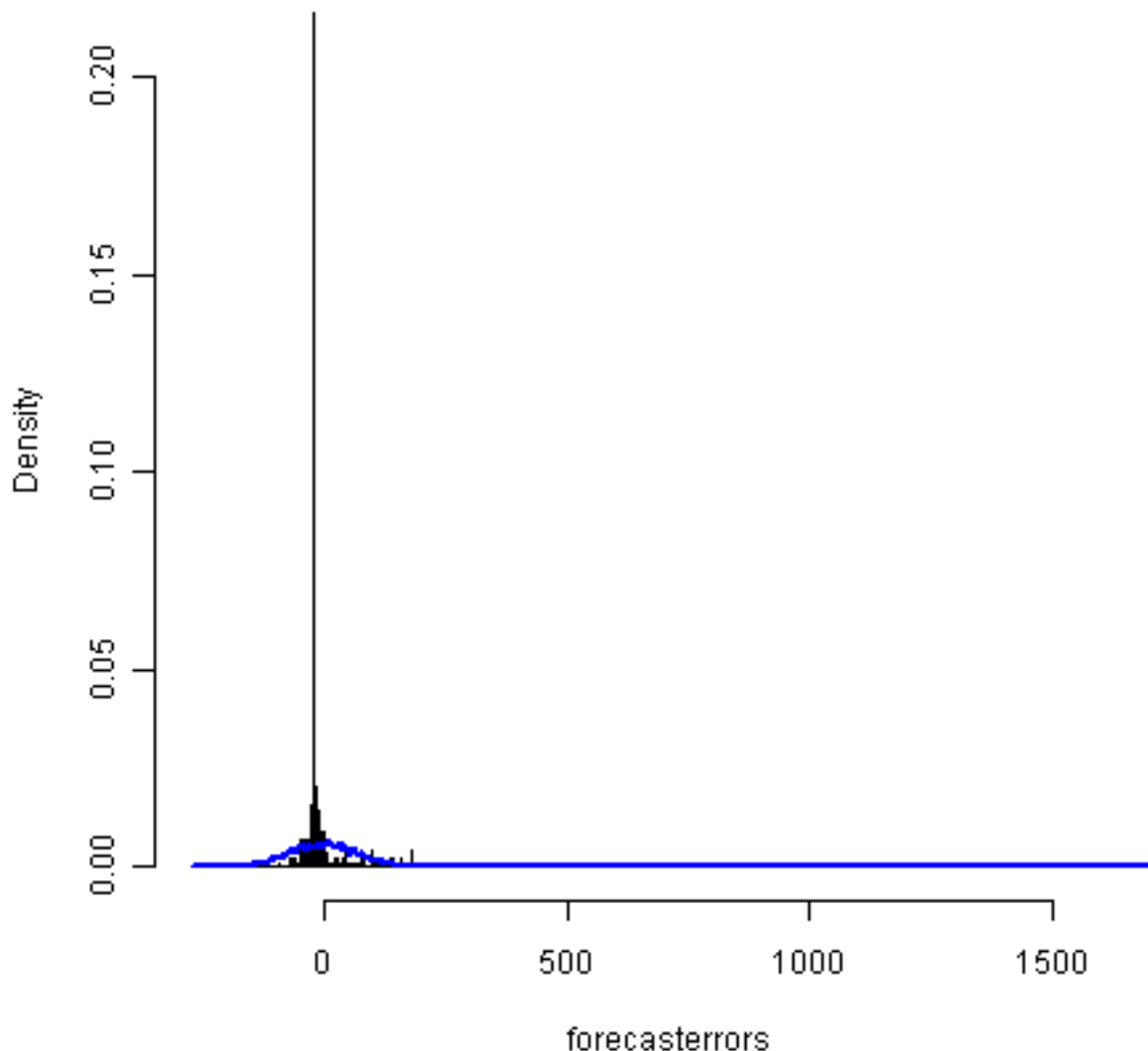


The correlogram shows that the sample autocorrelation at lag 20 exceeds the significance bounds. However, this is probably due to chance, since we would expect one out of 20 sample autocorrelations to exceed the 95% significance bounds. Furthermore, the p-value for the Ljung-Box test is 0.2, indicating that there is little evidence for non-zero autocorrelations in the forecast errors for lags 1-20.

To check whether the forecast errors are normally distributed with mean zero and constant variance, we make a time plot of the forecast errors, and a histogram:

```
> plot.ts(volcanodustseriesforecasts$residuals) # make time plot of ↵  
↵ forecast errors  
> plotForecastErrors(volcanodustseriesforecasts$residuals) # make a histogram
```





The time plot of forecast errors shows that the forecast errors seem to have roughly constant variance over time. However, the time series of forecast errors seems to have a negative mean, rather than a zero mean. We can confirm this by calculating the mean forecast error, which turns out to be about -0.22:

```
> mean(volcanodustseriesforecasts$residuals)
-0.2205417
```

The histogram of forecast errors (above) shows that although the mean value of the forecast errors is negative, the distribution of forecast errors is skewed to the right compared to a normal curve. Therefore, it seems that we cannot comfortably conclude that the forecast errors are normally distributed with mean zero and constant variance! Thus, it is likely that our ARIMA(2,0,0) model for the time series of volcanic dust veil index is not the best model that we could make, and could almost definitely be improved upon!

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.

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.

Acknowledgements

I am grateful to [Professor Rob Hyndman](#), for kindly allowing me to use the time series data sets from his [Time Series Data Library \(TSDL\)](#) in the examples in this booklet.

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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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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CHAPTER 3

Acknowledgements

I am grateful to Professor Rob Hyndman, for kindly allowing me to use the time series data sets from his [Time Series Data Library \(TSDL\)](#) in the examples in this booklet.

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CHAPTER 4

Contact

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

CHAPTER 5

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