

Session 1, Lesson 2. A Basic Introduction to R

R will not read anything preceded by #. When analyzing data, it is useful to use # to include a lot of comments so you can remember what you did.

R **input** is preceded by >

R **output** is preceded by [some number]

2.A. Using R as a calculator:

```
> 2+3+4+9
```

```
[1] 18
```

```
> 144^2
```

```
[1] 20736
```

```
> (144^0.5)/2*10
```

```
[1] 60
```

```
> sqrt(100)
```

```
[1] 10
```

```
> log(5)      # log in R equals the natural log (i.e. ln)
```

```
[1] 1.609438
```

```
> pi*4
```

```
[1] 12.56637
```

2.B. Handy functions

```
> data <- c(2,2,4,4,5,5,6,6,7,8,8,8,8,9,9,10,10,12,12,12,12)
```

```
# the c means "concatenate" which means individual numbers are  
# joined together in a vector. R really likes concatenated data.
```

```
> data
```

```
[1] 2  2  4  4  5  5  6  6  7  8  8  8  8  9  9 10 10 12 12 12 12
```

```
# yep it's there!
```

```
> mean(data)
```

```
[1] 7.571429
```

```
> min(data)
```

```
[1] 2
```

```
> max(data)
```

```
[1] 12
```

```
> range(data)
```

```
[1]  2 12
```

```
> sd(data)
```

```
[1] 3.1713
```

```
> var(data)
```

```
[1] 10.05714
```

```
> length(data)
```

```
[1] 21
```

2.C. Basic plotting

```
> hist(data) # you should see a histogram pop up in the graphics device.
```

```
x <- c(1,3,4,6,8,9,12,14)
y <- c(5,6,8,10,9,13,12,15)
plot(x, y)
```

```
# add some x and y labels:
plot(x,y, xlab="Explanatory Variable", ylab="Response Variable")
```

```
# change the symbol color:
plot(x,y, xlab="Explanatory Variable", ylab="Response Variable",
col="red")
```

```
# for a full list of colors:
colors() # test some of these out
```

```
# change the symbol type with pch (stands for "point character")
plot(x,y, xlab="Explanatory Variable", ylab="Response Variable",
col="red", pch=16)
plot(x,y, xlab="Explanatory Variable", ylab="Response Variable",
col="red", pch="m")
```

```
# to see the symbols, you need to install a package
> install.packages("Hmisc") # This only has to be done once.
```

```
# when you start R, it will only start the base package. If you
want to use a function in a package other than the base you must
access it from the library folder:
```

```
> library(Hmisc) #now you can use the functions in this package
> show.pch()
```

```
□ 0 ▽ 25 2 50 K 75 d 100 } 125 -150 -175 È 200 á 225 ú 250
◊ 1 26 3 51 L 76 e 101 ~ 126 — 151 ° 176 É 201 à 226 ù 251
△ 2 27 4 52 M 77 f 102 127 -152 ± 177 Ê 202 ä 227 ü 252
+ 3 28 5 53 N 78 g 103 € 128 ™ 153 º 178 Ë 203 å 228 ý 253
× 4 29 6 54 O 79 h 104 · 129 § 154 ¸ 179 Ì 204 à 229
◇ 5 30 7 55 P 80 i 105 · 130 › 155 · 180 Í 205 æ 230
▽ 6 31 8 56 Q 81 j 106 f 131 œ 156 μ 181 Î 206 ç 231
✱ 7 32 9 57 R 82 k 107 " 132 · 157 ¶ 182 Ï 207 è 232
* 8 ! 33 : 58 S 83 l 108 · 133 ž 158 · 183 Ð 208 é 233
⌘ 9 " 34 ; 59 T 84 m 109 † 134 Ÿ 159 ¸ 184 Ñ 209 ê 234
⊕ 10 # 35 < 60 U 85 n 110 ‡ 135 160 ¸ 185 Ò 210 ë 235
⌘ 11 $ 36 = 61 V 86 o 111 ~ 136 i 161 ¸ 186 Ó 211 ì 236
⊞ 12 % 37 > 62 W 87 p 112 % 137 ¢ 162 » 187 Ô 212 í 237
⊞ 13 & 38 ? 63 X 88 q 113 § 138 £ 163 ¼ 188 Õ 213 î 238
⊞ 14 · 39 @ 64 Y 89 r 114 ¸ 139 ¸ 164 ½ 189 Ö 214 ï 239
■ 15 ( 40 A 65 Z 90 s 115 Œ 140 ¥ 165 ¾ 190 × 215 ò 240
● 16 ) 41 B 66 [ 91 t 116 · 141 | 166 ¿ 191 Ø 216 ñ 241
▲ 17 * 42 C 67 \ 92 u 117 Ž 142 $ 167 Å 192 Ù 217 ò 242
• 18 + 43 D 68 ] 93 v 118 · 143 · 168 Å 193 Ú 218 ó 243
● 19 · 44 E 69 ^ 94 w 119 · 144 © 169 Å 194 Û 219 ô 244
● 20 - 45 F 70 - 95 x 120 · 145 ¸ 170 Å 195 Ü 220 ö 245
◊ 21 · 46 G 71 · 96 Y 121 · 146 « 171 Å 196 Ý 221 ø 246
◊ 22 / 47 H 72 a 97 z 122 ¸ 147 ¬ 172 Å 197 Þ 222 þ 247
◊ 23 0 48 l 73 b 98 { 123 " 148 - 173 Æ 198 ß 223 ø 248
◊ 24 1 49 J 74 c 99 | 124 · 149 @ 174 Ç 199 à 224 ù 249
```

2.D. Basic t-test: Getting started

```
# create a fake dataset
> length <- c(1.2, 1.3, 1.6, 1.4, 1.1, 2.0, 2.1, 2.8, 3.0, 2.6)
> gender <- rep(c("male", "female"), each=5)

> plot(length, gender)
# this may generate an error message because R may not know the
correct class to assign to "gender". Check the class:
> class(gender)
# How to reassign it:
> gender <- as.factor(gender)
# Test this
> gender

> plot(gender, length)

# Summarize the data
> mean(length)
> sd(length) # Standard deviation

# What if we want the mean and standard deviation for each gender?
We need to "subset" the data:
length[gender == "male"]
# R translation: "give me the length data for the males". Brackets are used for subsetting data in R
(more on this later). Subsetting is a critical, and often annoyingly difficult process in R. Notice that
double = signs are required. Notice that "male" is in quotes.
> mean(length[gender == "male"])
> sd(length[gender == "male"])
> mean(length[gender == "female"])
> sd(length[gender == "female"])
# Or, how about a loop?
tapply(length, gender, mean)

# tapply is one of the "apply" functions. This suite of functions performs different types of loops. In
this case, the loop goes through each category of "gender" and applies the function "mean" to the
"length" data.
```

2.E. Obtaining more information about functions

Our goal is to analyze the data using a t-test to determine whether males and females have significantly different lengths. First, we need to figure out which function to use to accomplish this. Sometimes (often) you won't know the name of the function for a particular analysis. From within R, there are a few ways to look:

```
help.search("t-test")
```

The problem is that you will often get zero, or way too many hits. If help.search() fails, you may want to search online instead. Once you know the name of a function, you can use the ? or help to find out more:

```
?t.test  
help(t.test)
```

This should open a help window with documentation for the function. At first, these windows may seem cryptic and useless, but after some time, you will probably start to rely on them heavily (I sure do!). I find the See Also and Examples sections especially helpful. Note that the Usage section tells you exactly how to execute the command (expected arguments, etc.), and details of the required arguments are given in the Arguments section.

Also try the example function to see the function in action, if it has an example:

```
example(t.test)
```

2.F. Conducting the t-test

```
t.test(length~gender)
```

Almost all models are defined in R with this syntax. It translates to: "length" as a function of "gender", or Y(response)~X(predictor/s).

Note that the returned results are for a "Welch Two Sample t-test." If you look at the function description, you'll see that the default analysis assumes the variances between the two groups are not equal (var.equal=FALSE). The output also returns 95% confidence intervals. These settings can be changed:

```
t.test(length~gender, var.equal=TRUE, conf.level=0.90)
```

2.G. Closing R

R will ask:

Save workspace image? [y / n / c] #Generally, choose **n**.

Session 1, Lesson 3. Loading Data

3.A. The Working Directory

What is the working directory? It is the location on your computer that R is working from – where it will read in files, and where it will write files. To determine the current working directory on your computer:

```
getwd()  
[1] "/Users/username"
```

It may help to imagine this as the room that R is in. It can see everything in the room, so you can refer directly to the things in the room. Otherwise, you have to tell R how to get to things that are outside of the room.

```
dir()  
[1] "Applications"  
[2] "Documents"  
[3] "Downloads"  
[4] "Movies"  
[5] "Pictures"  
[6] "chicken painting.jpg"  
...
```

To change the working directory:

```
setwd("~/Documents/RebeccaClark/R Manuals/OSOS Workshop  
Materials/")  
dir()
```

Now R will look in this directory for files and will also save to this directory.

Important things to notice:

1. I checked to make sure the function worked by using `dir()` to see if the correct files were listed.
2. If you are on a PC, try to get in the habit of using forward slashes “/” instead of back slashes “\” because back slashes are used as an escape character in R. See the documentation for [?Quotes](#) for more details.
3. It’s usually simplest to copy and paste in the file pathway to avoid typing errors.

3.B. Types of Data

Use `class()` to check

R class	Other terms	Examples
Numeric	Real, continuous, quantitative	1.34, 2.87, 1,000,005
Integer	Count data	1, 2, 3, 184
Factor (ordered)	Ordinal, categorical, discrete	Good, better, best; Large, extra large, grande
Factor (unordered)	Categorical, nominal, discrete	Red, green, blue; Alps, Rockies, Rainier
Date		11/12/2010*
Character		“accidentally smooshed”, “fell asleep”

*Time-based data can get complicated in terms of formatting. See *Data Manipulation With R*, by Phil Spector, for an in-depth treatment of the topic, if applicable.

Because R is an *object-oriented programming language*, the *class* of the data often determines how it is handled by a particular function. For practice, make a note of how R should interpret the class of each column in this spreadsheet:

Family	Insect	Life Stage	Feeding Type	Sample size	Insect %P	Insect N (%)	Plant %P	Plant %N
Drosophilidae	Drosophila arizonae	adult	generalist	1	0.995	8.800	0.576	3.720
Drosophilidae	Drosophila hydei	adult	generalist	1	0.880	7.650	0.576	3.720
Drosophilidae	Drosophila nigrospiracula	adult	generalist	1	0.850	7.900	0.020	0.829
Drosophilidae	Drosophila pseudoobscura	adult	generalist	1	1.000	8.850	0.576	3.720
Drosophilidae	Drosophila simulans	adult	generalist	1	1.090	9.500	0.576	3.720
Acrididae	Melanoplus bilituratus	adult	generalist	2	0.700	-	0.250	4.000
Acrididae	Hesperotettix speciosus	multiple instars	generalist	1	0.631	11.080	0.249	1.643
Acrididae	Melanoplus bivittatus	multiple instars	generalist	2	0.560	10.775	0.238	2.424
Acrididae	Melanoplus keeleri	multiple instars	generalist	1	0.633	10.680	0.258	1.995
Acrididae	Mermiria bivittata	-	generalist	1	0.470	10.000	0.194	1.124
Acrididae	Schistocerca americana	-	generalist	2	0.693	9.792	0.234	2.426
Acrididae	Melanoplus packardii	multiple instars	generalist (33 spp)	2	0.628	10.980	0.190	2.099
Acrididae	Schistocerca gregaria	-	generalist/polyphagous	1	0.903	9.430	0.260	2.555
Tortricidae	Choristoneura fumiferana	-	specialist	1	0.855	8.700	0.220	1.422
Drosophilidae	Drosophila mojavensis	adult	specialist	1	0.840	6.700	0.190	0.800
Drosophilidae	Drosophila pachea	adult	specialist	1	0.815	6.700	0.180	1.440
Sphingidae	Manduca sexta	larvae	specialist	2	1.124	9.500	0.209	4.500
Noctuidae	Spodoptera exempta	pupa	specialist	3	1.086	8.765	0.433	2.990
Diprionidae	Neodiprion sertifer	-	specialist	3	0.640	7.270	0.117	1.303
Chrysomelidae	Paropsis atomaria	larvae	specialist	1	0.929	6.693	0.236	1.175
Curculionidae	Sabinia setosa	adult	specialist	1	0.557	-	0.220	2.750

3.C. Importing Data into R: Workflow

```
# set the working directory
setwd("C:/YourPathHere/")
# get the data - remember to designate the separator
data <- read.table("FileName.txt", header=TRUE, sep="\t")
# look at your data
data
```

`lapply(data, class)` # check that the classes of the columns match with your expectations

Things to check before converting your Excel file to text:

1. You can only have one row of headers
2. Use short descriptive headers without spaces
 - a. Use “_” or caps between words (i.e. first_name or FirstName)
 - b. Headers are typed over, and over, and over, so keep them short
3. Don’t start a header with a number
 - a. R will accept it, but will put an X in front of it.
4. Remove all summary data
 - a. Average, sum, max, min, etc.
5. Check that all values in a column are of the same type
 - a. Number, date, character, etc.
6. Remove commas and # symbols throughout
 - a. Commas will screw up comma-delimited files
 - b. # indicates a comment in R
7. Missing data are okay, but keep an eye on it.
8. If R throws this error:

```
Error in scan(file, what, nmax, sep, dec, quote,
skip, nlines, na.strings, :
line 29 did not have 8 elements
```

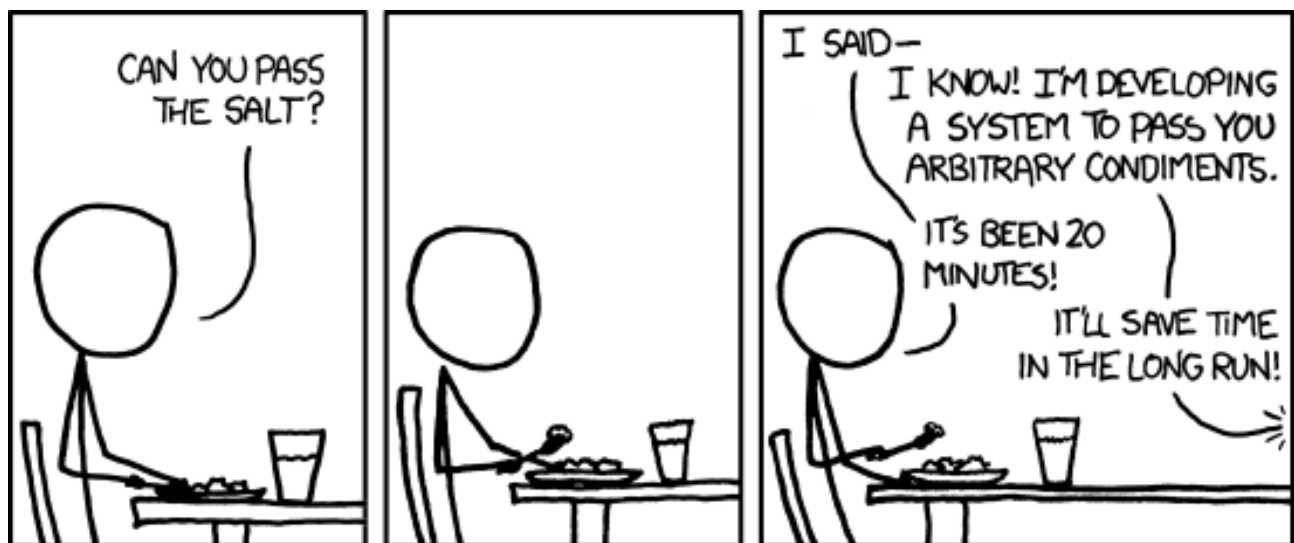
You probably have extra lines at the end of your .txt file. Open your text file in notepad. Move the cursor to the bottom of the file and backspace (delete) all of the extra lines. Save and try again (remember to send the read.table line again).

Handy shortcuts to try

```
read.table(file.choose()) # type this in and see what happens
```

```
setwd("~/") # resets working directory to your computer's home
directory (escape to home directory)
```

```
setwd("./FolderInCurrentDirectory/") # allows you to move from the
current directory into a subdirectory
```



Session 1, Lesson 4. Manipulating Data

Once you've read data into R, you can begin using some of the powerful workhorse aspects of the program to get your data organized and ready for analysis. This is where R can really shine...but also where it's easy to get lost and frustrated and give up. Here, we will walk through modified exercises that were originally designed by Jack Weiss at UNC-Chapel Hill.

4.A. R functions and commands demonstrated here

- [apply](#) is used to evaluate a function separately on the rows (second argument to apply is 1) or the columns (second argument to apply is 2) of a matrix or data frame
- [attach](#) adds a data frame to the default search path so that variables can be specified without reference to the data frame in which they reside
- [boxplot](#) produces a box plot or side-by-side box plots of a specified variable
- [c](#) the catenation function that turns the elements making up its arguments into a single vector
- [colnames](#) returns the column names of a data frame. Can also be used to assign column names to a data frame
- [data.frame](#) defines a data frame from its arguments which should be a set of vectors all of the same length
- [detach](#) undoes attach, removes a data frame from the search path
- [dim](#) returns the number of rows and columns of a data frame
- [dimnames](#) returns both the row names and the column names of a data frame in a list format
- [edit](#) invokes the R editor for modifying and viewing data frames
- [expression](#) creates an object of mode expression. We used it to create a mathematical expression in a graph axis label.
- [function](#) is not itself a function but is a key word to indicate that what follows is a function definition
- [history](#) opens up a history window in which you can view previously issued commands. For example, history(50) would display up to the last 50 commands issued. There is a 512 line default limit to what is saved, although this value can be changed.
- [is.na](#) is a logical function that returns TRUE if a value is missing (NA) and FALSE otherwise
- [jitter](#) randomly adds a small value to each element of its argument
- [length](#) returns the number of elements of a vector counting both non-missing and missing values
- [mean](#) calculates the mean of individual column entries of a data frame
- [names](#) displays names of variables in a data frame
- [objects](#) displays all created objects currently in workspace
- [points](#) adds individual points to the currently active plot
- [read.table](#) reads in text data from an external file
- [rep](#) is used to create patterned vectors of repeated units
- [reshape](#) interconverts 'wide' and 'long' data sets.
- [rm](#) is used to delete objects from the R workspace
- [round](#) rounds its argument to the number of decimals specified.
- [rownames](#) returns the row names of a data frame. Can also be used to assign row names to a data frame
- [sd](#) calculates the standard deviation of the individual column entries of a data frame

- [sqrt](#) is the square root function in R
- [sum](#) calculates the sum of all entries of a vector or matrix
- [tapply](#) stands for table apply. It applies a function (3rd argument) to a variable (1st argument) separately for each group specified by the second argument
- [unlist](#) unstacks the columns of a data frame into a vector
- <#> indicates a given line of code is a comment and should be ignored
- [<-](#) the assignment operator in R, a less than symbol followed by a dash, that is supposed to symbolize an arrow. The arrow points in the direction of assignment.
- [\[\]](#) used for specifying elements of vectors or portions of data frames and matrices
- [\[\[\]\]](#) denotes an element of a list
- [\\$](#) list notation symbol that can be used to reference columns of a data frame
- [!](#) is the logical not operator in R
- [^](#) denotes exponentiation
- [?](#) followed by a function name brings up a help window on that function
- [~](#) symbol used in defining expressions in R for model fitting. We used it in the boxplot function

R function options

- [cex](#)= (argument to many graphics functions) specifies the character expansion for plotting symbols when used with the points function
- [col](#)= (argument to many graphics functions) specifies the color to use in plotting points and/or line segments
- [header](#)= (argument to read.table) takes on values TRUE or FALSE, indicates whether the first line of a text file contains the variables names (TRUE) or not (FALSE)
- [pch](#)= stands for print character and is used to designate the plotting symbol for use in various plotting functions: plot, points, etc.
- [na.rm](#)= (argument to mean, sum, and sd) take on values TRUE or FALSE, indicates whether missing values should be removed (TRUE) before performing calculations. If set to FALSE and there are missing value the function returns NA as its value.
- [outline](#)= (argument to boxplot) when set to FALSE it turns off the display of outliers in a box plot
- [sep](#)= (argument to read.table) specifies the character that was used to separate fields in the text file to be read into R. For example, sep=',' indicates that the entries are separated by commas while sep='\t' indicates that the entries are separated by tabs.
- [skip](#)= (argument to read.table) specifies the number of lines to skip in the text file before reading the first line of data
- [xlab](#)= (argument of boxplot) a user-specified value to be used as the label for the x-axis, e.g., xlab="WSSTA"
- [ylab](#)= (argument of boxplot) a user-specified value to be used as the label for the y-axis, e.g., ylab="Disease Prevalence "

4.B. Data Entry

When R opens you are presented with Console window in which you can enter commands. In the Windows operating system to move back within a command line to correct mistakes you need to use the left and right arrow keys on the keyboard rather than the mouse. Previously issued commands can be recalled with the up arrow key.

To read data into R from a text file, use the `read.table` function. For this exercise, we'll read in a file directly from a class web site. The data files are in the following folder.

<http://www.unc.edu/courses/2007spring/enst/562/001/data/lab1/>

There are three files in this folder. The files contain the same data but in different formats.

NorwaySO4.xls is an Excel file. While a package exists that allows the direct importation of Excel files (the package is called RODBC), using it is far more trouble than it's worth. For a single worksheet it's far more convenient to first save the Excel file as a text file and then read the text file into R.

NorwaySO4.txt is a tab-delimited text file

NorwaySO4.csv is a comma-delimited text file

Each text file is set up in such a way that the first row of the file contains the word SO₄, identifying the variable whose measurements are contained in the file. The second row contains the names of the variables and the subsequent rows contain the data values. The first few lines of the tab-delimited file are shown in **Fig. 1**, while **Fig. 2** shows the comma-delimited file. The tabs are not visible but they exist as special characters separating the different columns that correspond to the different fields in the Excel file.

		SO ₄				
Lake	Latitude	Longitude	1976	1977	1978	1981
1	58	7.2	6.5	7.3	6	
2	58.1	6.3	5.5	6.2	4.8	
4	58.5	7.9	4.8	6.5	4.6	3.6
5	58.6	8.9	7.4	7.6	6.8	5.6
6	58.7	7.6	3.7	4.2	3.3	2.9
7	59.1	6.5	1.8		1.5	1.8
8	58.9	7.3	2.7	2.7	2.3	2.1

Fig. 1 Tab-delimited text file

The use of delimiters is not always necessary, but is usually a good idea. We must use delimiters here because of the presence of missing data. Excel indicates missing data with blanks. The use of delimiters correctly identifies these missing values. Notice in Fig. 2 that for Lake 1 the SO₄ concentration in 1977 is missing and so we find two commas in succession. In Fig. 1 there are accordingly two tabs in succession (not visible).

```

,,,SO4,,,
Lake,Latitude,Longitude,1976,1977,1978,1981
1,58,7.2,6.5,,7.3,6
2,58.1,6.3,5.5,,6.2,4.8
4,58.5,7.9,4.8,6.5,4.6,3.6
5,58.6,8.9,7.4,7.6,6.8,5.6
6,58.7,7.6,3.7,4.2,3.3,2.9
7,59.1,6.5,1.8,,1.5,1.8
8,58.9,7.3,2.7,2.7,2.3,2.1

```

Fig. 2 Comma-delimited text file

read.table is the name of an R function. R uses standard mathematical notation $f(x,y,z)$ to specify functions and their arguments, so parentheses are always required with functions although sometimes it is not necessary to specify any arguments.

The arguments we need to specify here:

1. The location of this file on the web with the complete path enclosed in quotes. You may use single or double quotes, but you must not mix them as part of the same argument.
2. The argument **skip=1** to tell R to skip the first line of the file.
3. The argument **header=TRUE** to indicate that the variable names appear at the top of the file.
4. The argument **sep=','** to indicate a comma-delimited file or the argument **sep='\t'** to indicate a tab-delimited file.
- 5.

To save the output of the **read.table** function, use the assignment operator, **<-**, to assign the output to an object in R

Read the tab-delimited file into R as follows. The name I choose for the result in R is **so4**. R is case-sensitive so **so4**, **So4**, **SO4** all represent different objects.

```

# Read in tab-delimited data from Web
> so4<-
read.table('http://www.unc.edu/courses/2007spring/enst/562/001/data/lab1/NorwaySO4.txt', skip=1, header=TRUE, sep='\t')
# Read in comma-delimited data from the Web
> so4<-
read.table('http://www.unc.edu/courses/2007spring/enst/562/001/data/lab1/NorwaySO4.csv', skip=1, header=TRUE, sep=',')

```

4.C. Getting Information about Data Frames

The object **so4** that we've created in R is called a data frame. Data frames look like matrices but the elements of data frames can be mixtures of character and numeric data. More formally data frames are tightly coupled collections of variables that share many of the properties of matrices and of lists. They are the fundamental data structures for most of **R**'s modeling functions.

The **dim** function is used to determine the dimensions of a data frame.

```
> dim(so4)
[1] 48 7
```

From the output we see that there are 48 rows and 7 columns. The output is a vector and we can access the individual entries using standard vector notation.

```
> dim(so4)[1]
[1] 48
> dim(so4)[2]
[1] 7
```

The functions **colnames** and **rownames** return the column names and row names of the data frame.

```
> colnames(so4)
[1] "Lake"      "Latitude"  "Longitude" "X1976"     "X1977"
"X1978"      "X1981"

> rownames(so4)
[1] "1" "2" "3" "4" "5" "6" "7" "8" "9" "10" "11" "12"
[13] "13" "14" "15" "16" "17" "18" "19" "20" "21" "22" "23" "24"
[25] "25" "26" "27" "28" "29" "30" "31" "32" "33" "34" "35" "36"
[37] "37" "38" "39" "40" "41" "42" "43" "44" "45" "46" "47" "48"
```

What's returned are vectors of character data. If you use just the **names** function you get the column names only.

```
> names(so4)
[1] "Lake"      "Latitude"  "Longitude" "X1976"     "X1977"
"X1978"      "X1981"
```

Observe that R has appended an X in front of the names of the years. Variable names cannot start with a number.

In S-Plus, the commercial cousin of R, the **rownames** and **colnames** functions don't exist. Instead use the **dimnames** function.

```

> dimnames(so4)
[[1]]
[1] "1" "2" "3" "4" "5" "6" "7" "8" "9" "10" "11" "12"
[13] "13" "14" "15" "16" "17" "18" "19" "20" "21" "22" "23" "24"
[25] "25" "26" "27" "28" "29" "30" "31" "32" "33" "34" "35" "36"
[37] "37" "38" "39" "40" "41" "42" "43" "44" "45" "46" "47" "48"
[[2]]
[1] "Lake" "Latitude" "Longitude" "X1976" "X1977"
"X1978" "X1981"

```

The **dimnames** function returns an object called a list. Notice the double bracket notation. Lists are useful when elements are of different lengths (as they are here) or of different types. To access the second element of this list, use the double bracket notation:

```

> dimnames(so4)[[2]]
[1] "Lake" "Latitude" "Longitude" "X1976" "X1977"
"X1978" "X1981"

```

To access the third element of the second element of the list:

```

> dimnames(so4)[[2]][3]
[1] "Longitude"

```

4.D. Accessing elements of data frames

Because a data frame is both a matrix and a list, we can use either notation to access its elements. Let's examine matrix notation first using row and column numbers.

so4[2,3] returns the element in row 2 and column 3 of the data frame so4.

```
> so4[2,3]
[1] 6.3
```

Specifying a row number followed by a comma and then no column number inside the brackets returns the entire row. Below I get the second row. The NA that appears in the output is the missing code in R. It stands for "not applicable".

```
> so4[2,]
  Lake Latitude Longitude X1976 X1977 X1978 X1981
2    2      58.1         6.3   5.5    NA    6.2   4.8
```

Specifying a comma followed by a number inside the brackets returns an entire column. Below I get the third column.

```
> so4[,3]
[1] 7.2 6.3 7.9 8.9 7.6 6.5 7.3 8.5 9.3 6.4 7.5 7.6 9.8
[14] 11.8 6.2 7.3 8.3 8.9 12.0 5.9 10.2 12.2 5.5 7.3 10.0 12.2
[27] 5.0 5.6 6.9 9.7 10.8 4.9 5.5 4.9 5.8 7.1 6.4 6.7 8.0
[40] 7.1 6.1 11.3 9.4 7.6 7.3 6.3 11.5 4.6
```

Get two adjacent rows. The colon notation is used to generate a sequence of numbers. Thus 2:5 yields the vector (2, 3, 4, 5).

```
> so4[2:3,]
  Lake Latitude Longitude X1976 X1977 X1978 X1981
2    2      58.1         6.3   5.5    NA    6.2   4.8
3    4      58.5         7.9   4.8   6.5   4.6   3.6
```

Get 3 rows not all adjacent. Here we use the **c** function of R to concatenate the terms into a vector.

```
> so4[c(2:3,5),]
  Lake Latitude Longitude X1976 X1977 X1978 X1981
2    2      58.1         6.3   5.5    NA    6.2   4.8
3    4      58.5         7.9   4.8   6.5   4.6   3.6
5    6      58.7         7.6   3.7   4.2   3.3   2.9
```

We can also specify column elements by name (row elements too if they had names). Here I select the 1976 SO4 values. Notice that the variable name appears in quotes and is used instead of the column number.

```
> so4[, "X1976"]
[1] 6.5 5.5 4.8 7.4 3.7 1.8 2.7 3.8 8.4 1.6 2.5 3.2 4.6 7.6 1.6 1.5 1.4
[18] 4.6 5.8 1.5 4.0 5.1 NA 1.4 3.8 5.1 2.8 1.6 1.5 3.2 2.8 3.0 0.7 3.1
[35] 2.1 3.9 1.9 5.2 5.3 2.9 1.6 13.0 5.5 2.8 1.6 2.0 5.8 NA
```

An alternative way of obtaining the same column is with list notation. In list notation we specify the data frame name followed by a \$ sign followed by the variable name (unquoted).

```
> so4$X1976
[1] 6.5 5.5 4.8 7.4 3.7 1.8 2.7 3.8 8.4 1.6 2.5 3.2 4.6 7.6 1.6 1.5 1.4
[18] 4.6 5.8 1.5 4.0 5.1 NA 1.4 3.8 5.1 2.8 1.6 1.5 3.2 2.8 3.0 0.7 3.1
[35] 2.1 3.9 1.9 5.2 5.3 2.9 1.6 13.0 5.5 2.8 1.6 2.0 5.8 NA
```

4.E. Attaching a data frame

Notice that to access a variable in a data frame we had to also specify the name of the data frame. Using the name of a variable all by itself does not work.

```
> X1976
Error: object "X1976" not found
> "X1976"
[1] "X1976"
```

The reason for this is that the data frame is currently not part of the R search path. R doesn't try to look in the data frame for the variables. To add a data frame to the search path use the **attach** function.

```
> attach(so4)
```

Now R can see the variable.

```
> X1976
[1] 6.5 5.5 4.8 7.4 3.7 1.8 2.7 3.8 8.4 1.6 2.5 3.2 4.6 7.6 1.6 1.5 1.4
[18] 4.6 5.8 1.5 4.0 5.1 NA 1.4 3.8 5.1 2.8 1.6 1.5 3.2 2.8 3.0 0.7 3.1
[35] 2.1 3.9 1.9 5.2 5.3 2.9 1.6 13.0 5.5 2.8 1.6 2.0 5.8 NA
```

Attaching data frames can lead to confusion. If you change an entry in a variable from a data frame that has been attached, e.g., `X1976[5] <- 10`, R makes another copy of the variable in the workspace with the changed entry, but doesn't change the variable in the data frame itself. A worse situation can arise if a variable name in a data frame matches a variable name for an object that already existed in the workspace. When this happens the latest variable shadows the first. If you're not aware that this has happened you may end up referencing the wrong variable. Because of the confusion that can result I recommend not attaching data sets as a general practice, but you will see this used in vignettes and examples. To undo the attachment, use the detach function.

```
> detach(so4)
```

Now the variable X1976 is again invisible to R.

4.F. Descriptive Statistics For Data Frames

The **mean** function calculates the mean of variables. If we try to use it to obtain the mean of the 1976 sulfate concentrations we get a surprise.

```
> mean(so4[, 4])  
X1976  
NA
```

The problem is that there are missing values in this variable and arithmetic on missing values is undefined. We need to remove them first. The **mean** function has an optional argument that will do this for us. Recall that, to get help on a function you can enter a **?** followed by the name of the function. This brings up the help window.

```
> ?mean
```

From the help window you should see that there is an argument, **na.rm**, which can be used to remove missing values. We just need to set its value to TRUE.

```
> mean(so4[, 4], na.rm=TRUE)  
X1976  
3.743478
```

The help screen for mean tells us that "there are methods for numeric data frames, numeric vectors and dates". R is an object-oriented language meaning functions are written in such a way that they behave differently for different kinds of objects. If we apply mean to the four columns containing sulfate concentrations in different years we get the mean for each year.

```
> mean(so4[, 4:7], na.rm=TRUE)  
X1976 X1977 X1978 X1981  
3.743478 3.978125 3.715217 3.334091
```

You can also round the values. The second argument to the round function is the number of decimals to display.

```
> round(mean(so4[, 4:7], na.rm=TRUE), 2)  
X1976 X1977 X1978 X1981  
3.74 3.98 3.72 3.33
```

Not all functions behave this way. The function **sum** returns a single number when given a matrix because it is not vectorized the way mean is.

```
> sum(so4[, 4:7], na.rm=TRUE)  
[1] 617.1
```

To force the sum function to return separate sums for each column, use the **apply** function. The **apply** function has three required arguments:

1. The first argument is a matrix to operate on.
2. The second argument is the number 1 if we wish to operate on the rows of the matrix or the number 2 if we wish to operate on columns.
3. The last argument is the function we wish to apply to the matrix.

The **sum** function behaves like the **mean** function when it encounters missing values.

```
> apply(so4[,4:7],2,sum)
X1976 X1977 X1978 X1981
      NA     NA     NA     NA
```

We need to pass the **na.rm=TRUE** argument to sum in order to first remove the missing values. This can be done by specifying it as an additional argument to **apply**.

```
> apply(so4[,4:7],2,sum,na.rm=TRUE)
X1976 X1977 X1978 X1981
172.2 127.3 170.9 146.7
```

An alternative approach is to create what's called a generic function. This is a function that's created on the fly. A generic function begins with the key word function followed by parentheses with the variable for the function inside the parentheses. This is followed by a formula using that variable. Here's how we would write a generic function within the **apply** function that takes the sums of non-missing values.

```
> apply(so4[,4:7],2,function(x) sum(x,na.rm=TRUE))
X1976 X1977 X1978 X1981
172.2 127.3 170.9 146.7
```

4.G. Changing the Form of a Data Set from Wide to Long

Currently the `so4` data frame has the sulfate concentrations spread across four columns. Each column corresponds to a different year of sampling. While this was a convenient way to enter the data, it is not a format that is useful for statistical analysis. For example, we might want to plot the sulfate concentrations for each year, which means we want to treat the concentration as the y -variable and year as the x -variable. For this we need the four columns of sulfate concentrations stacked in a single column and there should be a second column that records the year in which the sulfate concentration was measured. The lake, latitude, and longitude columns would need to be adjusted accordingly.

As you might expect, because moving between the two formats is a fairly common task, there is an R function that does this. It's called **reshape**. Rather than illustrate this function I'm going to show you how this can be done using the more primitive functions **unlist** and **rep** because these functions are very useful in their own right.

Stacking the four columns of sulfate concentrations in a single column is easily done with the **unlist** function.

```
> unlist(so4[,4:7])
x19761 x19762 x19763 x19764 x19765 x19766 x19767 x19768
6.5 5.5 4.8 7.4 3.7 1.8 2.7 3.8
x19769 x197610 x197611 x197612 x197613 x197614 x197615 x197616
8.4 1.6 2.5 3.2 4.6 7.6 1.6 1.5
x197617 x197618 x197619 x197620 x197621 x197622 x197623 x197624
1.4 4.6 5.8 1.5 4.0 5.1 NA 1.4
x197625 x197626 x197627 x197628 x197629 x197630 x197631 x197632
3.8 5.1 2.8 1.6 1.5 3.2 2.8 3.0
x197633 x197634 x197635 x197636 x197637 x197638 x197639 x197640
0.7 3.1 2.1 3.9 1.9 5.2 5.3 2.9
x197641 x197642 x197643 x197644 x197645 x197646 x197647 x197648
1.6 13.0 5.5 2.8 1.6 2.0 5.8 NA
x19771 x19772 x19773 x19774 x19775 x19776 x19777 x19778
NA NA 6.5 7.6 4.2 NA 2.7 3.7
x19779 x197710 x197711 x197712 x197713 x197714 x197715 x197716
9.1 2.6 2.7 NA NA 9.1 2.4 1.3
x197717 x197718 x197719 x197720 x197721 x197722 x197723 x197724
1.6 NA 6.2 1.6 3.9 5.7 NA 1.0
x197725 x197726 x197727 x197728 x197729 x197730 x197731 x197732
3.3 5.8 3.2 NA 1.5 NA 1.7 1.9
x197733 x197734 x197735 x197736 x197737 x197738 x197739 x197740
1.8 NA 1.9 1.5 1.9 NA NA NA
x197741 x197742 x197743 x197744 x197745 x197746 x197747 x197748
1.5 15.0 5.9 NA 1.6 NA 6.9 NA
x19781 x19782 x19783 x19784 x19785 x19786 x19787 x19788
7.3 6.2 4.6 6.8 3.3 1.5 2.3 3.6
x19789 x197810 x197811 x197812 x197813 x197814 x197815 x197816
8.8 1.8 2.8 2.7 4.9 9.6 2.6 1.9
x197817 x197818 x197819 x197820 x197821 x197822 x197823 x197824
1.8 5.3 5.9 NA 4.9 5.4 1.4 1.1
x197825 x197826 x197827 x197828 x197829 x197830 x197831 x197832
3.1 5.0 1.6 NA 1.4 2.6 1.9 1.5
x197833 x197834 x197835 x197836 x197837 x197838 x197839 x197840
```

1.5	2.4	1.3	1.7	1.5	5.6	5.4	2.9
X197841	X197842	X197843	X197844	X197845	X197846	X197847	X197848
1.7	13.0	5.7	2.6	1.4	2.4	5.9	2.3
X19811	X19812	X19813	X19814	X19815	X19816	X19817	X19818
6.0	4.8	3.6	5.6	2.9	1.8	2.1	3.8
X19819	X198110	X198111	X198112	X198113	X198114	X198115	X198116
8.7	1.5	2.9	2.9	4.9	7.6	2.0	1.7
X198117	X198118	X198119	X198120	X198121	X198122	X198123	X198124
1.8	4.2	5.4	NA	4.3	4.3	1.3	1.2
X198125	X198126	X198127	X198128	X198129	X198130	X198131	X198132
NA	4.2	NA	1.6	1.6	2.3	1.8	1.7
X198133	X198134	X198135	X198136	X198137	X198138	X198139	X198140
1.5	2.2	1.6	NA	1.7	3.9	4.2	2.2
X198141	X198142	X198143	X198144	X198145	X198146	X198147	X198148
1.9	10.0	4.8	3.0	1.8	2.0	5.8	1.6

From the output and the labels R has created we see that the values are arranged by year with all the 1976 values coming first, followed by the 1977 values, etc.

To generate the year labels and to reorganize the lake, latitude, and longitude columns we use the **rep** function. I start by illustrating how **rep** works for some simple examples. The **rep** function takes two arguments.

1. The first argument is the object to replicate. It can be a scalar or a vector.
2. The second argument describes how many times it should be repeated. This value can be a scalar or a vector and the choice yields very different consequences, as I'll now illustrate.

4.H. Examples on Use of the **rep function**

Repeat the number 5 ten times:

```
> rep(5,10)
[1] 5 5 5 5 5 5 5 5 5 5
```

Create the sequence 2,5,2,5, ..., 2,5 where 2,5 appears ten times:

```
> rep(c(2,5),10)
[1] 2 5 2 5 2 5 2 5 2 5 2 5 2 5 2 5 2 5 2 5
```

Create a sequence of ten 2s followed by ten 5s:

```
> rep(c(2,5),c(10,10))
[1] 2 2 2 2 2 2 2 2 2 2 5 5 5 5 5 5 5 5 5 5
```

This can also be accomplished by nesting a rep within a rep:

```
> rep(c(2,5),rep(10,2))
[1] 2 2 2 2 2 2 2 2 2 2 5 5 5 5 5 5 5 5 5 5
```

4.I. ...Back to Creating the Long Data Set

For years we need 48 values of 1976, followed by 48 copies of 1977, etc. This is the third example of using rep given above.

```
> rep(c(1976:1978, 1981), rep(48, 4))
[1] 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976
[14] 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976
[27] 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976 1976
[40] 1976 1976 1976 1976 1976 1976 1976 1976 1976 1977 1977 1977 1977
[53] 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977
[66] 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977
[79] 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977 1977
[92] 1977 1977 1977 1977 1977 1978 1978 1978 1978 1978 1978 1978 1978
[105] 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978
[118] 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978
[131] 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978 1978
[144] 1978 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981
[157] 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981
[170] 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981
[183] 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981 1981
```

For lakes we need the entire sequence of lake values repeated four times. (Latitude and longitude should be handled the same way.) This is the second example illustrating the use of rep above.

```
> rep(so4$Lake, 4)
[1] 1 2 4 5 6 7 8 9 10 11 12 13 15
[14] 17 18 19 20 21 24 26 30 32 34-1 36 38 40
[27] 41 42 43 46 47 49 50 57 58 59 65 80 81
[40] 82 83 85 86 87 88 89 94 95-1 1 2 4 5
[53] 6 7 8 9 10 11 12 13 15 17 18 19 20
[66] 21 24 26 30 32 34-1 36 38 40 41 42 43 46
[79] 47 49 50 57 58 59 65 80 81 82 83 85 86
[92] 87 88 89 94 95-1 1 2 4 5 6 7 8 9
[105] 10 11 12 13 15 17 18 19 20 21 24 26 30
[118] 32 34-1 36 38 40 41 42 43 46 47 49 50 57
[131] 58 59 65 80 81 82 83 85 86 87 88 89 94
[144] 95-1 1 2 4 5 6 7 8 9 10 11 12 13
[157] 15 17 18 19 20 21 24 26 30 32 34-1 36 38
[170] 40 41 42 43 46 47 49 50 57 58 59 65 80
[183] 81 82 83 85 86 87 88 89 94 95-1
48 Levels: 1 10 11 12 13 15 17 18 19 2 20 21 24 26 30 32 34-1 ... 95-1
```

To assemble the individual columns into a new data frame we use the **data.frame** function. I enter things in the order concentrations, years, lakes, latitude, longitude.

```
> temp2 <- data.frame(unlist(so4[,4:7]), rep(c(1976:1978, 1981),
rep(48,4)), rep(so4$Lake, 4), rep(so4$Latitude, 4),
rep(so4$Longitude, 4))
```

By default the columns are named with the formulas we used to create each column. To change the names to something sensible use the **colnames** function again but this time by assigning new values for the column names. Also change the row names to just the sequential row numbers.

```
> colnames(temp2)<-c('SO4','Year','Lake','Latitude','Longitude')
> rownames(temp2)<-1:dim(temp2)[1]
```

Examine the first ten rows of the new data frame we've created:

```
> temp2[1:10,]
   SO4 Year Lake Latitude Longitude
1  6.5 1976   1    58.0         7.2
2  5.5 1976   2    58.1         6.3
3  4.8 1976   4    58.5         7.9
4  7.4 1976   5    58.6         8.9
5  3.7 1976   6    58.7         7.6
6  1.8 1976   7    59.1         6.5
7  2.7 1976   8    58.9         7.3
8  3.8 1976   9    59.1         8.5
9  8.4 1976  10    58.9         9.3
10 1.6 1976  11    59.4         6.4
```

Suppose we wanted again to obtain the mean sulfate concentration for all lakes in each year, but using the new data frame in which concentrations and years are in separate columns. Once again a member of the "apply" family comes to the rescue. The **tapply** function is designed to do what's called subset analysis. It requires three arguments.

1. The name of the variable to which a function will be applied.
2. A categorical variable (or list of categorical variables) defining the subsets for which we want separate summaries.
3. The function to use, either a name of a function or a formula.

If we are using a named function that has additional arguments, these arguments can appear as additional arguments to **tapply** and are listed after the function name. The following use of **tapply** attempts to get the mean sulfate concentration in each year.

```
> tapply(temp2$SO4,temp2$Year,mean)
1976 1977 1978 1981
   NA   NA   NA   NA
```

We get a missing mean for each year because there are missing values in each year. We need to strip out the missing values using the **na.rm=TRUE** option of the mean function. Here are two correct ways of getting the results.

Specify **na.rm=TRUE** as a fourth argument to **tapply**.

```
> tapply(temp2$SO4,temp2$Year,mean,na.rm=T)
1976    1977    1978    1981
3.743478 3.978125 3.715217 3.334091
```

Write a generic function that uses **mean** but in which we specify **na.rm=TRUE** explicitly as an argument.

```
> tapply(temp2$SO4,temp2$Year,function(x) mean(x,na.rm=T))
      1976      1977      1978      1981 
3.743478 3.978125 3.715217 3.334091
```

4.J. Graphing the Data

To compare the distributions of the samples in the four years a nice graphical device is to produce side-by-side boxplots. This can be done with the **boxplot** function in R. The basic syntax is `boxplot(y~x)` where *y* is the variable to be plotted and *x* is the grouping variable. I elect to use list notation (the `$` notation) to reference the variables in the data frame. **Fig. 5** shows the result.

```
> boxplot(temp2$SO4~temp2$Year)
```

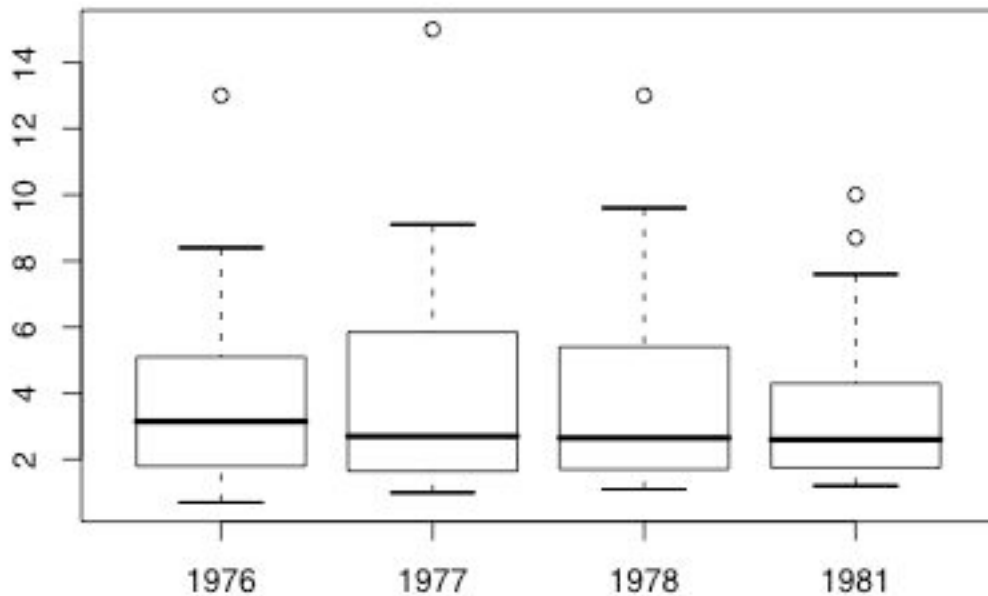


Fig. 5 Box plot of sulfate concentrations by year

The box locates the middle 50% of the data. The bottom edge of the box denotes the 1st quartile, the top edge locates the 3rd quartile, and the horizontal line inside the box corresponds to the median. The distance between the quartiles is called the inter-quartile range (IQR). The "whiskers" run out to the smallest and largest observations inside the inner fences that are located 1.5 times the IQR beyond each quartile. Observations beyond the inner fences are plotted individually and are outliers.

A nice addition to a box plot is to include the location of the mean for each group. The **boxplot** function is an example of a high-level graphics command in R. A high-level graphics function is one that clears the graph window and produces a new plot when it is used. There are many low-level graphics functions that will add elements to existing plots. One of these functions is **points**.

The **points** function does not use the `~` notation. Instead the first argument is a list of *x*-coordinates and the second argument is the corresponding list of *y*-coordinates. Additional arguments can follow, including the following:

1. **pch=** followed by a number that denotes the desired print character.

2. **col=** followed by the number 1 through 8 to denote one of R's base colors, or one of the more than 600 colors available in R that can be specified by name. To see a full list of colors go to <http://research.stowers-institute.org/efg/R/Color/Chart/index.htm>.

3. **cex=** followed by a number that indicates the character expansion ratio. A number like 0.5 would plot symbols at one half the default size.

The years are actually plotted at locations 1:4 in the plot (not the actual year values as is obvious from the fact that the years are equally spaced in Fig. 5). The means for each year were obtained using the **tapply** function above. I add a red asterisk to each box to denote the mean.

```
> points(1:4, tapply(temp2$SO4, temp2$Year, function(x)
mean(x, na.rm=T)), pch=8, col=2, cex=1.1)
```

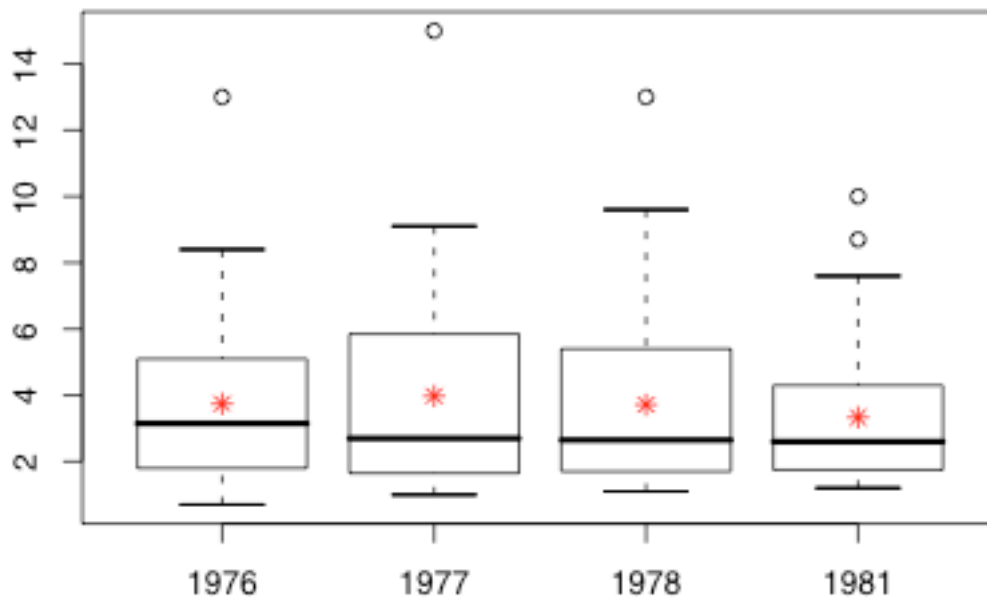


Fig. 6 Adding the group means to the box plots

If there aren't too many data values it can be useful to superimpose the raw data on top of the box plots. Here we have 48 observations per year, which may be a bit much, but I'll go ahead anyway.

The raw data can be added with another **points** call this time specifying the actual *x*-locations on the boxplot as the *x*-values and *temp2\$SO4* as the *y*-values. The locations are 1:4 and we will need to repeat each of them 48 times. The years are in consecutive order so `rep(1:4, rep(48, 4))` will correctly plot the concentrations at the proper years. Here's what I have in mind.

```
> points(rep(1:4, rep(48, 4)), temp2$SO4, pch=16, col='seagreen',
cex=.5)
```

A problem with the above command is that data values all end up along the midline of the boxes with many of them overlapping. We can get around this by jittering the points randomly in the *x*-direction by applying the *jitter* function to the *x*-coordinates as shown below.

```
> points(jitter(rep(1:4, rep(48, 4))), temp2$SO4, pch=16,
col='seagreen', cex=.5)
```


One problem with this plot (left side of Fig. 7) is that the outliers are being plotted twice, once from the **boxplot** command and then a second time in the **points** command. Because they are jittered the second time the two versions don't coincide on the plot. There is an option in the boxplot function, **outline=FALSE**, that turns off the printing of the outliers. I rerun the **boxplot** command and the two points commands to produce the plot shown in the right half of Fig. 7.

```
> boxplot(temp2$SO4~temp2$Year, outline=FALSE)
> points(1:4,tapply(temp2$SO4,temp2$Year, function(x)
mean(x,na.rm=T)), pch=8, col=2, cex=1.1)
> points(jitter(rep(1:4,rep(48,4))), temp2$SO4, pch=16, col='seagreen', cex=.5)
```

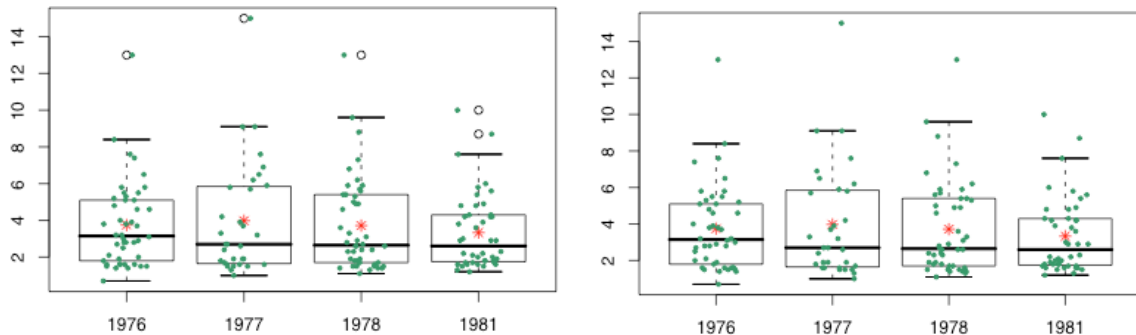


Fig. 7 Adding the jittered raw data to the plot. In the right graph the option `outline=FALSE` was used in `boxplot` to suppress the plotting of outliers

Finally it would be nice to have a label on the y-axis to indicate that SO_4 concentrations are being plotted. Labels for y- and x-axes are specified with the `ylab` and `xlab` arguments to `boxplot`. R supports mathematical typesetting and we can specify SO_4 in the label as follows:
`ylab=expression("SO"[4])` . Here's the final boxplot call.

```
> boxplot(temp2$SO4~ temp2$Year, outline=FALSE,
ylab=expression("SO"[4]))
> points(1:4,tapply(temp2$SO4, temp2$Year, function(x)
mean(x,na.rm=T)), pch=8, col=2, cex=1.1)
> points(jitter(rep(1:4, rep(48,4))), temp2$SO4, pch=16,
col='seagreen', cex=.5)
```

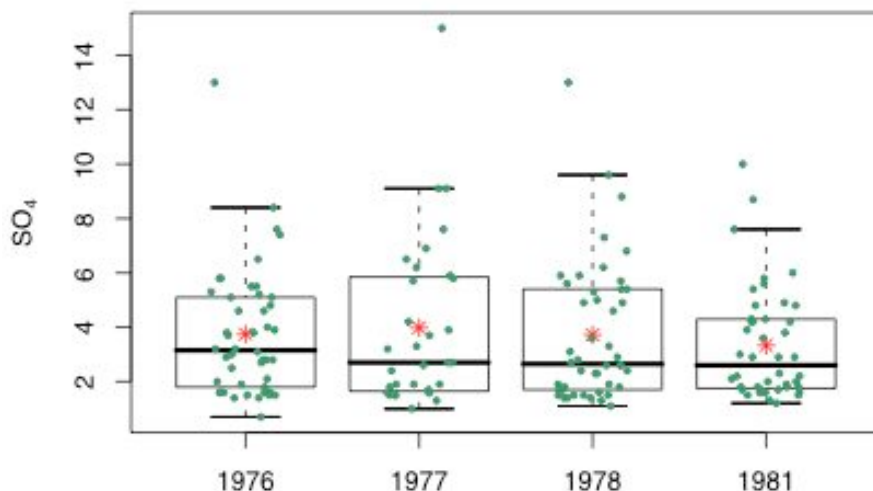


Fig. 8 Final box plot

4.K. Basic Statistics

Now, what if you wish to analyze the data you've just plotted? The basic statistical functions in R use the same 'formula' method that you have just observed in action, for generating plots. For example, model notation for the relationship between a continuous response variable y and two predictor variables x_1 and x_2 , but excluding the intercept, would be:

```
> y ~ x1 + x2 - 1
```

For a "full" model that includes an interaction term and the intercept:

```
> y ~ x1 + x2 + x1:x2
```

Or, shorthand notation:

```
> y ~ x1*x2
```

There are two potential ways we could examine the relationship between lake sulfate content (SO4) and the measurement year. We could treat Year as a continuous variable, and perform a regression to observe how sulfate levels change across the measurement years. Or, we could treat Year as a categorical variable, and use an Analysis of Variance to determine if there are different sulfate contents in the different years. Here, we will use both approaches because that method will allow you to observe some handy features of using R for your statistical analysis.

Just in case you were unable to complete the previous section due to time constraints, here's a faster way to convert data from 'wide' to 'long' format, using the **reshape** function:

```
> temp2 <- reshape(so4, direction="long",  
  varying=list(names(so4)[4:7]), v.names="SO4", idvar=c("Lake",  
  "Latitude", "Longitude"), timevar="Year",  
  times=c(1976,1977,1978,1981))  
> temp2 <- na.omit(temp2) # Remove all missing values
```

I personally find this method less intuitive than methods from the *reshape* package, so I recommend checking out the package if you find yourself frequently needing to rearrange data frames.

First, regression:

```
> so4lm <- lm(SO4 ~ Year, data=temp2)  
> class(so4lm) # Note that this has created an object of class  
'lm'. This means that functions used on this object will behave  
accordingly.  
> summary(so4lm)
```

```

Call:
lm(formula = SO4 ~ Year, data = temp2)

Residuals:
    Min       1Q   Median       3Q      Max
-3.1774 -1.8777 -0.9277  1.4212 11.2223

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) 200.90816   198.90266    1.010   0.314
Year        -0.09971    0.10055   -0.992   0.323

Residual standard error: 2.487 on 166 degrees of freedom
(24 observations deleted due to missingness)
Multiple R-squared:  0.005889,    Adjusted R-squared:  -0.0001
F-statistic: 0.9833 on 1 and 166 DF,  p-value: 0.3228

```

As you can see here, neither the intercept nor the variable of interest is significant. Back to the drawing board!

Also try:

```

> plot(so4lm) # Generates a set of 4 diagnostic plots
> residuals(so4lm) # Will spit out a long list of the residuals
for all of the values, excluding rows with missing data. You can
use this to extract the residuals and create your own plots if
you're looking for more information about your data.

```

Next, Analysis of Variance. You can actually perform an Analysis of Variance on an object of class 'lm'!

```

> anova(so4lm)

```

Analysis of Variance Table

```

Response: SO4
      Df Sum Sq Mean Sq F value Pr(>F)
Year    1    6.08   6.0810   0.9833 0.3228
Residuals 166 1026.59   6.1843

```

Alternatively, you can create an object of class 'aov' using the aov() function:

```

> so4aov <- aov(SO4 ~ Year, data=temp2)
> summary(so4aov) # Notice that this generates almost identical
output as the anova() function above.

```

Now, it's possible that any annual effects have been overshadowed by differences between the lakes. Let's examine an Analysis of Variance that includes "Lake" as a factor:

```
> so4aov2 <- aov(SO4 ~ Year*Lake, data=temp2)
> summary(so4aov2)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Year	1	6.1	6.081	20.367	2.44e-05 ***
Lake	47	987.0	20.999	70.330	< 2e-16 ***
Year:Lake	47	18.1	0.386	1.293	0.161
Residuals	72	21.5	0.299		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

In this model, both "Year" and "Lake" are significant, with a non-significant interaction. Looks great! ...Except for one quirk of R. R uses Type I Sums of Squares as its default Sums of Squares for the Analysis of Variance. This means that the **order of the terms in the model matters**. Compare:

```
> so4aov3 <- aov(SO4~Lake*Year, data=temp2)
> summary(so4aov3)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Lake	47	986.3	20.986	70.287	< 2e-16 ***
Year	1	6.7	6.685	22.388	1.08e-05 ***
Lake:Year	47	18.1	0.386	1.293	0.161
Residuals	72	21.5	0.299		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Notice that the sums of squares, all the way through the P-values, are different between the two models. To construct a model with Type III Sums of Squares (what's reported by many other statistical software programs), it's simplest to use the **Anova()** function from the *car* package (don't forget to use **install.packages()** if using the *car* package for the first time):

```
> library(car)
> Anova(so4aov2, type="III")
```

Anova Table (Type III tests)

Response: SO4

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	0.2129	1	0.7131	0.4012
Year	0.2021	1	0.6769	0.4134
Lake	18.2861	47	1.3031	0.1538
Year:Lake	18.1393	47	1.2926	0.1612
Residuals	21.4977	72		

Like a person with two watches, I cannot tell you which analysis is correct. You will need to think through your assumptions and statistical questions carefully to determine the appropriate answer.

Lesson 4 Wrap-Up

Hopefully you have typed the above commands into a script file, along with your personal notes and comments. At this point, save your script file so you can return to it later and either re-run commands or refer back to your notes on how to do things. You may also want to start creating your own RefCard at this stage.

Learning how to import data, manipulate it, and analyze it in R will take time, and the initial learning curve is steep. However, with some practice, you will find that soon you are spending less time performing rote, tedious tasks, and more time customizing and streamlining your data analysis pipeline, which will free you to get back to the remaining aspects of your scientific work.

I have aggregated a collection of additional recommended resources on my website if this initial taste of R has inspired you to continue. There's an overwhelming wealth of information available for beginners, though, so the best advice is to just find a starting point, buckle down, get to work, and take good notes.

<http://www.acromyrmex.net/RWorkshop2-5apr12.html>