

# **Overview and History of R**

# What is R?

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R is a dialect of the S language.

# What is S?

- S is a language that was developed by John Chambers and others at Bell Labs.
- S was initiated in 1976 as an internal statistical analysis environment—originally implemented as Fortran libraries.
- Early versions of the language did not contain functions for statistical modeling.
- In 1988 the system was rewritten in C and began to resemble the system that we have today (this was Version 3 of the language). The book *Statistical Models in S* by Chambers and Hastie (the white book) documents the statistical analysis functionality.
- Version 4 of the S language was released in 1998 and is the version we use today. The book *Programming with Data* by John Chambers (the green book) documents this version of the language.

# Historical Notes

- In 1993 Bell Labs gave StatSci (now Insightful Corp.) an exclusive license to develop and sell the S language.
- In 2004 Insightful purchased the S language from Lucent for \$2 million and is the current owner.
- In 2006, Alcatel purchased Lucent Technologies and is now called Alcatel-Lucent.
- Insightful sells its implementation of the S language under the product name S-PLUS and has built a number of fancy features (GUIs, mostly) on top of it—hence the “PLUS”.
- In 2008 Insightful is acquired by TIBCO for \$25 million
- The fundamentals of the S language itself has not changed dramatically since 1998.
- In 1998, S won the Association for Computing Machinery's Software System Award.

# S Philosophy

In “Stages in the Evolution of S”, John Chambers writes:

“[W]e wanted users to be able to begin in an interactive environment, where they did not consciously think of themselves as programming. Then as their needs became clearer and their sophistication increased, they should be able to slide gradually into programming, when the language and system aspects would become more important.”

<http://www.stat.bell-labs.com/S/history.html>

# Back to R

- 1991: Created in New Zealand by Ross Ihaka and Robert Gentleman. Their experience developing R is documented in a 1996 *JCGS* paper.
- 1993: First announcement of R to the public.
- 1995: Martin Mächler convinces Ross and Robert to use the GNU General Public License to make R free software.
- 1996: A public mailing list is created (R-help and R-devel)
- 1997: The R Core Group is formed (containing some people associated with S-PLUS). The core group controls the source code for R.
- 2000: R version 1.0.0 is released.
- 2013: R version 3.0.2 is released on December 2013.

# Features of R

- Syntax is very similar to S, making it easy for S-PLUS users to switch over.
- Semantics are superficially similar to S, but in reality are quite different (more on that later).
- Runs on almost any standard computing platform/OS (even on the PlayStation 3)
- Frequent releases (annual + bugfix releases); active development.

# Features of R (cont'd)

- Quite lean, as far as software goes; functionality is divided into modular packages
- Graphics capabilities very sophisticated and better than most stat packages.
- Useful for interactive work, but contains a powerful programming language for developing new tools (user -> programmer)
- Very active and vibrant user community; R-help and R-devel mailing lists and Stack Overflow

# Features of R (cont'd)

It's free! (Both in the sense of beer and in the sense of speech.)

# Free Software

With *free software*, you are granted

- The freedom to run the program, for any purpose (freedom 0).
- The freedom to study how the program works, and adapt it to your needs (freedom 1). Access to the source code is a precondition for this.
- The freedom to redistribute copies so you can help your neighbor (freedom 2).
- The freedom to improve the program, and release your improvements to the public, so that the whole community benefits (freedom 3). Access to the source code is a precondition for this.

<http://www.fsf.org>

# Drawbacks of R

- Essentially based on 40 year old technology.
- Little built in support for dynamic or 3-D graphics (but things have improved greatly since the “old days”).
- Functionality is based on consumer demand and user contributions. If no one feels like implementing your favorite method, then it's *your job!*
  - (Or you need to pay someone to do it)
- Objects must generally be stored in physical memory; but there have been advancements to deal with this too
- Not ideal for all possible situations (but this is a drawback of all software packages).

# Design of the R System

The R system is divided into 2 conceptual parts:

1. The “base” R system that you download from CRAN
2. Everything else.

R functionality is divided into a number of *packages*.

- The “base” R system contains, among other things, the **base** package which is required to run R and contains the most fundamental functions.
- The other packages contained in the “base” system include **utils**, **stats**, **datasets**, **graphics**, **grDevices**, **grid**, **methods**, **tools**, **parallel**, **compiler**, **splines**, **tcltk**, **stats4**.
- There are also “Recommend” packages: **boot**, **class**, **cluster**, **codetools**, **foreign**, **KernSmooth**, **lattice**, **mgcv**, **nlme**, **rpart**, **survival**, **MASS**, **spatial**, **nnet**, **Matrix**.

# Design of the R System

And there are many other packages available:

- There are about 4000 packages on CRAN that have been developed by users and programmers around the world.
- There are also many packages associated with the Bioconductor project (<http://bioconductor.org>).
- People often make packages available on their personal websites; there is no reliable way to keep track of how many packages are available in this fashion.

# Some R Resources

Available from CRAN (<http://cran.r-project.org>)

- An Introduction to R
- Writing R Extensions
- R Data Import/Export
- R Installation and Administration (mostly for building R from sources)
- R Internals (not for the faint of heart)

# Some Useful Books on S/R

## Standard texts

- Chambers (2008). *Software for Data Analysis*, Springer. (your textbook)
- Chambers (1998). *Programming with Data*, Springer.
- Venables & Ripley (2002). *Modern Applied Statistics with S*, Springer.
- Venables & Ripley (2000). *S Programming*, Springer.
- Pinheiro & Bates (2000). *Mixed-Effects Models in S and S-PLUS*, Springer.
- Murrell (2005). *R Graphics*, Chapman & Hall/CRC Press.

## Other resources

- Springer has a series of books called *Use R!*
- A longer list of books is at <http://www.r-project.org/doc/bib/R-books.html>

# Getting Help

# Finding Answers

- Try to find an answer by searching the archives of the forum you plan to post to.
- Try to find an answer by searching the Web.
- Try to find an answer by reading the manual.
- Try to find an answer by reading a FAQ.
- Try to find an answer by inspection or experimentation.
- Try to find an answer by asking a skilled friend.
- If you're a programmer, try to find an answer by reading the source code.

# Asking Questions

- It's important to let other people know that you've done all of the previous things already
- If the answer is in the documentation, the answer will be "Read the documentation"
  - one email round wasted

# Example: Error Messages

```
> library(datasets)
> data(airquality)
> cor(airquality)
Error in cor(airquality) : missing observations in cov/cor
```

# Google is your friend

A screenshot of a Google search results page. The search bar at the top contains the query "missing observations in cov/cor". Below the search bar, it says "About 508,000 results (0.28 seconds)". On the right side of the search bar is a user icon. The main area displays several search results, each consisting of a blue link, a snippet of text, and a small green link below it.

## [\[R\] Error in cor.default\(x1, x2\) : missing observations in cov/cor](#)

<https://stat.ethz.ch/pipermail/r-help/2008.../155523.html> - Block stat.ethz.ch

Mar 1, 2008 – [R] Error in cor.default(x1, x2) : missing observations in cov/cor. Daniel Malter daniel at umd.edu. Thu Feb 28 01:40:58 CET 2008. Previous message: [R] Error in ...

[\[R\] Null values In R](#) - Dec 3, 2008

[\[R\] cor\(data.frame\) infelicities](#) - Dec 3, 2007

[\[BioC\] maanova: missing observations in cov/cor](#) - Aug 25, 2006

[\[R-sig-Geo\] Some comments on calculations with 'asc' \(and 'kasc' ...\)](#) - Mar 27, 2005

More results from stat.ethz.ch »

## [EMBnet 2007 Course - Introduction to Statistics for Biologists](#)

[www.ch.embnet.org/CoursEMBnet/Basel07/tp2b.html](http://www.ch.embnet.org/CoursEMBnet/Basel07/tp2b.html) - Block ch.embnet.org

you will get an error: Error in cor(thuesen) : missing observations in cov/cor . [You will have seen a similar message above with sd .] This is because of the ...

## [R help - Error in cor.default\(x1, x2\) : missing observations in cov/cor](#)

[r.789695.n4.nabble.com/Error-in-cor-default-x1-x2-missing-...](http://r.789695.n4.nabble.com/Error-in-cor-default-x1-x2-missing-...) - Block

[r.789695.n4.nabble.com](http://r.789695.n4.nabble.com)

13 posts - 5 authors - Feb 27, 2008

Error in cor.default(x1, x2) : missing observations in cov/cor. Hello, I'm trying to do cor(x1,x2) and I get the following error: Error in cor.default(x1, ...

# Asking Questions

- What steps will reproduce the problem?
- What is the expected output?
- What do you see instead?
- What version of the product (e.g. R, packages, etc.) are you using?
- What operating system?
- Additional information

# Subject Headers

- Stupid: "Help! Can't fit linear model!"
- Smart: "R 3.0.2 lm() function produces seg fault with large data frame, Mac OS X 10.9.1"
- Smarter: "R 3.0.2 lm() function on Mac OS X 10.9.1 -- seg fault on large data frame"

# Do

- Describe the goal, not the step
- Be explicit about your question
- Do provide the minimum amount of information necessary (volume is not precision)
- Be courteous (it never hurts)
- Follow up with the solution (if found)

# Don't

- Claim that you've found a bug
- Grovel as a substitute for doing your homework
- Post homework questions on mailing lists (we've seen them all)
- Email multiple mailing lists at once
- Ask others to debug your broken code without giving a hint as to what sort of problem they should be searching for

# Introduction to the R Language

# Objects

R has five basic or “atomic” classes of objects:

- character
- numeric (real numbers)
- integer
- complex
- logical (True/False)

The most basic object is a vector

- A vector can only contain objects of the same class
- BUT: The one exception is a *list*, which is represented as a vector but can contain objects of different classes (indeed, that's usually why we use them)

Empty vectors can be created with the `vector()` function.

# Numbers

- Numbers in R are generally treated as numeric objects (i.e. double precision real numbers)
- If you explicitly want an integer, you need to specify the `L` suffix
- Ex: Entering `1` gives you a numeric object; entering `1L` explicitly gives you an integer.
- There is also a special number `Inf` which represents infinity; e.g. `1 / 0`; `Inf` can be used in ordinary calculations; e.g. `1 / Inf` is 0
- The value `NaN` represents an undefined value (“not a number”); e.g. `0 / 0`; `NaN` can also be thought of as a missing value (more on that later)

# Attributes

R objects can have attributes

- names, dimnames
- dimensions (e.g. matrices, arrays)
- class
- length
- other user-defined attributes/metadata

Attributes of an object can be accessed using the `attributes()` function.

# Entering Input

At the R prompt we type expressions. The `<-` symbol is the assignment operator.

```
> x <- 1
> print(x)
[1] 1
> x
[1] 1
> msg <- "hello"
```

The grammar of the language determines whether an expression is complete or not.

```
> x <- ## Incomplete expression
```

The `#` character indicates a comment. Anything to the right of the `#` (including the `#` itself) is ignored.

# Evaluation

When a complete expression is entered at the prompt, it is evaluated and the result of the evaluated expression is returned. The result may be auto-printed.

```
> x <- 5  ## nothing printed
> x        ## auto-printing occurs
[1] 5
> print(x) ## explicit printing
[1] 5
```

The [1] indicates that x is a vector and 5 is the first element.

# Printing

```
> x <- 1:20  
> x  
[1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15  
[16] 16 17 18 19 20
```

The `:` operator is used to create integer sequences.

# Creating Vectors

The `c()` function can be used to create vectors of objects.

```
> x <- c(0.5, 0.6)      ## numeric
> x <- c(TRUE, FALSE)   ## logical
> x <- c(T, F)          ## logical
> x <- c("a", "b", "c")  ## character
> x <- 9:29              ## integer
> x <- c(1+0i, 2+4i)    ## complex
```

Using the `vector()` function

```
> x <- vector("numeric", length = 10)
> x
[1] 0 0 0 0 0 0 0 0 0 0
```

# Mixing Objects

What about the following?

```
> y <- c(1.7, "a")    ## character
> y <- c(TRUE, 2)     ## numeric
> y <- c("a", TRUE)   ## character
```

When different objects are mixed in a vector, *coercion* occurs so that every element in the vector is of the same class.

# Explicit Coercion

Objects can be explicitly coerced from one class to another using the `as.*` functions, if available.

```
> x <- 0:6
> class(x)
[1] "integer"
> as.numeric(x)
[1] 0 1 2 3 4 5 6
> as.logical(x)
[1] FALSE  TRUE  TRUE  TRUE  TRUE  TRUE  TRUE
> as.character(x)
[1] "0" "1" "2" "3" "4" "5" "6"
```

# Explicit Coercion

Nonsensical coercion results in NAs.

```
> x <- c("a", "b", "c")
> as.numeric(x)
[1] NA NA NA
Warning message:
NAs introduced by coercion
> as.logical(x)
[1] NA NA NA
> as.complex(x)
[1] NA NA NA
Warning message:
NAs introduced by coercion
```

# Matrices

Matrices are vectors with a *dimension* attribute. The dimension attribute is itself an integer vector of length 2 (nrow, ncol)

```
> m <- matrix(nrow = 2, ncol = 3)
> m
 [,1] [,2] [,3]
[1,]    NA    NA    NA
[2,]    NA    NA    NA
> dim(m)
[1] 2 3
> attributes(m)
$dim
[1] 2 3
```

# Matrices (cont'd)

Matrices are constructed *column-wise*, so entries can be thought of starting in the “upper left” corner and running down the columns.

```
> m <- matrix(1:6, nrow = 2, ncol = 3)
> m
   [,1] [,2] [,3]
[1,]    1    3    5
[2,]    2    4    6
```

# Matrices (cont'd)

Matrices can also be created directly from vectors by adding a dimension attribute.

```
> m <- 1:10
> m
[1] 1 2 3 4 5 6 7 8 9 10
> dim(m) <- c(2, 5)
> m
 [,1] [,2] [,3] [,4] [,5]
[1,]    1    3    5    7    9
[2,]    2    4    6    8   10
```

# cbind-ing and rbind-ing

Matrices can be created by *column-binding* or *row-binding* with `cbind()` and `rbind()`.

```
> x <- 1:3
> y <- 10:12
> cbind(x, y)
     x   y
[1,] 1 10
[2,] 2 11
[3,] 3 12
> rbind(x, y)
 [,1] [,2] [,3]
x     1     2     3
y    10    11    12
```

# Lists

Lists are a special type of vector that can contain elements of different classes. Lists are a very important data type in R and you should get to know them well.

```
> x <- list(1, "a", TRUE, 1 + 4i)
> x
[[1]]
[1] 1

[[2]]
[1] "a"

[[3]]
[1] TRUE

[[4]]
[1] 1+4i
```

# Factors

Factors are used to represent categorical data. Factors can be unordered or ordered. One can think of a factor as an integer vector where each integer has a *label*.

- Factors are treated specially by modelling functions like `lm()` and `glm()`
- Using factors with labels is *better* than using integers because factors are self-describing; having a variable that has values “Male” and “Female” is better than a variable that has values 1 and 2.

# Factors

```
> x <- factor(c("yes", "yes", "no", "yes", "no"))
> x
[1] yes yes no yes no
Levels: no yes
> table(x)
x
no yes
 2   3
> unclass(x)
[1] 2 2 1 2 1
attr(,"levels")
[1] "no"  "yes"
```

# Factors

The order of the levels can be set using the `levels` argument to `factor()`. This can be important in linear modelling because the first level is used as the baseline level.

```
> x <- factor(c("yes", "yes", "no", "yes", "no"),
               levels = c("yes", "no"))
> x
[1] yes yes no yes no
Levels: yes no
```

# Missing Values

Missing values are denoted by `NA` or `NaN` for undefined mathematical operations.

- `is.na()` is used to test objects if they are `NA`
- `is.nan()` is used to test for `NaN`
- `NA` values have a class also, so there are integer `NA`, character `NA`, etc.
- A `NaN` value is also `NA` but the converse is not true

# Missing Values

```
> x <- c(1, 2, NA, 10, 3)
> is.na(x)
[1] FALSE FALSE TRUE FALSE FALSE
> is.nan(x)
[1] FALSE FALSE FALSE FALSE FALSE
> x <- c(1, 2, NaN, NA, 4)
> is.na(x)
[1] FALSE FALSE TRUE TRUE FALSE
> is.nan(x)
[1] FALSE FALSE TRUE FALSE FALSE
```

# Data Frames

Data frames are used to store tabular data

- They are represented as a special type of list where every element of the list has to have the same length
- Each element of the list can be thought of as a column and the length of each element of the list is the number of rows
- Unlike matrices, data frames can store different classes of objects in each column (just like lists); matrices must have every element be the same class
- Data frames also have a special attribute called `row.names`
- Data frames are usually created by calling `read.table()` or `read.csv()`
- Can be converted to a matrix by calling `data.matrix()`

# Data Frames

```
> x <- data.frame(foo = 1:4, bar = c(T, T, F, F))
> x
  foo    bar
1   1  TRUE
2   2  TRUE
3   3 FALSE
4   4 FALSE
> nrow(x)
[1] 4
> ncol(x)
[1] 2
```

# Names

R objects can also have names, which is very useful for writing readable code and self-describing objects.

```
> x <- 1:3
> names(x)
NULL
> names(x) <- c("foo", "bar", "norf")
> x
foo bar norf
  1   2   3
> names(x)
[1] "foo"  "bar"  "norf"
```

# Names

Lists can also have names.

```
> x <- list(a = 1, b = 2, c = 3)
> x
$a
[1] 1

$b
[1] 2

$c
[1] 3
```

# Names

And matrices.

```
> m <- matrix(1:4, nrow = 2, ncol = 2)
> dimnames(m) <- list(c("a", "b"), c("c", "d"))
> m
   c d
a 1 3
b 2 4
```

# Summary

## Data Types

- atomic classes: numeric, logical, character, integer, complex \
- vectors, lists
- factors
- missing values
- data frames
- names

# Reading Data

There are a few principal functions reading data into R.

- `read.table`, `read.csv`, for reading tabular data
- `readLines`, for reading lines of a text file
- `source`, for reading in R code files (`inverse` of `dump`)
- `dget`, for reading in R code files (`inverse` of `dput`)
- `load`, for reading in saved workspaces
- `unserialize`, for reading single R objects in binary form

# Writing Data

There are analogous functions for writing data to files

- `write.table`
- `writeLines`
- `dump`
- `dput`
- `save`
- `serialize`

# Reading Data Files with `read.table`

The `read.table` function is one of the most commonly used functions for reading data. It has a few important arguments:

- `file`, the name of a file, or a connection
- `header`, logical indicating if the file has a header line
- `sep`, a string indicating how the columns are separated
- `colClasses`, a character vector indicating the class of each column in the dataset
- `nrows`, the number of rows in the dataset
- `comment.char`, a character string indicating the comment character
- `skip`, the number of lines to skip from the beginning
- `stringsAsFactors`, should character variables be coded as factors?

# read.table

For small to moderately sized datasets, you can usually call `read.table` without specifying any other arguments

```
data <- read.table("foo.txt")
```

R will automatically

- skip lines that begin with a #
- figure out how many rows there are (and how much memory needs to be allocated)
- figure what type of variable is in each column of the table Telling R all these things directly makes R run faster and more efficiently.
- `read.csv` is identical to `read.table` except that the default separator is a comma.

# Reading in Larger Datasets with `read.table`

With much larger datasets, doing the following things will make your life easier and will prevent R from choking.

- Read the help page for `read.table`, which contains many hints
- Make a rough calculation of the memory required to store your dataset. If the dataset is larger than the amount of RAM on your computer, you can probably stop right here.
- Set `comment.char = ""` if there are no commented lines in your file.

# Reading in Larger Datasets with `read.table`

- Use the `colclasses` argument. Specifying this option instead of using the default can make '`read.table`' run MUCH faster, often twice as fast. In order to use this option, you have to know the class of each column in your data frame. If all of the columns are "numeric", for example, then you can just set `colClasses = "numeric"`. A quick and dirty way to figure out the classes of each column is the following:

```
initial <- read.table("datatable.txt", nrows = 100)
classes <- sapply(initial, class)
tabAll <- read.table("datatable.txt",
                      colClasses = classes)
```

- Set `nrows`. This doesn't make R run faster but it helps with memory usage. A mild overestimate is okay. You can use the Unix tool `wc` to calculate the number of lines in a file.

# Know Thy System

In general, when using R with larger datasets, it's useful to know a few things about your system.

- How much memory is available?
- What other applications are in use?
- Are there other users logged into the same system?
- What operating system?
- Is the OS 32 or 64 bit?

# Calculating Memory Requirements

I have a data frame with 1,500,000 rows and 120 columns, all of which are numeric data. Roughly, how much memory is required to store this data frame?

$$1,500,000 \times 120 \times 8 \text{ bytes/numeric}$$

$$= 1440000000 \text{ bytes}$$

$$= 1440000000 / 2^{20} \text{ bytes/MB}$$

$$= 1,373.29 \text{ MB}$$

$$= 1.34 \text{ GB}$$

# Textual Formats

- dumping and dputing are useful because the resulting textual format is editable, and in the case of corruption, potentially recoverable.
- Unlike writing out a table or csv file, dump and dput preserve the *metadata* (sacrificing some readability), so that another user doesn't have to specify it all over again.
- Textual formats can work much better with version control programs like subversion or git which can only track changes meaningfully in text files
- Textual formats can be longer-lived; if there is corruption somewhere in the file, it can be easier to fix the problem
- Textual formats adhere to the “Unix philosophy”
- Downside: The format is not very space-efficient

# dput-ing R Objects

Another way to pass data around is by deparsing the R object with dput and reading it back in using dget.

```
> y <- data.frame(a = 1, b = "a")
> dput(y)
structure(list(a = 1,
              b = structure(1L, .Label = "a",
                            class = "factor")),
              .Names = c("a", "b"), row.names = c(NA, -1L),
              class = "data.frame")
> dput(y, file = "y.R")
> new.y <- dget("y.R")
> new.y
  a  b
1 1  a
```

# Dumping R Objects

Multiple objects can be deparsed using the `dump` function and read back in using `source`.

```
> x <- "foo"
> y <- data.frame(a = 1, b = "a")
> dump(c("x", "y"), file = "data.R")
> rm(x, y)
> source("data.R")
> y
  a  b
1 1  a
> x
[1] "foo"
```

# Interfaces to the Outside World

Data are read in using *connection* interfaces. Connections can be made to files (most common) or to other more exotic things.

- `file`, opens a connection to a file
- `gzfile`, opens a connection to a file compressed with gzip
- `bzfile`, opens a connection to a file compressed with bzip2
- `url`, opens a connection to a webpage

# File Connections

```
> str(file)
function (description = "", open = "", blocking = TRUE,
           encoding = getOption("encoding"))
```

- `description` is the name of the file
- `open` is a code indicating
  - “r” read only
  - “w” writing (and initializing a new file)
  - “a” appending
  - “rb”, “wb”, “ab” reading, writing, or appending in binary mode (Windows)

# Connections

In general, connections are powerful tools that let you navigate files or other external objects. In practice, we often don't need to deal with the connection interface directly.

```
con <- file("foo.txt", "r")
data <- read.csv(con)
close(con)
```

is the same as

```
data <- read.csv("foo.txt")
```

# Reading Lines of a Text File

```
> con <- gzfile("words.gz")
> x <- readLines(con, 10)
> x
[1] "1080"      "10-point"   "10th"       "11-point"
[5] "12-point"   "16-point"   "18-point"   "1st"
[9] "2"          "20-point"
```

`writeLines` takes a character vector and writes each element one line at a time to a text file.

# Reading Lines of a Text File

`readLines` can be useful for reading in lines of webpages

```
## This might take time
con <- url("http://www.jhsph.edu", "r")
x <- readLines(con)
> head(x)
[1] "<!DOCTYPE HTML PUBLIC "-//W3C//DTD HTML 4.0 Transitional//EN">"
[2] ""
[3] "<html>"
[4] "<head>"
[5] "\t<meta http-equiv=\"Content-Type\" content=\"text/html; charset=utf-8
```

# Subsetting

There are a number of operators that can be used to extract subsets of R objects.

- `[` always returns an object of the same class as the original; can be used to select more than one element (there is one exception)
- `[[]` is used to extract elements of a list or a data frame; it can only be used to extract a single element and the class of the returned object will not necessarily be a list or data frame
- `$` is used to extract elements of a list or data frame by name; semantics are similar to that of `[[]`.

# Subsetting

```
> x <- c("a", "b", "c", "c", "d", "a")
> x[1]
[1] "a"
> x[2]
[1] "b"
> x[1:4]
[1] "a" "b" "c" "c"
> x[x > "a"]
[1] "b" "c" "c" "d"
> u <- x > "a"
> u
[1] FALSE TRUE TRUE TRUE TRUE FALSE
> x[u]
[1] "b" "c" "c" "d"
```

# Subsetting a Matrix

Matrices can be subsetted in the usual way with  $(i,j)$  type indices.

```
> x <- matrix(1:6, 2, 3)
> x[1, 2]
[1] 3
> x[2, 1]
[1] 2
```

Indices can also be missing.

```
> x[1, ]
[1] 1 3 5
> x[, 2]
[1] 3 4
```

# Subsetting a Matrix

By default, when a single element of a matrix is retrieved, it is returned as a vector of length 1 rather than a  $1 \times 1$  matrix. This behavior can be turned off by setting `drop = FALSE`.

```
> x <- matrix(1:6, 2, 3)
> x[1, 2]
[1] 3
> x[1, 2, drop = FALSE]
     [,1]
[1,] 3
```

# Subsetting a Matrix

Similarly, subsetting a single column or a single row will give you a vector, not a matrix (by default).

```
> x <- matrix(1:6, 2, 3)
> x[1, ]
[1] 1 3 5
> x[1, , drop = FALSE]
[,1] [,2] [,3]
[1,]    1    3    5
```

# Subsetting Lists

```
> x <- list(foo = 1:4, bar = 0.6)
> x[1]
$foo
[1] 1 2 3 4

> x[[1]]
[1] 1 2 3 4

> x$bar
[1] 0.6
> x[["bar"]]
[1] 0.6
> x[ "bar"]
$bar
[1] 0.6
```

# Subsetting Lists

```
> x <- list(foo = 1:4, bar = 0.6, baz = "hello")
> x[c(1, 3)]
$foo
[1] 1 2 3 4

$baz
[1] "hello"
```

# Subsetting Lists

The `[[]` operator can be used with *computed* indices; `$` can only be used with literal names.

```
> x <- list(foo = 1:4, bar = 0.6, baz = "hello")
> name <- "foo"
> x[[name]] ## computed index for 'foo'
[1] 1 2 3 4
> x$name     ## element 'name' doesn't exist!
NULL
> x$foo
[1] 1 2 3 4 ## element 'foo' does exist
```

# Subsetting Nested Elements of a List

The `[ [` can take an integer sequence.

```
> x <- list(a = list(10, 12, 14), b = c(3.14, 2.81))
> x[[c(1, 3)]]
[1] 14
> x[[1]][[3]]
[1] 14

> x[[c(2, 1)]]
[1] 3.14
```

# Partial Matching

Partial matching of names is allowed with [ [ and \$.

```
> x <- list(aardvark = 1:5)
> x$a
[1] 1 2 3 4 5
> x[["a"]]
NULL
> x[["a", exact = FALSE]]
[1] 1 2 3 4 5
```

# Removing NA Values

A common task is to remove missing values (NAs).

```
> x <- c(1, 2, NA, 4, NA, 5)
> bad <- is.na(x)
> x[ !bad]
[1] 1 2 4 5
```

# Removing NA Values

What if there are multiple things and you want to take the subset with no missing values?

```
> x <- c(1, 2, NA, 4, NA, 5)
> y <- c("a", "b", NA, "d", NA, "f")
> good <- complete.cases(x, y)
> good
[1] TRUE TRUE FALSE TRUE FALSE TRUE
> x[good]
[1] 1 2 4 5
> y[good]
[1] "a" "b" "d" "f"
```

# Removing NA Values

```
> airquality[1:6, ]
   Ozone Solar.R Wind Temp Month Day
1     41      190  7.4   67     5    1
2     36      118  8.0   72     5    2
3     12      149 12.6   74     5    3
4     18      313 11.5   62     5    4
5     NA       NA 14.3   56     5    5
6     28       NA 14.9   66     5    6

> good <- complete.cases(airquality)
> airquality[good, ][1:6, ]
   Ozone Solar.R Wind Temp Month Day
1     41      190  7.4   67     5    1
2     36      118  8.0   72     5    2
3     12      149 12.6   74     5    3
4     18      313 11.5   62     5    4
7     23      299  8.6   65     5    7
```

# Vectorized Operations

Many operations in R are *vectorized* making code more efficient, concise, and easier to read.

```
> x <- 1:4; y <- 6:9
> x + y
[1] 7 9 11 13
> x > 2
[1] FALSE FALSE TRUE TRUE
> x >= 2
[1] FALSE TRUE TRUE TRUE
> y == 8
[1] FALSE FALSE TRUE FALSE
> x * y
[1] 6 14 24 36
> x / y
[1] 0.1666667 0.2857143 0.3750000 0.4444444
```

# Vectorized Matrix Operations

```
> x <- matrix(1:4, 2, 2); y <- matrix(rep(10, 4), 2, 2)
> x * y      ## element-wise multiplication
 [,1] [,2]
[1,]    10   30
[2,]    20   40
> x / y
 [,1] [,2]
[1,]  0.1  0.3
[2,]  0.2  0.4
> x %*% y    ## true matrix multiplication
 [,1] [,2]
[1,]    40   40
[2,]    60   60
```