

SIAM: Getting Started with R

Mark M. Fredrickson

`fredric3@illinois.edu`

March 13, 2014

Which implementation performs better?

- Imagine you have two implementations of an algorithm. You want to know which performs better on a data set.

Which implementation performs better?

- Imagine you have two implementations of an algorithm. You want to know which performs better on a data set.
- Strategy 1: Run each implementation once. Pick a winner based on that one run.

Which implementation performs better?

- Imagine you have two implementations of an algorithm. You want to know which performs better on a data set.
- Strategy 1: Run each implementation once. Pick a winner based on that one run.
- Strategy 2: Run the first implementation 100 times and then run the second implementation 100 times. Compare the average run time.

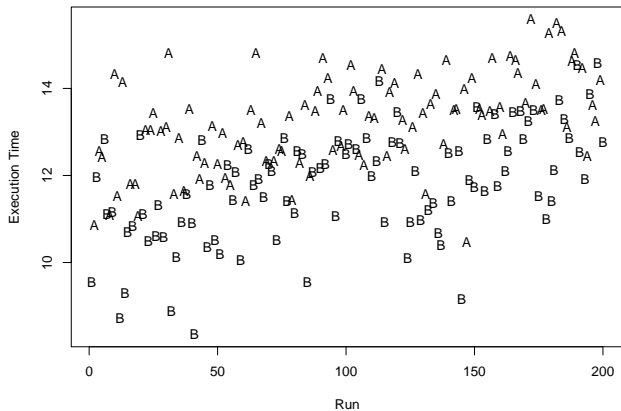
Which implementation performs better?

- Imagine you have two implementations of an algorithm. You want to know which performs better on a data set.
- Strategy 1: Run each implementation once. Pick a winner based on that one run.
- Strategy 2: Run the first implementation 100 times and then run the second implementation 100 times. Compare the average run time.
- Strategy 3: Randomly assign order of tests. Perform Wilcoxon-Mann-Whitney test of hypothesis that there is no difference in the two implementations.

Running experiment

```
> # number of times to run each implementation
> replicates <- 100
> # if z is 1, run A then B, otherwise run B then A
> z <- rbinom(replicates, size = 1, p = 0.5)
> times <- sapply(z, function(i) {
  if (i == 1) {
    return(c(A(), B()))
  } else {
    return(c(B(), A()))
  }
})
```

Graphing the data



Hypothesis test: Two algorithms perform the same

```
> wilcox.test(times[1,], times[2,],  
              paired = TRUE, exact = TRUE)
```

Wilcoxon signed rank test

data: times[1,] and times[2,]

V = 2195, p-value = 0.2585

alternative hypothesis: true location shift is not equal to 0

What is R?

- A language for statistical analysis (data manipulation, modeling, visualization).
- S started at Bell Labs in 1970s and 1980s.
- GNU R is an open source port of the language.
- Currently in version 3.0.x.
- Interpreted language with bindings to C/C++, Fortran, other languages
- Available for Windows, Mac, UNIXes; extensive package repository

Why use R?

- Basic statistical programming
- Graphics
- Interface with other languages
- Access to large repository of statistical tools
- Reproducible research
- Free and open source
- Marketable skill

Variables

- Variables can be assigned using either `<-` or `=`

```
> a <- 7  
> b = c(1, 2, 3, 4)
```

- The basic data type is a vector (with optional names)

```
> is.vector(c(a = 3, foo = 1, 4, last123 = 1))  
[1] TRUE  
> is.vector(3)  
[1] TRUE
```

- Assigning via special functions like `names<-`:

```
> names(b) <- c("A", "B", "C", "D")  
> b  
  
A B C D  
1 2 3 4
```

- Objects have a *class* and a *mode*

```
> m <- matrix(c(1,2,3,4,5,6,7,8,9), nrow = 3)
> class(m)
[1] "matrix"
> mode(m)
[1] "numeric"
```

- Usual suspects for modes:

- logical
- numeric (integer, double, complex, factor)
- character (strings)
- raw
- list

Exercise: Variables

- Create a vector with three numbers (use the `c` function).
- Create a vector with six numbers.
- Add them together. What happens?

Exercise: Variables

- Create a vector with three numbers (use the `c` function).
- Create a vector with six numbers.
- Add them together. What happens?
- R will “recycle” vectors to the length of the longer one.

Loops

The usual for and while constructs exist:

```
> a <- 0
> for (i in 1:5) {
  a <- a + i
}
> print(a)
[1] 15
```

The *apply family of functions perform maps over vectors:

```
> sapply(c(1,2,3,4), function(x) { x * x })
[1] 1 4 9 16
```

Many explicit loops can be avoided with “vectorization”:

```
> square <- function(x) { x * x }  
> square(c(1,2,3))  
[1] 1 4 9
```

There are some built in functions to “vectorize” other functions.

Functions: Creating and Passing

Functions are created like regular variables and can be treated like any other object:

```
> withfile <- function(fname, f) {  
  sink(fname)  
  f()  
  sink()  
}  
> withfile("myoutput.txt", function() {  
  print("hi")  
  print("bye")  
})
```

Functions: Arguments

Arguments can be named and given default values. Special ... argument captures any other passed arguments.

```
> f <- function(a, b, c = 0.5, ...) {  
  round(a:b * c, ...)  
}
```

```
> f(1, 3)
```

```
[1] 0 1 2
```

```
> f(b = 3, a = 1)
```

```
[1] 0 1 2
```

```
> f(c = 1/3, 1 , 3, digits = 3)
```

```
[1] 0.333 0.667 1.000
```

Booleans and Comparisons

- Standard boolean operations:

```
> c(TRUE && TRUE, TRUE && FALSE, FALSE || TRUE)
[1] TRUE FALSE TRUE
```

- Single boolean if-else statements; switch function

- Elementwise boolean operations | and &:

```
> c(TRUE, TRUE, FALSE) | c(FALSE, TRUE, FALSE)
[1] TRUE TRUE FALSE
```

- Elementwise comparisons:

```
> ifelse(c(1,2,3,4,5) %% 2 == 0, "even", "odd")
[1] "odd" "even" "odd" "even" "odd"
```

Exercise: Function to compute multiples

From Project Euler Problem 1:

If we list all the natural numbers below 10 that are multiples of 3 or 5, we get 3, 5, 6 and 9. The sum of these multiples is 23.

Find the sum of all the multiples of 3 or 5 below 1000.

- Write a function `isThreeOrFive` that returns a boolean (hint: `%%` is modulo).
- Apply the function to all values from 1 to 1000 (hint: `1:1000`).
- Use the `sum` function to answer the question.

Example solutions

■ Vectorization:

```
> isThreeOrFive <- function(x) {  
  # by using elementwise operation, this is vector  
  (x %% 3 == 0) | (x %% 5 == 0)  
}  
> sum((1:999)[isThreeOrFive(1:999)])  
[1] 233168
```

■ Explicit looping:

```
> s <- 0  
> for (x in 1:999) {  
  if (isThreeOrFive(x)) s <- s + x  
}  
> s  
[1] 233168
```

■ Functional one liner:

```
> sum(Filter(x = 1:1000, f = isThreeOrFive))
```

Missing Values

- Missing values for any data type is notated with the special NA value.
- Missing values (NA) are neither true or false, but short circuiting can still occur:

```
> c(FALSE && NA, TRUE || NA)
```

```
[1] FALSE TRUE
```

```
> c(TRUE && NA, FALSE || NA)
```

```
[1] NA NA
```

- Many functions will have special NA handling arguments:

```
> nas <- c(1, 2, 3, NA, 5)
```

```
> mean(nas)
```

```
[1] NA
```

```
> mean(nas, na.rm = TRUE)
```

```
[1] 2.75
```

The `matrix` class holds a single mode of data in a square format.

- Convenient subscripting notation style:
- Standard linear algebra tools available.
- The `array` class generalizes to dimensions > 2 .

```
> matrix <- matrix(1:12, nrow = 3)
```

```
> m[1:2, 2:3]
```

| | [,1] | [,2] |
|------|------|------|
| [1,] | 4 | 7 |
| [2,] | 5 | 8 |

Data Frames

The `data.frame` class holds multiple modes, `$` operator to get specific columns as vectors.

```
> df <- data.frame(nums = 1:10, letters = letters[1:10])
> df[1:3, ]
  nums letters
1     1      a
2     2      b
3     3      c
> df$letters
[1] a b c d e f g h i j
Levels: a b c d e f g h i j
```


A common interface is a formula with a left and right hand side:

```
> y ~ x1 + x2 + x3 * x4 + log(x5)
```

- Used in many model fitting and plotting routines.
- Short hand notation for interactions (: and *).
- Many functions permitted.
- Can pull variables from the enviroment, but usally better to combine with a `data = mydata` argument.

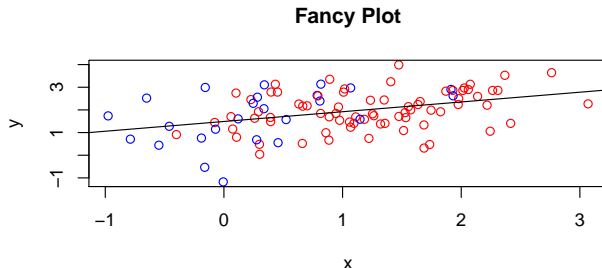
Example: Building a linear model

```
> library(MASS)
> randoms <- as.data.frame(
  mvrnorm(n = 100,
          mu = c(1,2),
          Sigma = matrix(c(1, 0.5, 0.5, 1),
                          nrow = 2)))
> colnames(randoms) <- c("x", "y")
> randoms$w <- (randoms$x + rnorm(100)) > 0
> model <- lm(y ~ x, data = randoms)
```

Plotting Basics

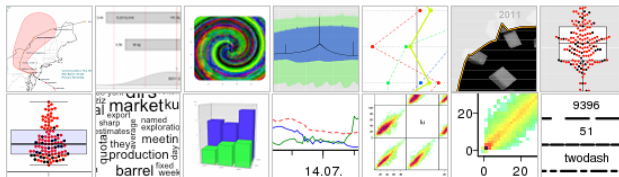
- Many objects have `plot` methods.
- These can be combined with other plotting primitives to create nice graphics.
- Output can be viewed interactively or saved as PDF, SVG, PNG, JPG, and others.

Example: Plotting regression model



```
> colors <- ifelse(randoms$w == 1, "red", "blue")
> plot(y ~ x, data = randoms, col = colors,
      main = "Fancy Plot")
> cs <- model$coefficients
> abline(a = cs[1], b = cs[2])
```

More examples



» Random entries

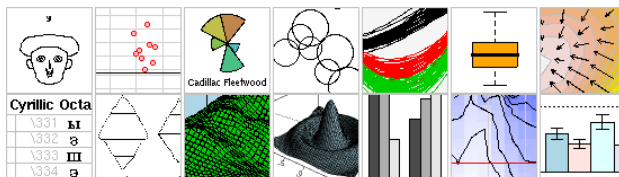
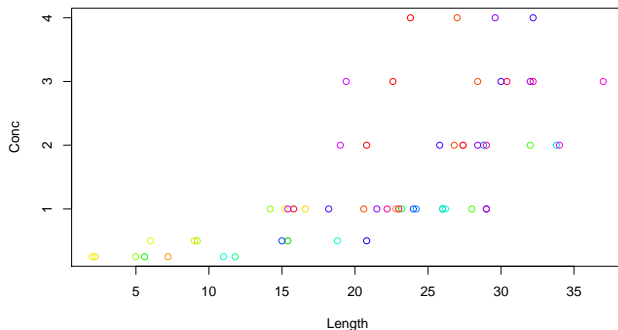


Figure : Mini examples from R Graphics Gallery

Exercise: Plotting Heart Muscle Experiment

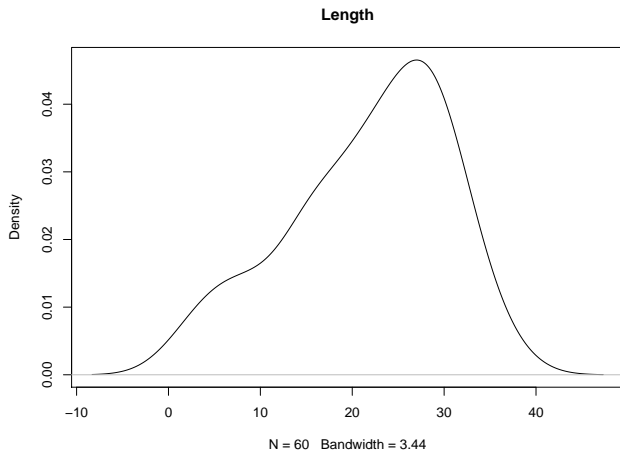
- Load the rat heart muscle experiment data: `data(muscle)`
- Plot `Conc` versus `Length`
- What is the distribution of the `Length` variable? (Hint: try plotting the results of `density` function)

Exercise: Plotting Heart Muscle Experiment



```
> cols <- rainbow(nlevels(muscle$Strip))  
> plot(Conc ~ Length, data = muscle,  
       col = cols[muscle$Strip])
```

Exercise: Length density plot



```
> plot(density(muscle$Length), main = "Length")
```


The Comprehensive R Archive Network(CRAN) is a repository for community packages.

- 5066 packages as of 2013-12-30
- Easy to use with `install.packages("packageName")`
- Packages for different statistical techniques, plotting/graphics, parsing, development tools.
- Pre-built binaries for Windows and OS X. Source builds for other platforms.

Installing and Using Packages

```
> install.packages("e1071")  
  
> library(e1071)  
> data(Titanic)  
> m <- naiveBayes(Survived ~ ., data = Titanic)  
> me <- list(class = "3rd", Sex = "Male",  
             Age = "Adult")  
> predict(m, newdata = me)  
[1] No  
Levels: No Yes
```

Some recommend packages

- `caret`: Machine learning meta package
- `lattice` and `ggplot`: Advance plotting packages.
- `xtable`: Formats tables as \LaTeX and HTML
- `Rcpp`: Simplifies interfacing with C/C++.
- `plyr`: Data manipulation routines.

- Embed R in \LaTeX (e.g. these slides)
- Chunks are evaluated and (optionally) output TeX.
- Figures can be generated as well

file.Rnw

```
<<chunkname, eval = TRUE>>=
c(1, 2, 3) + c(4, 5, 6)
@
```

file.tex

```
\begin{Schunk}
\begin{Sinput}
> c(1, 2, 3) + c(4, 5, 6)
\end{Sinput}
\begin{Soutput}
[1] 5 7 9
\end{Soutput}
\end{Schunk}
```

Using R to Create Artifacts

- Projects with multiple languages, phases
- We use `make` to map out dependencies and run R
- The `save` function serializes most data types.
- Typical workflow:
 - Load data (usually a `.csv` or similar)
 - Process data using R and save `.rda` file
 - Analysis phases consume `data.rda` and produce more `.rda` files
 - Figures, tables, etc. rely on these items and are built via `Makefile`
 - Output documents (`paper.pdf`, `presentation.pdf`) depend on entire collection.

Interfacing R with Other Languages

- R is largely built on C and Fortran and interfacing is pretty straight forward.
- Rcpp and inline packages make it even easier (including compiling writing C++ as a string)
- RInside is a package to allow calling R from C++
- RPy2, RJava, RinRuby, statistics::R, probably others
- foreign library can read many formats
- RSQLite: interact with sqlite3 files, bindings for most languages

- *The Art of R Programming* by Norman Matloff
- *Software for Data Analysis: Programming with R* by John Chambers
- *Reproducible Research in R and RStudio* by Christopher Gandrud
- O'Reilly R cookbooks
- Many books that teach specific statistical techniques with R demonstrations

- `r-project.org`: downloads, introductory guides, packages
- Searching the web for “R” is an extreme frustration (get used to it)
- R Inferno: common pitfalls and workarounds
- Mailing lists: `r-help`, `r-devel`
- `stackoverflow.com` and `stats.stackexchange.com`
- `r-bloggers.com`

- R for Windows and OS X ship with REPL and editor
- Rcmdr and tinR attempt to add a full GUI
- emacs: *Emacs Speaks Statistics* is a set of modes, including a REPL and Sweave interaction
- vim: syntax highlighting, I was never able to get interactive stuff to work (I use emacs + EVIL + ESS)
- RStudio: commercial IDE freeware; available as Java app and in-browser interface

Presentation can be found at:
<https://github.com/SIAM-at-Illinois/Getting-Started-Series>