BIOS 545 Week 1

Department of Biostatistics and Bioinformatics

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Why R ?

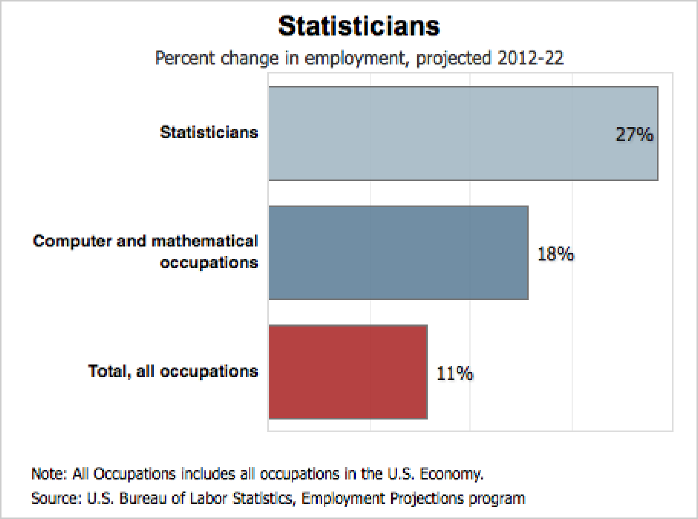
Occupational Outlook Handbook 2014

Employment of computer and information research scientists is projected to grow 18 percent from 2012 to 2022, faster than the average for all occupations. Employment of statisticians is projected to grow 27 percent from 2012 to 2022, much faster than the average for all occupations.

Rapid growth in data collection by businesses may lead to an increased need for data mining services Information research scientists are likely to enjoy excellent job prospects.

Graduates with a master's degree in statistics and a strong background in a related discipline, such as finance, biology, engineering, or computer science, are projected have the best prospects of finding jobs in their field of study.

Why R ?


Statisticians
Percent change in employment, projected 2012-22
Statisticians
27%
Computer and mathematical occupations
18%
Total, all occupations
11%
Note: All Occupations includes all occupations in the U.S. Economy.
Source: U.S. Bureau of Labor Statistics, Employment Projections program

New York Times

Data Analysts Captivated by R's Power

Left, Stuart Isett for The New York Times; right, Kieran Scott for The New York Times

R first appeared in 1996, when the statistics professors Robert Gentleman, left, and Ross Ihaka released the code as a free software package.

By ASHLEE VANCE
Published: January 6, 2009

http://tinyurl.com/cxa774n

Who Uses R ?

Company	How R is Used
Bank of America	Modeling and visualization
Facebook	User analysis and interaction
FDA	Used in parallel with SAS
Ford Motor Company	Decision support
Google	Calculate ROI on advertising
John Deere	Time series modeling and geospatial analysis
National Weather Service	Visualization for flood forecasting
New York Times Newspaper	Data visualization
Nordstrom	Recommendation systems
Orbitz Travel	Search result optimization
Twitter	User experience analysis
Trulia Real Estate	Housing cost predictions
OK Cupid Online Dating	Trend analysis
Lloyd's of London Insurance	Investment recommendation

`http://www.revolutionanalytics.com/companies-using-r`

Why R ?

- R is an interactive framework for data and statistical analysis that also happens to have a builtin programming language.
- Compare this to languages such as Python, Perl, and Java that have data analysis addons
- Which language to use ? Use them all if necessary but if data analysis is a large part of the work then R is the "go to" language
- R can reference or call code written in C, C++, Perl, Python, Java, and FORTRAN.
- Most of the effort in using R relates to shaping data for analysis and understanding the available functions and packages.
- To be a good *programmer* in R one must first be a knowledgeable *user* of R.

Why R ?

Differences between R and other statistical packages

“When talking about user friendliness of computer software I like to the analogy of cars vs. busses. Using this analogy programs like SPSS are busses, easy to use for the standard things, but very frustrating if you want to do something that is not already preprogrammed.”

“R is a 4-wheel drive SUV with a bike on the back, a kayak on the top, good walking and running shoes in the passenger seat, and a mountain climbing and spelunking gear in the back.”

“R can take you anywhere you want to go if you take the time to learn how to use the equipment, but that is going to take longer than learning where the bus stops are in SPSS.”

Greg Snow, R-help (May 2006)

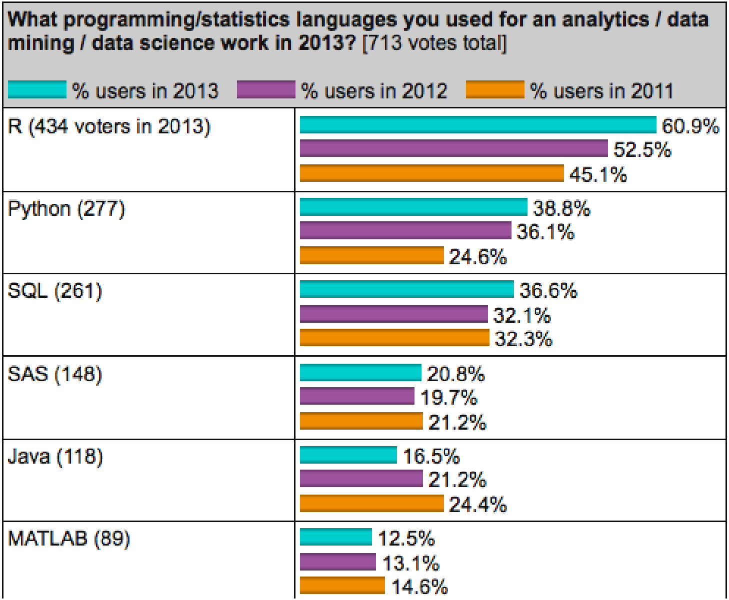
Why R ?

Cool things about R

- Vast capabilities with a wide range of statistical and graphics techniques
- Written primarily by statisticians
- Free of cost
- Collaborative development with over 6,092 user contributed packages
- Excellent community support with mailing lists, blogs, and tutorials
- Excellent "google" support
- Wildly popular in Academia and increasingly so in the business world

`www.slideshare.net/izahn/rintro`

R vs Other Languages - kdnuggets.com



Obtaining R

- Go to `http://cran.revolutionanalytics.com/`
- Click on your platform which will be either Windows or Apple OSX
- You will be redirected to another page which has a download link near the top
- Click it to download and begin installation. Wait till it is finished
- Go to `http://www.rstudio.com/products/rstudio/download/` to download the RStudio GUI
- Double click the installer to initiate the installation of RStudio
- Once finished start up Rstudio

Base Packages

It is important to note that R comes with a base set of packages as part of every installation.

```
> getOption("defaultPackages")
[1] "datasets"  "utils"     "grDevices" "graphics"  "stats"     "methods"

> search()
[1] ".GlobalEnv"        "package:stats"     "package:graphics"  "package:grDevices"
[5] "package:utils"     "package:datasets"  "package:methods"   "Autoloads"
[9] "package:base"

> library(help="stats")
```

Base Packages

```
> library(help="stats")
Description:

Package:       stats
Version:       3.1.2
Priority:      base
Title:         The R Stats Package
Author:        R Core Team and contributors worldwide
Maintainer:    R Core Team <R-core@r-project.org>
Description:   R statistical functions
License:       Part of R 3.1.2
Built:         R 3.1.2; x86_64-apple-darwin13.4.0; 2014-10-31 20:19:14 UTC; unix

Index:

.checkMFClasses         Functions to Check the Type of Variables passed
                        to Model Frames
AIC                     Akaike's An Information Criterion
ARMAacf                 Compute Theoretical ACF for an ARMA Process
ARMAtoMA                Convert ARMA Process to Infinite MA Process
Beta                    The Beta Distribution
Binomial                The Binomial Distribution
Box.test                Box-Pierce and Ljung-Box Tests
C                       Sets Contrasts for a Factor
```

Base Packages

Many packages come with example data that is helpful when attempting to understand how various functions work. To see what data sets are available in a given package, do something like:

```
> search()
[1] ".GlobalEnv" "package:lattice" "package:stats" "package:graphics"
[5] "package:grDevices" "package:utils" "package:datasets" "package:methods"
[9] "Autoloads" "package:base"

> data(package="stats")  # Find data included in package "stats"

Data sets in package "datasets":
AirPassengers           Monthly Airline Passenger Numbers 1949-1960
BJsales                 Sales Data with Leading Indicator
BJsales.lead (BJsales)  Sales Data with Leading Indicator
BOD                     Biochemical Oxygen Demand
CO2                     Carbon Dioxide Uptake in Grass Plants
DNase                   Elisa assay of DNase
EuStockMarkets          Daily Closing Prices of Major European
..
```

CRAN Packages

One of the most powerful aspects of R is the ability to install user-contributed addon packages available in CRAN, (Comprehensive R Archive Network). As of December 2014 there are over 6,000 packages available.

To obtain information on the wide variety of packages then vist the following URL to see some of the areas covered. `cran.cnr.berkeley.edu` Also go to the "Task Views' You can also see packages grouped by domain at `http://cran.r-project.org/web/views/`

CRAN Packages

Here are some of the areas covered. There are many more of course

CRAN Task Views

Bayesian	Bayesian Inference
ChemPhys	Chemometrics and Computational Physics
ClinicalTrials	Clinical Trial Design, Monitoring, and Analysis
Cluster	Cluster Analysis & Finite Mixture Models
DifferentialEquations	Differential Equations
Distributions	Probability Distributions
Econometrics	Computational Econometrics
Environmetrics	Analysis of Ecological and Environmental Data
ExperimentalDesign	Design of Experiments (DoE) & Analysis of Experimental Data
Finance	Empirical Finance
Genetics	Statistical Genetics
Graphics	Graphic Displays & Dynamic Graphics & Graphic Devices & Visualization
HighPerformanceComputing	High-Performance and Parallel Computing with R
MachineLearning	Machine Learning & Statistical Learning
MedicalImaging	Medical Image Analysis

CRAN Packages

If you are using RStudio there are menu items that can simplify the process of identifying and installing packages. However, you can also do this from the command prompt. Let's say you want to install the "actuar" package from CRAN.

```
> install.packages("actuar",dependencies=TRUE)

trying URL 'http://mirrors.nics.utk.edu/cran/bin/macosx/contrib/2.15/
actuar_1.1-5.tgz'
Content type 'application/x-gzip' length 1837121 bytes (1.8 Mb)
opened URL
==================================================

downloaded 1.8 Mb
> library(actuar) # Brings the package into the workspace
```

CRAN Packages

When we use the **library** command to load the contents of the **actuar** package it will show up when we execute the **search()** function. Check it out.

```
> library(actuar) # Brings the package into the workspace

> search()

[1] ".GlobalEnv" "package:actuar" "package:lattice" "package:stats"
[5] "package:graphics" "package:grDevices" "package:utils"
[8] "package:datasets" "package:methods" "Autoloads" "package:base"
```

CRAN Packages

On occasion you will need to install a package from a specific repository such as `omegahat.org` or R-forge. RStudio has menu items that can help with this but you can also do it from the command line.

```
> install.packages("GeoIP", repos = "http://www.omegahat.org/R")
```

Sometimes you download packages written by colleagues and you have to install them from your local hard drive. Again, RStudio can help but you could also do something like:

```
$ R CMD INSTALL GeoIP.tar.gz
```

CRAN Packages

There are lots of free books and tutorials on the web.

```
> install.packages("GeoIP", repos = "http://www.omegahat.org/R")
```

Sometimes you download packages written by colleagues and you have to install them from your local hard drive. Again, RStudio can help but you could also do something like:

```
$ R CMD INSTALL GeoIP.tar.gz
```

Finding Documentation

There are lots of free books on the web

Resource	URL
The R Inferno	http://www.burns-stat.com/documents/books/the-r-inferno/
R Programming Wiki	http://en.wikibooks.org/wiki/R_Programming
Intro to Stats Using R	http://ipsur.org
Stats with R	http://zoonek2.free.fr/UNIX/48_R/all.html
Lattice Graphics	http://lmdvr.r-forge.r-project.org
Contributed R Info	http://cran.r-project.org/other-docs.html
simpleR Intro Stats	http://cran.r-project.org/doc/contrib/Verzani-SimpleR.pdf
DIY Intro to R	http://www.unt.edu/rss/class/Jon/R_SC/
R Bloggers	http://www.r-bloggers.com/
R Journal	http://journal.r-project.org/
R Tutorial	http://www.r-tutor.com/r-introduction
Google Style Guide	https://github.com/hadley/devtools/wiki/Style
Applied Epi Using R	http://www.medepi.net/docs/EpidemiologyUsingR.pdf

Finding Documentation

There are some good books you can buy although for this class they aren't required.

Book	**Author**
R Cookbook	Paul Teetor
R in a Nutshell	Joseph Adler
The Art of Programming	Norman Matloff
Data Manipulation with R	Phil Spector
ggplot2: Elegant Graphics for Data Analyses	Hadley Wickham
Intro to Scientific Programming and Simulation Using R	Jones, Maillardet, Robinson
Introductory Statistics with R	Peter Dalgaard
The R Book	Michael J. Crawley
Discovering Statistics Using R	Andy Field

Mailing Lists

- Here are some mailing lists that accept questions relative to R and BioConductor.
- Moderators and participants in these lists take questions seriously, sometimes too seriously,
- Please don't ask a question without first searching through the archives to see if your question has already been answered. Chances are it has.

Mailing Lists	**URL**
R-Help	`http://stat.ethz.ch/mailman/listinfo/r-help`
Cross Validated	`http://stats.stackexchange.com`
Stack Overflow	`http://stackoverflow.com/questions/tagged`

Getting Help

R has a number of ways to get help. Rstudio has a Help menu item. Other ways include the following:

```
> help.start()          # Launches a web browser with search capability

> help(function_name)  # Get help on "function_name"

>?function_name        # Equivalent to the above

> args(function_name)    # See what arguments the function accepts

> example(function_name) # See an example of the function

> example(mean)

mean> x <- c(0:10, 50)
mean> xm <- mean(x)
mean> c(xm, mean(x, trim = 0.10))
[1] 8.75 5.50
```

Getting Help

R has a number of ways to get help. Rstudio has a Help menu item. Other ways include the following:

```
# Find all functions and data having to do with time series

> help.search("time series")

>??"time series"    # Equivalent to the above

Help files with alias or concept or title matching "time series"
using fuzzy matching:

boot::tsboot           Bootstrapping of Time Series
datasets::austres      Quarterly Time Series of the Number of Australian Residents
datasets::beavers      Body Temperature Series of Two Beavers
ggplot2::economics     US economic time series.
lattice::xyplot.ts     Time series plotting methods
MASS::beav1            Body Temperature Series of Beaver 1
MASS::beav2            Body Temperature Series of Beaver 2
stats::StructTS        Fit Structural Time Series
stats::ar              Fit Autoregressive Models to Time Series
stats::ar.ols          Fit Autoregressive Models to Time Series by OLS
..
```

Things to Know !

- Everything in R is an object
- The great thing about R is that there are many different ways to do something
- The bad thing about R is that there are many different ways to do something
- Everything that happens in R is a function call
- Supports procedural programming with functions and object oriented programming
- R is based on a “read-eval-print” loop
- Interpreted langauge

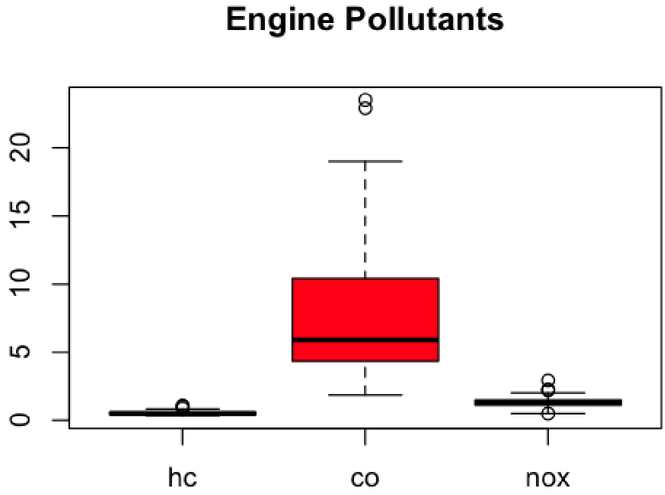
Walkthrough

```
url <- "http://steviep42.bitbucket.org/YOUTUBE.DIR/table_7_3.csv"

engine <- read.table(url, sep = ",", header=TRUE)
engine <- engine[,-1]

head(engine) # 3 engine pollutants

    hc co nox
1 0.50 5.01 1.28
2 0.65 14.67 0.72
3 0.46 8.60 1.17
4 0.41 4.42 1.31
5 0.41 4.95 1.16

summary(engine)
     en hc co nox
Min.   : 1.00   Min.   :0.3400   Min.   : 1.850  Min.   :0.490
1st Qu.:12.75   1st Qu.:0.4375   1st Qu.: 4.388  1st Qu.:1.110
Median :24.50   Median :0.5100   Median : 5.905  Median :1.315
Mean   :24.00   Mean   :0.5502   Mean   : 7.879  Mean   :1.340
3rd Qu.:35.25   3rd Qu.:0.6025   3rd Qu.:10.015  3rd Qu.:1.495
Max.   :46.00   Max.   :1.1000   Max.   :23.530  Max.   :2.940
```

http://www.cyclismo.org/tutorial/R/hwI.html

Walkthrough

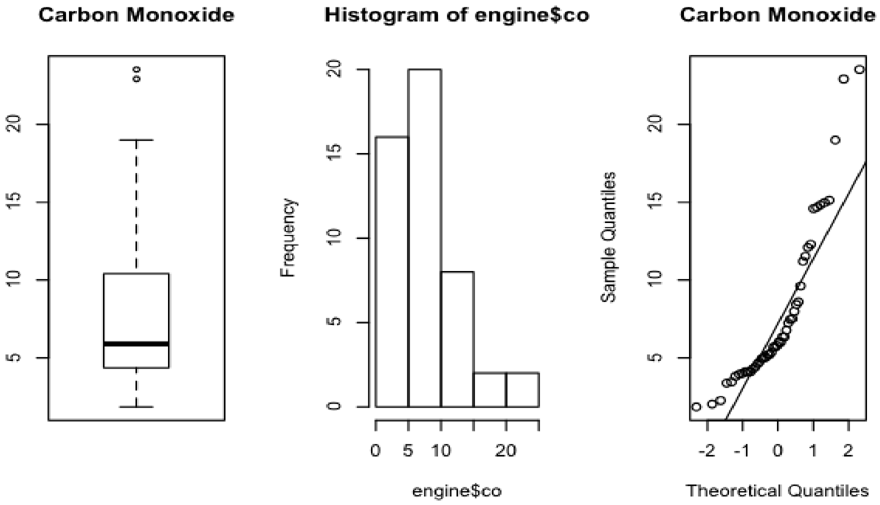
```
boxplot(engine,col="red",main="Engine Pollutants")
```



Walkthrough

```
par(mfrow=c(1,3))

boxplot(engine$co,main="Carbon Monoxide")

hist(engine$co)

qqnorm(engine$co,main="Carbon Monoxide")

qqline(engine$co)
```

Walkthrough



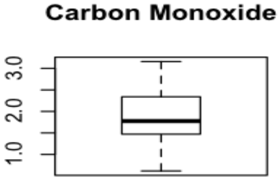
Walkthrough

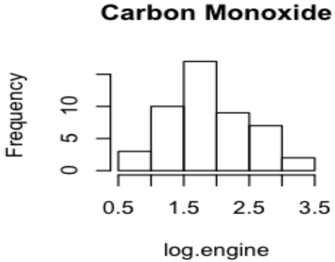
```
# The null hypothesis is that the data is normal

shapiro.test(engine$co)

   Shapiro-Wilk normality test

data: engine$co
W = 0.8357, p-value = 9.289e-06

# Take the log of the CO

log.engine <- log(engine$co)

shapiro.test(log.engine)

  Shapiro-Wilk normality test

data: log.engine
W = 0.9693, p-value = 0.2379
```

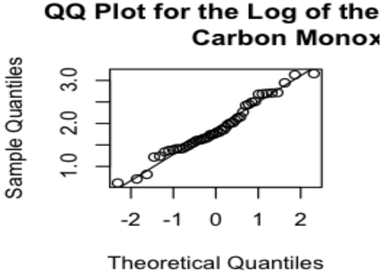
Walkthrough

```
par(mfrow=c(2,2))

log.engine <- log(engine$co)

boxplot(log.engine,main="Carbon Monoxide")

hist(log.engine,main="Carbon Monoxide")

qqnorm(log.engine,main="QQ Plot for the Log of the
                        Carbon Monoxide")

qqline(log.engine)
```

Walkthrough







Walkthrough

```
# Let's build a confidence interval

my.mean <- mean(log.engine)
my.sd < sd(log.engine)
n <- length(log.engine)

# Get standard error
se <- my.sd/sqrt(n)

error <- se*qt(0.975,df=n-1)

left <- my.mean - error

right <- my.mean + error

c(left,right)
[1] 1.709925 2.057431

c(exp(left),exp(right))
[1] 5.528548 7.825840
```

Walkthrough

```
# Test H0: mu = 5.4
# HA:mu != 5.4

lNull <- log(5.4) - error

rNull <- log(5.4) + error

c(lNull,rNull)
[1] 1.512646 1.860152

my.mean
[1] 1.883678
```

So the mean is outside the range thus we reject the null. There is a low probability that we would have obtained our sample mean if the true mean really was 5.4

Walkthrough

We could have calculated a p-value by hand

```
p.val <- 2*(1-pt((my.mean-log(5.4))/se,df=n-1))

p.val
[1] 0.02692539

# But its easier to call a procedure to do it all !!!!

t.test(log.engine,mu = log(5.4),alternative = "two.sided")
   One Sample t-test
data: log.engine
t = 2.2841, df = 47, p-value = 0.02693
alternative hypothesis: true mean is not equal to 1.686399
95 percent confidence interval:
  1.709925 2.057431
sample estimates:
mean of x
1.883678
```

First R Session

```
?mean              # Get help on the mean function

example(kmeans)    # Run an example of kmeans (if it exists)

pi                 # Some popular quantities are built-?âĂŘin to R
[1] 3.141593

sqrt(2) # Basic arithmetic
[1] 1.414214

print(pi) # Print the comments of the pi variable
[1] 3.141593

X <- 3; Y <- 4 # Semicolon lets you enter 2 commands on the same line

Z <- sqrt(X^2 + Y^2) # Variables contain information

# List all variables in the "environment"

ls()
[1] "X" "Y" "Z"
```

```
log(10)
[1] 2.302585

log10(100)
[1] 2

sin(pi/2)
[1] 1

cos(pi/2)
[1] 6.123234e-17

1.3e6
[1] 1300000

9 %% 2
[1] 1

floor(5.7)
[1] 5
```

```
ceiling(6.8)
[1] 7

round(6.889,2)
[1] 6.89

3/0
[1] Inf

0/0
[1] NaN

is.finite(3)
[1] TRUE

x <- c(1:8,NA)
[1] 1 2 3 4 5 6 7 8 NA

mean(x)
NA
```

```
2+3
[1] 5

3/2
[1] 1.5

2^3
[1] 8

(56-14)/6 - 4*7*10/(5^2-5)
[1] -7

abs(2-4)
[1] 2
```

Common Operators

```
# RELATIONAL OPERATORS

Equal to                == if (myvar == "test") {print("EQ")}
                        == if (mnynum == 3)     {print("EQ")}
Not equal to            != if (myvar != "test") {print("NE")}
Less than or equal to   <= if (number <= 5)     {print("LTE")}
Less than               <  if (number < 10)     {print("LT")}
Greater than or equal to   >= if (number >= 10)    {print("GTE")}
Greater than               >  if (number > 12)     {print("GT")}

# BOOLEAN OPERATORS

And                     &    if ((myvar == "test") & (num <= 10) ) {
                                   print("Equal and less than")
                             }

Not                     !    if (!complete.cases(myvec)) {
                                   print("Non complete cases")
                             }

Or                      |    if ((num > 3) | (num < -3)) {
                                   print("Only one of these has to be true")
                             }
```

More Examples

Here are some popular math formulas rewritten in R. Note that the variables must first exist in order for the formula to do an actual computation.

```
# a^2 + b^2 = c^2                  # Pythagorean Theorem

a <- 2; b <- 4

c <- sqrt(a^2 + b^2)               # To solve the PT for c

a <- 2; b <- 4; c <- 1

(-b + sqrt(b^2-4*a*c)) / (2*a)     # First case quadratic formula solution

(-b - sqrt(b^2 - 4*a*c)) / (2*a)  # Second case quadratic formula solution
r <- 4; h <- 6; b <- 3

circumference <- 2*pi*r              # circumference of a circle

area <- (b*h)/2 # Area of a triangle
```

Expressions

We can create functions that contain resuable code for later use

```
my.quad <- function(a,b,c) {
  r1 <- (-b + sqrt(b^2 - 4*a*c)) / (2*a)
  r2 <- (-b - sqrt(b^2 - 4*a*c)) / (2*a)
  my.roots = c(r1,r2)
  return(my.roots)
}

# Solve for ax^2 + bx + c where a = 1, b=6, and c=8

my.quad(1,6,8)
```

Startup

- You can use the Preferences menu item in RStudio to specify your default home directory
- When R starts it looks for a file called .Rprofile within your home directory
- You can influence the R environment by setting a number of “startup” variables therein
- Use your favorite editor to create/edit this file in your default folder
- You can change many of these variables or options during an R session but if you want them to be permanent then you will need to edit the .Rpfofile file

Startup .Rprofile

```
# Things you might want to change

options(editor="notepad")
cd = setwd
pwd = getwd
lss = dir

# R interactive prompt
setwd("/Users/fender/steve.test") # Set's my default directory for me.
options(prompt="> ")
options(continue="+ ")

# General options
options(digits=3)
options(width = 130)
options(graphics.record=TRUE)
.First <- function(){               # You can load functions
library(Hmisc)
cat("\nWelcome at", date(), "\n")
}
.Last <- function(){
cat("\nGoodbye at ", date(), "\n")
}
```

Workspace - Being Organized

Being organized helps ! Knowing how to find stuff quickly is essential. Create a master folder that will contain your work in this class.

You can create subfolders according to your projects. Note that some people do this on a DropBox folder to insure that all work is backed up.

```
$ ls RProjects
RProjects
    Data_Files
    Genomes
            1000_Genomes
            Centenarians
    HIV
            Replicates
    Hepatitis
            Hep_A
            Hep_B
```

Workspace - Navigating Directories

There are a number of functions that allow you to “move” around in your folder structure. These are important to know because sometimes you will need to write code that needs to refer to specific folders and files during execution.

```
getwd()
[1] "/Users/fender/TEST.DIR"

setwd("/Users/fender")
getwd()
[1] "/Users/fender"

setwd("/Users/fender/TEST.DIR")
getwd()
[1] "/Users/fender/TEST.DIR"

dir()
[1] "coolpkg" "coolpkg_1.0.tar.gz" "coolpkg.pdf" "coolpkg.Rcheck"
"g.Rd" "stuff.R"
```

Workspace - Listing Files

R also has some functions that list files in a folder. You can do this visually within R Studio although sometimes you will need to use these commands to open and read in files as part of a program.

```
myfiles <- list.files()

str(myfiles)
 chr [1:29] "001.csv" "002.csv" "003.csv" "004.csv" "005.csv" "006.csv" ...

myfiles[1:5]
[1] "001.csv" "002.csv" "003.csv" "004.csv" "005.csv"

# You could write a for-loop to process each and every file

for (ii in 1:length(myfiles)) {
    file <- myfiles[ii]
    # Do something
}
```

Workspace - ls()

R creates an environment for each session you initiate. This is very useful because it accumulates all your variables and objects while you experiment with data.

Over time your environment will accumulate lots of variables. In general this is good because you don't lose anything. The **ls()** function can show you what objects you currently have in your environment.

```
ls()
 [1] "access_log"                       "cntr"
 [3] "ii"                               "init"
 [5] "mpg"                              "mtcars"
 [7] "mymean"                           "myrle"
 [9] "mystr"                            "nhanes1"
[11] "retvec"                           "retvectr"
[13] "SacramentocrimeJanuary2006"       "Sacramentorealestatetransactions"
[15] "SalesJan2009"
```

Workspace - rm()

You can remove one or more objects using the **rm()** function

```
ls()
 [1] "access_log"                         "cntr"
 [3] "ii"                                 "init"
 [5] "mpg"                                "mtcars"
 [7] "mymean"                             "myrle"
 [9] "mystr"                              "nhanes1"
[11] "retvec"                             "retvectr"
[13] "SacramentocrimeJanuary2006"         "Sacramentorealestatetransactions"
[15] "SalesJan2009"

rm(access_log)    # Removes the object named "access_log"

access_log        # Now R can't find it
Error: object 'access_log' not found

rm(mystr,retvec,init)     # Remove more than one object at once
```

Workspace - .Rdata

When you quit R you will be asked if you wish to save your current environment to disk. If you type “y” then all objects, (and their values), will be written to a file called **.Rdata**

This is useful because when you restart R in the same folder it will read **.Rdata** which contains all previously saved information.

```
> q()
Save workspace image? [y/n/c]: y
Goodbye at Mon Oct 1 14:26:47 2012

fenders-macbook:TEST.DIR fender$ ls .Rdata
.Rdata
```

The **.Rdata** file is a “binary” file, (its contents are unintelligible to the eye), that contains all the R objects and values in between sessions. This file could be shared with others if you wanted.

Workspace - save()

You can also save one or more objects to a file using the **save()** function. The inverse of the **save()** function is the **load()** function.

```
my.lm <- lm(mpg ~ wt,mtcars)

ls(my.lm)
[1] "assign" "call" "coefficients" "df.residual" "effects" "fitted.values"
[7] "model"   "qr" "rank" "residuals" "terms" "xlevels"

save(my.lm,file="/Users/myhome/mylmresults")

# You can come back later and load this file

mylmstuff <- load("/Users/myhome/mylmresults")
```

Variables

As in most programming languages, it is customary to store or hold the results of an operation in a variable name.

In R such results are assigned with the symbols "<-" or "=". Variable names are case sensitive.

```
A <- 2.5    # The "<-" is the preferred method of assignment

A = 2.5     # This is equivalent to the above although using the "=" is
            # discouraged except in setting function arguments.

A
[1] 2.5

mynewvar <- X + 3

MYNEWVAR <- X + 3    # Two different variables
```

Variables

- R has several one-letter reserved words: c, q, s, t, C, D, F, I, T
- Variables cannot begin with the period characters "."
- Variable names are case sensitive, so "myvar" is different from "Myvar"
- Variable names cannot begin with numbers or symbols (%,$,_)
- Variable names cannot contain spaves in the name ("my var")

Variables

```
mean.height          .mean.height
smoker               _myvariable
non.smoker           _Mean.height
temp.var             1variable
patient_id           1_variable
Eye.Color            %some.var
State_Population     some.var
disease.state        "some var"
White_Cell_Count     $myvar
jobTitle
```

Reading and Writing Files

R has a number of builtin example data frames. One common way to import data is via ".csv" files. Before we consider reading a .csv file let's first create one.

```
head(mtcars)
                mpg cyl disp hp drat wt qsec vs am gear carb
Mazda RX4       21.0 6 160 110 3.90 2.620 16.46 0 1 4 4
Mazda RX4 Wag   21.0 6 160 110 3.90 2.875 17.02 0 1 4 4
Datsun 710      22.8 4 108  93 3.85 2.320 18.61 1 1 4 1
Hornet 4 Drive  21.4 6 258 110 3.08 3.215 19.44 1 0 3 1

write.table(mtcars,file="mtcars.csv",
            row.names=TRUE,               # Row names get saved
            col.names=TRUE,               # Header gets saved
            sep=",")                      # Field seperator is ,

$ head mtcars.csv
"mpg","cyl","disp","hp","drat","wt","qsec","vs","am","gear","carb"
"Mazda RX4",21,6,160,110,3.9,2.62,16.46,0,1,4,4
"Mazda RX4 Wag",21,6,160,110,3.9,2.875,17.02,0,1,4,4
```

Reading and Writing Files

The first line of mtcars.csv describes the column names. Each subsequent row represents an observation with each field being separated by a ",". Let's read it in:

```
mycars <- read.table("mtcars.csv",header=TRUE,sep=",")

head(mycars)
                   mpg cyl disp  hp drat    wt  qsec vs am gear carb
Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
Valiant           18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
```

Reading Files from an URL

You can read CSV files from the Internet as long as you know the URL. Here is a simple case

```
url <- "https://raw.githubusercontent.com/steviep42/bootcamp/master/data/airports.csv"
airports <- read.csv(url)
head(airports)
```

```
 faa                            name      lat       lon  alt tz dst
1 04G             Lansdowne Airport 41.13047 -80.61958 1044 -5   A
2 06A  Moton Field Municipal Airport 32.46057 -85.68003  264 -5   A
3 06C           Schaumburg Regional 41.98934 -88.10124  801 -6   A
4 06N               Randall Airport 41.43191 -74.39156  523 -5   A
5 09J         Jekyll Island Airport 31.07447 -81.42778   11 -4   A
6 0A9 Elizabethton Municipal Airport 36.37122 -82.17342 1593 -4   A
```

Reading Files - Commas

Sometimes we get numerical data that has delimiters within it. Like with numbers in the thousands. They can contain commas to offeset every three zeroes. If you make no effort R will think that they are characters.

```
url <- "https://raw.githubusercontent.com/steviep42/bootcamp/master/data/employees.csv"
employees <- read.csv(url,sep="\t")

head(employees)
          name age salary
1  Frank,Smith  34 10,000
2   Jones,Carl  22 12,000
3   Smith,Mary  26 13,000
4 Johnson,Lisa  32 13,500

str(employees)
'data.frame': 4 obs. of  3 variables:
 $ name  : Factor w/ 4 levels "Frank,Smith",..: 1 3 4 2
 $ age   : int  34 22 26 32
 $ salary: Factor w/ 4 levels "10,000","12,000",..: 1 2 3 4
```

Reading Files - Commas

- We can use **coercion** to “persuade” a variable that is character to be a numeric variable
- First we use a function to eliminate the comma since its presence is what makes R think the variable is a character.
- Then we use the **as.numeric()** function to change the variable into a numeric.

```
url <- "https://raw.githubusercontent.com/steviep42/bootcamp/master/data/employees.csv"
employees <- read.csv(url,sep="\t")

employees$salary <- as.numeric(gsub(",","",employees$salary))

str(employees)
'data.frame': 4 obs. of  3 variables:
 $ name  : Factor w/ 4 levels "Frank,Smith",..: 1 3 4 2
 $ age   : int  34 22 26 32
 $ salary: num  10000 12000 13000 13500
```

A Real Example

Check out the Federal Election Commission Website for information on Campaign Contributions by Individuals. There are other types of information also but for now we will look at donations from people.

http://www.fec.gov/finance/disclosure/ftpdet.shtml

A Real Example

If you go to the download link and find the file corresponding to individual contributions you will see that the file has 12,395,164 records. There is also a link to the data dictionary link that you can click. `http://www.fec.gov/finance/disclosure/metadata/indiv_header_file.csv` The size of the file is about 426 Megabytes. We won't work with that. Instead we will work with a prepared file that has information relating only to Georgia.

`http://www.fec.gov/finance/disclosure/ftpdet.shtml#a2015_2016`

2015 - 2016 Data Files

Name	Data File	Total Records	Updated	Format Description
Committee Master File	cm16.zip	17175	06-SEP-2016	CM Data Dictionary
Candidate Master File	cn16.zip	7331	06-SEP-2016	CN Data Dictionary
Candidate Committee Linkage File	ccl16.zip	6292	06-SEP-2016	CCL Data Dictionary
Any Transaction from One Committee to Another	oth16.zip	893643	04-SEP-2016	OTH Data Dictionary
Contributions to Candidates (and other expenditures) from Committees	pas216.zip	233391	04-SEP-2016	PAS2 Data Dictionary
Contributions by Individuals	indiv16.zip	12395164	04-SEP-2016	INDIV Data Dictionary
Operating Expenditures	oppexp16.zip	1196454	04-SEP-2016	OPPEXP Data Dictionary

A Real Example

Let's get to work on this file.

```
url <- "https://raw.githubusercontent.com/steviep42/bootcamp/master/data/georgia_campaign.txt"

# Rather than read it directly from the Internet we'll first download it

download.file(url,"georgia_campaign.txt")

# Let's take a peek at the first three lines

system("head -3 georgia_campaign.txt")

C00076182|N|Q1|P|15951125081|15|IND|JAMES, JIM|HOSCHTON|GA|305481390|MAREL STORK POULTRY PROCESSING|VP OF TECHN
C00076182|N|Q1||15951125081|15|IND|JAMES, JIM|HOSCHTON|GA|305481390|MAREL STORK POULTRY PROCESSING|VP OF TECHNI
C00186064|N|M4||15970338248|15|IND|NUNNERY, JOHN|COLUMBUS|GA|319062001|PNC BANK NA|SR. VICE PRESIDENT|03312015|

# Read it in

gacamp <- read.csv("georgia_campaign.txt",sep="|",header=FALSE)

head(gacamp,1)
         V1 V2 V3 V4          V5 V6  V7         V8       V9 V10       V11
1 C00076182  N Q1  P 15951125081 15 IND JAMES, JIM HOSCHTON  GA 305481390

                            V12                     V13     V14 V15 V16
1 MAREL STORK POULTRY PROCESSING VP OF TECHNICAL SERVICES 3242015 300

1 A0DAECF187E8D4B41ACF 1002289        4.04132e+18
2 A49D962C4ECF047AB97B 1002289        4.04132e+18
```

A Real Example

Let's get to work on this file.

```
url <- "http://www.fec.gov/finance/disclosure/metadata/indiv_header_file.csv"

( colnames <- read.csv(url,header=FALSE) )

 [1] CMTE_ID        AMNDT_IND      RPT_TP         TRANSACTION_PGI IMAGE_NUM
 [6] TRANSACTION_TP ENTITY_TP      NAME           CITY            STATE
[11] ZIP_CODE       EMPLOYER       OCCUPATION     TRANSACTION_DT  TRANSACTION_AMT
[16] OTHER_ID       TRAN_ID        FILE_NUM       MEMO_CD         MEMO_TEXT
[21] SUB_ID
<0 rows> (or 0-length row.names)

names(gacamp) <- as.vector(colnames)
```

Reading Tabular Data

You already know that you can read CSV files directly a URL. But you can also read data directly from a table from a website. Take a look at this example. Let's say we want to get the data from this link on Wikipedia `https://en.wikipedia.org/wiki/World_population`. This appears to be the 6th table on the page.

10 most populous countries

Rank	Country / Territory	Population	Date	Approx. % of world population	Source
1	China[note 2]	1,378,580,000	September 5, 2016	18.8%	[94]
2	India	1,330,600,000	September 5, 2016	18.1%	[95]
3	United States	324,405,000	September 5, 2016	4.42%	[96]
4	Indonesia	257,900,000	March 16, 2016	3.43%	[97]
5	Brazil	206,610,000	September 5, 2016	2.81%	[98]
6	Pakistan	194,169,000	September 5, 2016	2.64%	[99]
7	Nigeria	187,200,000	March 16, 2016	2.36%	[100]
8	Bangladesh	161,030,000	September 5, 2016	2.19%	[101]
9	Russia	141,800,000	March 16, 2016	1.99%	[102]
10	Japan	126,700,000	March 16, 2016	1.73%	[103]

Reading Tabular Data

```
url <- "https://en.wikipedia.org/wiki/World_population"

# The following will "parse" the underlying HTML for the page

my_html <- read_html(url)

# Next we want to get the "nodes" from the parsed HTML that correspond
# to tables. There are in fact many tables on this page but we are
# trying to target the one that has the ten most populous countries

my_tables <- html_nodes(my_html,"table")[[6]]

populous_table <- html_table(my_tables)
```

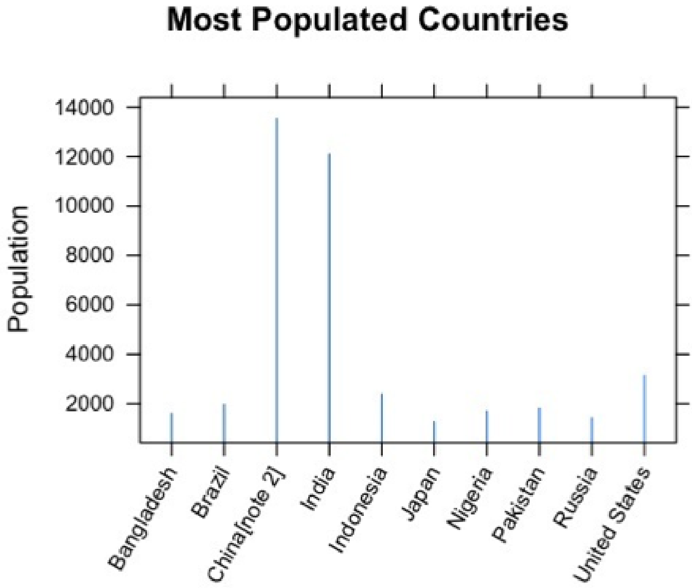
Reading Tabular Data

```
Rank Country / Territory    Population              Date
1      1        China[note 2] 1,378,580,000 September 5, 2016
2      2                India 1,330,600,000 September 5, 2016
3      3        United States   324,405,000 September 5, 2016
4      4            Indonesia   257,900,000    March 16, 2016
5      5               Brazil   206,610,000 September 5, 2016
6      6             Pakistan   194,169,000 September 5, 2016
7      7              Nigeria   187,200,000    March 16, 2016
8      8           Bangladesh   161,030,000 September 5, 2016
9      9               Russia   141,800,000    March 16, 2016
10    10                Japan   126,700,000    March 16, 2016
   Approx. % of world\npopulation Source
1                           18.8%   [94]
2                           18.1%   [95]
3                           4.42%   [96]
4                           3.43%   [97]
5                           2.81%   [98]
6                           2.64%   [99]
7                           2.36%  [100]
8                           2.19%  [101]
9                           1.99%  [102]
10                          1.73%  [103]
```

Reading Tabular Data

```
# Okay this looks close but there is more work to be done to clean it
# all up. We don't need columns 4 through 6

populous_table <- populous_table[,-4:-6]

populous_table$Population <- as.numeric(gsub(",","",
                                       populous_table$Population))/100000

names(populous_table) = c("Rank","Country","Population")

library(lattice)
xyplot(Population ~ as.factor(Country), populous_table,
       scales = list(x = c(rot=60)),
       type="h",main="Most Densely Populated Countries")
```

Reading Tabular Data



Reading External Files

Here is a summary of tools to read in various external files, other statistical package formats, and relational databases:

Package/Function	Description
readxl	Reads Excel Worksheets and Workbooks
gdata	Reads Excel Worksheets and Workbooks
XLConnect	Reads Excel Worksheets and Workbooks
RODBC	Reads Excel Worksheets and Workbooks
reader	Read flat/tabular text files from disk
read.table	Read tabular data from disk
read.csv	Read tabular data from disk
fread	Read large data files from disk
haven	Import SAS, STATA, and SPSS files
foreign	Import SAS, STATA, SPSS, Systat, and Weka files
RMySQL	Connect to MySQL Databases
ROracle	Connect to Oracle Databases
RPostgres	Connect to Postgres Databases

Reading External Files

Here is an example of reading a SAS dataset. Note that this is a proprietary binary format used by SAS although the format can be decoded using functions found in the haven addon package.

```
# SAS datsets can be found at http://www.stats.ox.ac.uk/pub/datasets/csb/
# For a list of cool places to find interesting data look at
# https://catalog.data.gov/dataset?groups=education2168#topic=education_navigation
# http://www.census.gov/programs-surveys/acs/news/data-releases.html
# https://github.com/caesar0301/awesome-public-datasets

library(haven)

sasdataset <- "http://www.principlesofeconometrics.com/poe4/data/sas/lasvegas.sas7bdat"

las_vegas_loans <- read_sas(sasdataset)

head(las_vegas_loans)
  LVR REF INSUR   RATE AMOUNT CREDIT TERM ARM DELINQUENT
1  80   0     1  6.355 1.5760    532   30   1          0
2  89   1     1  6.875 3.1595    703   30   1          0
3  80   1     1  7.080 1.7600    648   30   1          0
4  80   0     0 12.855 1.9680    599   30   1          1
5  70   1     0  5.760 1.8620    626   30   1          0
6  80   0     1  5.555 2.0800    742   30   1          0
```

Reading Excel Files

It is possible to read an Excel spreadsheet although the best thing to do is to first save the spreadsheet into a .csv file and then import it into R using **read.table()** function. However, you can read the spreadsheet directly from a file using the add on **RODBC** package.

```
library(RODBC)

channel <- odbcConnectExcel("examp.xls")

## list the spreadsheets
sqlTables(channel)
  TABLE_CAT TABLE_SCHEM TABLE_NAME TABLE_TYPE REMARKS
1 C:\\bdr NA Sheet1$ SYSTEM TABLE NA
2 C:\\bdr NA Sheet2$ SYSTEM TABLE NA
3 C:\\bdr NA Sheet3$ SYSTEM TABLE NA
4 C:\\bdr NA Sheet1$Print_Area TABLE NA

## retrieve the contents of sheet 1, by either of

sh1 <- sqlFetch(channel, "Sheet1")
sh1 <- sqlQuery(channel, "select * from [Sheet1$]")
```

Reading Files from Other Packages

R can process XML files which is a format that underlies many websites that distribute interesting data. As an example we can use R and XML to "geocode" cities.

`https://developers.google.com/maps/documentation/geocoding/`

Reading XML


```
- <GeocodeResponse>
    <status>OK</status>
  - <result>
      <type>locality</type>
      <type>political</type>
      <formatted_address>Atlanta, GA, USA</formatted_address>
    - <address_component>
        <long_name>Atlanta</long_name>
        <short_name>Atlanta</short_name>
        <type>locality</type>
        <type>political</type>
      </address_component>
    - <address_component>
        <long_name>Fulton</long_name>
        <short_name>Fulton</short_name>
        <type>administrative_area_level_2</type>
        <type>political</type>
      </address_component>
```

Reading XML

As an example we'll get the latitude and longitude corresponding to the city of Atlanta, Georgia

```
library(RCurl)
library(XML)

my.url <- "http://maps.googleapis.com/maps/api/geocode/xml?
address <- Atlanta,GA&sensor=false"
txt <- getURL(my.url)
hold <- xmlTreeParse(txt,useInternalNodes=TRUE)

hold
<?xml version="1.0" encoding="UTF-8"?>
<GeocodeResponse>
<status>OK</status>
<result>
<type>locality</type>

place <- getNodeSet(hold,"//GeocodeResponse/result[1]/geometry/location[1]/*")
as.numeric(sapply(place,xmlValue))
[1] 33.74900 -84.38798
```

Sinking Your Work

You can capture the output of your work using the **save()** function. But you can use the **cat**, **write** to print out variable values as your code executes.

But you can also **sink** or dump variable values into a file for later inspection. Let's say we have the following code.

```
set.seed(123)
x <- rnorm(10)
y <- rnorm(10)

print(x)
cat("y =", y, "\n")

t.test(x,y)
plot(x,y)
```

The output from this code is on the next slide

Sinking Your Work

```
set.seed(123)
x <- rnorm(10)
y <- rnorm(10)

print(x)
[1] -0.56047565 -0.23017749 1.55870831 0.07050839 0.12928774 1.71506499
[7] 0.46091621 -1.26506123 -0.68685285 âĂŘ0.44566197

cat ("y =", y, "\n")
y = 1.224082 0.3598138 0.4007715 0.1106827 âĂŘ0.5558411 1.786913 0.4978505
   -1.966617 0.7013559 -04727914

t.test(x,y)
     Welch Two Sample t-?âĂŘtest
data: x and y
t = -0.3006, df = 17.872, p-value = 0.7672
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.0710488 0.8030562
sample estimates:
mean of x mean of y
0.07462564 0.20862196
```

Sinking Your Work

If desired we could redirect all the output from the print, cat, t.test to a file. When we run the following we don't see any output. To see the output we have to look at the file `my.results.txt`

```
sink("my.results.txt") # All output will now go to "my.results.txt"

set.seed(123)
x <- rnorm(10)
y <- rnorm(10)

print(x)

cat ("y =", y, "\n")

t.test(x,y)

plot(x,y)

sink()     # This will deactivate the redirection
```

Sinking Your Work

Check out the file my.results.txt Note that any graphics files created by the plot command will go into a file called Rplots.pdf

```
$ more my.results.txt
[1] -0.56047565 -0.23017749 1.55870831 0.07050839 0.12928774 1.71506499
[7] 0.46091621 -1.26506123 -0.68685285 -0.44566197
y = 1.224082 0.3598138 0.4007715 0.1106827 -0.5558411 1.786913 0.4978505
-1.966617 0.7013559 -0.4727914

Welch Two Sample t-test

data: x and y
t = -0.3006, df = 17.872, p-value = 0.7672
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -1.0710488 0.8030562
sample estimates:
  mean of x mean of y
0.07462564 0.20862196
```

Sinking Your Work

If you want more control of the format of the plot output then you can use one of the functions desgined to create plots in a known format (PNG, JPEG, PDF).

```
set.seed(123)
x <- rnorm(10)
y <- rnorm(10)

print(x)
cat ("y =", y, "\n")

t.test(x,y)

pdf("myplots.pdf") # Redirects plots to myplots.pdf

plot(x,y)

dev.off() # Turns off plot redirection
```