

R Tutorial - Introduce R

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What is R?

R is a language and environment for statistical computing and graphics....R provides a wide variety of statistical (linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, clustering, ...) and graphical techniques, and is highly extensible. The S language is often the vehicle of choice for research in statistical methodology, and R provides an Open Source route to participation in that activity.

—The R Project for Statistical Computing, http://www.r-project.org/

Open source + highly extensibility + era of data science

→ Currently 6438 packages in CRAN package repository (the official one)



R is vectorized

```
f = 1 * 11 + 2 * 22 + 3 * 33

> A = c(1, 2, 3)

> B = c(11, 22, 33)

> f = A * B

> f

[1] 11 44 99
```

Good for statistics Good for data



R for data science

Advantage: designed for statistical analysis, more straightforward. For example: linear regression can be performed with a single line in R. While in Python, it requires the use of several third-party libraries to represent the data (NumPy), perform the analysis (SciPy), and visualize the results (mat-plotlib).

Disadvantage: does not scale well with large data.

Big companies like Google use R as their "data sandbox" to play with data and experiment with new machine learning methods. If it works well, further use something like C.

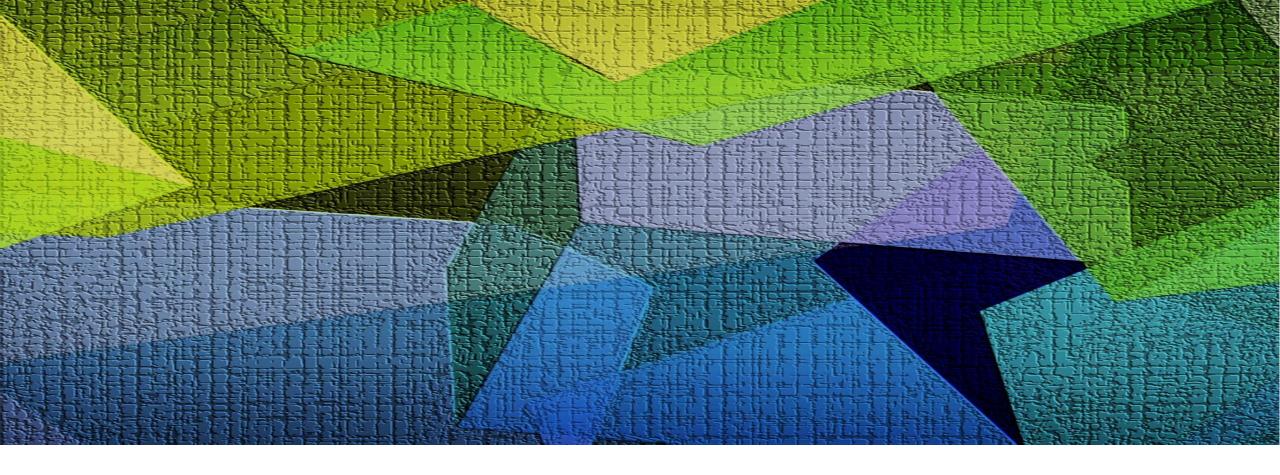
This doesn't mean we cannot use R for big data – sample!



Overview

- R data types
- Basic operations
- Reading and writing data
- Statistical simulation
- Basic plotting systems (overview)





R Tutorial - R Data Types

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Hello world

```
C <- "Hello World" # type Enter
print(c) # print some text
# anything after a hash (#) is a comment</pre>
```



Basic data types

Five basic classes (atomic classes)

Character, Numeric, Integer, Complex, Logical

Assignment operator

```
n <- 10  # assign value 10 to variable 'n'
0.3 -> s  # the arrow can go both ways
m = TRUE  # can also use equal (=) operator for assignment
<- and = do have some difference, mainly about the scope...
Google's R style guide simplifies this issue by prohibiting the
"=" for assignment. Not a bad choice.(http://google-
styleguide.googlecode.com/svn/trunk/google-r-
style.html#assignment)

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```

Numbers

Integer:

Numbers in R are generally treated as numeric objects (i.e. double precision real numbers like 3.1415926...)

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.

Infinity (Inf):

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.

Case sensitive! And in general, objects in R is case sensitive.



Dates and times

Date: represented by the date class

Time: POSIXct class (a very large integer);

POSIXIt class (as a list, stores a bunch of useful meta-data)

```
> x <- as.Date("2015-03-26")
```



Dates and times

```
> x < - Sys.time()
> X
[1] "2015-03-23 21:28:10 PDT"
> p < - as.POSIXlt(x)
> names(unclass(p)) # unclass(p) is a list object
 [1] "sec" "min" "hour" "mday" "mon"
 "year" "wday" "yday"
 [9] "isdst" "zone" "qmtoff"
> p$sec
[1] 10.89086
```



Dates and times

details

```
strptime function in case your times are written in
a different format as characters

> timeString <- "March 26, 2015 12:30"
> x <- strptime(timeString, "%B %d, %Y %H:%M")
> class(x)
[1] "POSIXIt" "POSIXt"
> x
[1] "2015-03-26 12:30:00 PDT"
```

For the formatting strings, check ?strptime for

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Compound objects

```
Vector,
List,
Factor,
Matrix,
Data frame, etc.
```



Vector

The most basic object is a vector

A vector can only contain objects of the same class



Vector - using the vector() function

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

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



Vector - creating vectors (1)

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

```
> x <- c(0.5, 0.6) #number
> x <- c(TRUE, FALSE) # logical
> x <- c(T, F) #logical
> x <- c("a", "b", "c") #character
> x <- c(1+0i, 2+4i) #complex</pre>
```



Vector - creating vectors (2)

: operator

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

The : operator is used to create integer sequences.



List

List is a special type of vector:

- 1. Can contain elements of different classes (either basic class or compound class);
- 2. Each element of list can have name.

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
```



List

```
> x <- list(a=c(T,T,F,F), b=2)
> x
$a
[1] TRUE TRUE FALSE FALSE
$b
[1] 2
```



Factor

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.

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.

```
> x <- factor(c("yes",</pre>
"yes", "no", "yes",
"no"))
> x
[1] yes yes no yes no
Levels: no yes
> table(x)
X
 no yes
```



Factor - changing the order of levels

The order of the levels can be set using the levels argument to factor().

This can be important in linear modeling because the first level is used as the baseline level.

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



Matrix

Matrix is 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
```



Matrix - column-wise construction

Matrix is constructed *column-wise*, so entries can be thought of starting in the "upper left" corner and running down the columns.

```
> 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]
[1,] 1 3 5 7
> n < -1:10
> dim(n) = c(3,5)
Error in dim(n) = c(3, 5):
 dims [product 15] do not match
the length of object [10]
```



Matrix - cbind() and rbind()

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



Matrix - naming matrix



Data frames!

Data frames are used to store tabular data.

Unlike matrices, data frames can store different classes of objects in each column; while 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()

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



Coercion

```
> y <- c(1.7, "a") #character
> y
[1] "1.7" "a"
> y <- c(TRUE, 2) #numeric
> y
[1] 1 2
```

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

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Coercion - 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)
    "0" "1" "2" "3" "4"
11511 11611
> as.complex()
complex(0)
> as.complex(x)
[1] 0+0i 1+0i 2+0i 3+0i
4+0i 5+0i 6+0i
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```

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Missing values

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

NaN: Not a Number (like 2/0)
NA: a missing value and has various forms - NA_integer_,
NA_character_, etc.

NaN value is also NA but the converse is not true.

```
> 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 creation

- c(...) generic function to combine arguments with the default forming a vector; with recursive=TRUE descends through lists combining all elements into one vector
- from: to generates a sequence; ":" has operator priority; 1:4 + 1 is "2,3,4,5"
- seq(from, to) generates a sequence by= specifies increment; length=
 specifies desired length
- seq(along=x) generates 1, 2, ..., length(along); useful for for loops
- rep(x,times) replicate x times; use each= to repeat "each" element of x each times; rep(c(1,2,3),2) is 1 2 3 1 2 3; rep(c(1,2,3),each=2) is 1 1 2 2 3 3
- data.frame(...) create a data frame of the named or unnamed
 arguments; data.frame(v=1:4, ch=c("a", "B", "c", "d"), n=10);
 shorter vectors are recycled to the length of the longest
- list(...) create a list of the named or unnamed arguments;
 list(a=c(1,2),b="hi",c=3i);
- array(x,dim=) array with data x; specify dimensions like dim=c(3,4,2); elements of x recycle if x is not long enough
- matrix(x,nrow=,ncol=) matrix; elements of x recycle
- factor (x,levels=) encodes a vector x as a factor
- gl(n,k,length=n*k,labels=1:n) generate levels (factors) by specifying the pattern of their levels; k is the number of levels, and n is the number of replications
- expand.grid() a data frame from all combinations of the supplied vectors or factors
- **rbind(...)** combine arguments by rows for matrices, data frames, and others
- cbind(...) id. by columns



Variable conversion

```
as.array(x), as.data.frame(x), as.numeric(x),
       as.logical(x), as.complex(x), as.character(x),
       ... convert type; for a complete list, use methods (as)
Variable information
is.na(x), is.null(x), is.array(x), is.data.frame(x),
       is.numeric(x), is.complex(x), is.character(x),
       ... test for type; for a complete list, use methods (is)
length (x) number of elements in x
dim(x) Retrieve or set the dimension of an object; dim(x) < -c(3,2)
dimnames (x) Retrieve or set the dimension names of an object
nrow(x) number of rows; NROW(x) is the same but treats a vector as a one-
      row matrix
ncol(x) and NCOL(x) id. for columns
class(x) get or set the class of x; class(x) <- "myclass"</pre>
unclass (x) remove the class attribute of x
attr(x, which) get or set the attribute which of x
attributes (obj) get or set the list of attributes of obj
```



Summary of R Data Types

- 1. Basic data types (dates and times)
- 2. Compound objects
- 3. Coercion
- 4. Missing values



Exercise

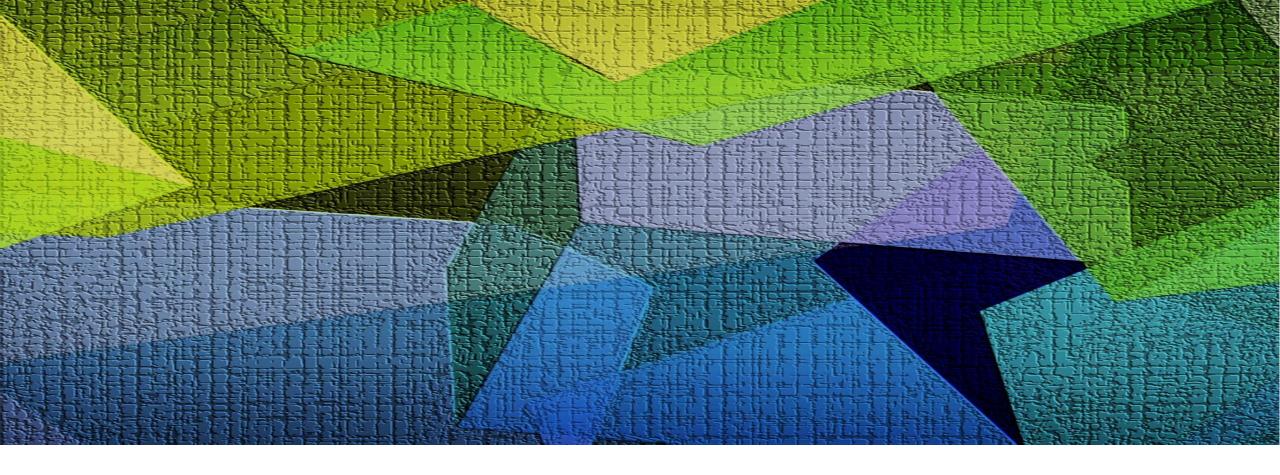
Declare two vectors with 3 elements each. Call these x and y. Now do the following:

- ➤ Use rbind() and cbind() to create a matrix from these two variables. Observe the difference in structure resulting from cbind() and rbind() functions.
- >Name the columns of the matrix.
- Create a data frame from x and y and give the columns appropriate names.



Exercise





R Tutorial - Basic Operations

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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 object. 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 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 – in vector and matrix

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

```
> x <- matrix(1:6, 2, 3)
> x[1,2]
[1] 3
> x[1,] # Entire first row.
[1] 1 3 5
> x[,2] # Entire second
column.
[1] 3 4
```



Subsetting - in matrix (the exception of [)

By default, when a single element of a matrix is retrieved, it is returned as a vector of length 1 rather than a 1 × 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
> x[1,]
```

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

```
> x[1,,drop=FALSE]
     [,1] [,2] [,3]
[1,] 1 3 5
```



Subsetting - in list

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

Extracting multiple elements of a list:

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

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Subsetting - partial matching

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

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



Control structures: conditional

Conditional:

```
if (logical.expression) {
   statements
else if (another.logical.expression) {
   statements
else
   alternative.statements
```

else if, else branch is optional



Control structures: loop

for-loop:

```
for(i in 1:10) {
   print(i*i)
repeat-loop:
i=1
Repeat {
 i = i + 1
 if (i>=10) break # the
only
# way to get out of the
loop
```

while-loop:

```
i=1
while(i<=10) {
    print(i*i)
    i=i+sqrt(i)
}</pre>
```



Control structures: loop

R can support looping. But

1. Looping is not recommended for compound objects like lists, vectors, or data.frames, etc. For example, a loop could be used to multiply all elements by 2, but the loop is implicit.

$$> x < - c(1, 2, 3)$$

> $x * 2$
[1] 2 4 6

2. Control structures mentioned here are primarily useful for writing programs; for command-line interactive work, the *apply functions (like lapply, sapply, etc.) are more useful.



Build-in functions

Numeric functions:

```
abs(x) absolute value
sqrt(x) square root
ceiling(x) ceiling(3.475) is
4
floor(x) floor(3.475) is 3
trunc(x) trunc(5.99) is 5
round(x, digits=n)
round(3.475, digits=2) is
3.48
```

• • •

Character functions:

```
paste(..., sep="") Concatenate strings
after using sep string to seperate them.
paste("x",1:3,sep="") returns c("x1","x2"
"x3")
paste("x",1:3,sep="M") returns
c("xM1","xM2" "xM3")
grep(pattern, x , ignore.case=FALSE,
fixed=FALSE) Search for pattern in x.
If fixed =FALSE then pattern is a regular
expression. If fixed=TRUE then pattern is
a text string. Returns matching indices.
grep("A", c("b","A","c"), fixed=TRUE)
returns 2
```



Build-in functions

```
Statistical functions
rnorm(), dunif(), mean(), sum()...

More complete list:
http://www.statmethods.net/management/fun
ctions.html
```



User-written function

```
foo <- function(x,y=1,...) {
  cat("extra args:",...,"\n")
  sqrt(x)+sin(y)

foo(1,2,3,"bar")

foo(1)
foo(y=3,x=7) # named arguments in any order</pre>
The three-dots allows:
1 .an arbitrary number and variety of arguments
other functions
```

Type function name to see code (works for any function)

foo



str function

```
str compactly displays the internal structure of an R
object (data object or function)
1. A diagnostic function and an alternative to summary()
for data object
2. It's especially well suited to compactly display the
  (abbreviated) contents of (possibly nested) list
It tells you what's in the object.
Used for functions: tells you the function's arguments.
Try: > str(lm)
```





```
apply: apply a function over the margins of an array
> x < - matrix(c(1, 2, 3, 4), 2, 2)
> X
    [,1] [,2]
[1,] 1 3
[2,] 2 4
> apply(x, 1, sum)
[1] 4 6
> apply(x, 2, sum)
[1] 3 7
```



```
tapply: apply a function over subsets of a vector
> score <- c(90, 79, 94, 85)
> gender <- factor(c("Male", "Female", "Female", "Male"))
> tapply(score, gender, mean)
Female Male 86.5 87.5
```



```
split: an auxiliary function. A common idiom is split
followed by lapply
> score <- c(90, 79, 94, 85)
> gender <- factor(c("Male", "Female", "Female", "Male"))</pre>
> splitted <- split(score, gender)</pre>
> splitted
$Female
[1] 79 94
$Male
[1] 90 85
> lapply(splitted, mean)
$Female
[1] 86.5
$Male
[1] 87.5
```



```
mapply: multi-variable input, applies a function in
parallel over a set of arguments

> mapply(rep, c(0,2), c(3,5)) # input certain combinations
## <- list(rep(0,3), rep(2,5)), it vectorizes a function
[[1]]
[1] 0 0 0

[[2]]
[1] 2 2 2 2 2 2</pre>
```



Don't worry if you forget the logics of *apply functions. You can always use ?lapply, str(lapply), or Google/Bing to check.

> str(tapply)
function (X, INDEX, FUN = NULL, ..., simplify = TRUE)



Packages

For almost everything you want to do with R, there's probably a package written to do just that.

A list of packages in the official packages repository CRAN can be found here: http://cran.fhcrc.org/web/packages/.

If you need a package, it can be installed very easily from within R using the command:

```
install.packages("packagename") # if package already
installed, it'll bypass
```

Libraries in Github can be installed using devtools library.



Working directory & R script

You can set the working directory from the menu if using the R-gui (*Change dir...*) or from the R command line:

To see a list of the files in the current directory:

```
dir() # returns a list of
strings of file names
dir(pattern=".R$") # list of
files ending in ".R"
dir("C:\\Users") # show files in
directory C:\Users
```

Run a script:

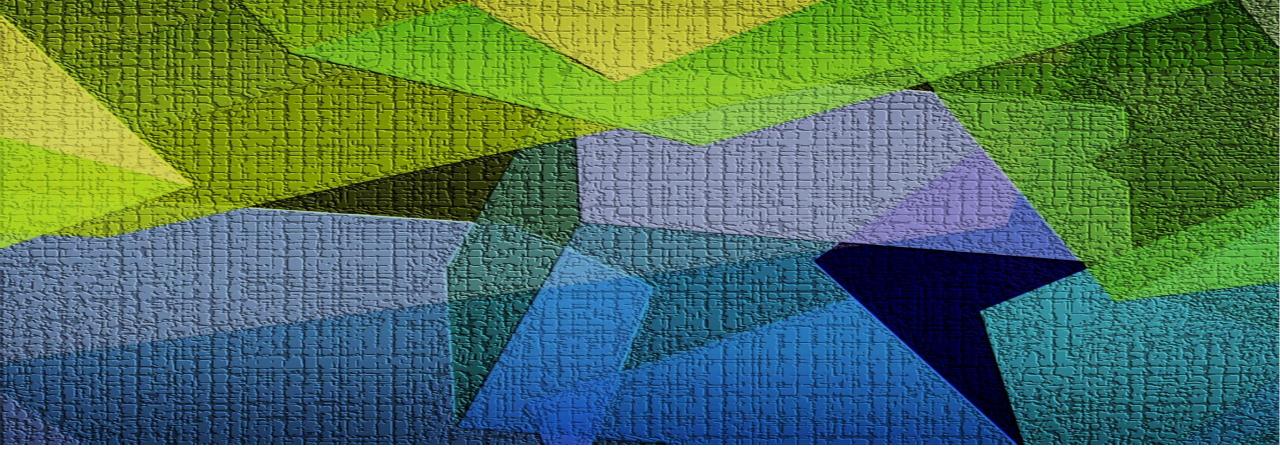
```
source("helloworld.R") # execute
a script
```



Summary of Basic Operations

- 1. Subsetting
- 2. Control structures
- 3. Build-in functions
- 4. User written function
- 5. "*apply"
- 6. Packages
- 7. working directory and R script





R Tutorial

- Reading and Writing Data

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Reading/writing local flat files

read.table, read.csv, and readLines

CSV stands for 'Comma Separated Values'

```
> titanic_data <- read.csv("Titanic.csv")
> head(titanic_data, 3)

X Class Sex Age Survived Freq
1 1 1st Male Child No 0
2 2 2nd Male Child No 0
3 3 3rd Male Child No 35
```



Reading/writing local flat files

```
> line1 <- readLines("Titanic.csv", 1)
> line1
[1]
"\",\"Class\",\"Sex\",\"Age\",\"Survived\",\"Freq\""
```

write.table, write.csv, and wirteLines

CSV stands for 'Comma Separated Values'

```
> write.table(titanic data, "new Titanic.csv")
```



Reading/writing local flat files

Notice the parameters before reading/writing!

Ex.: 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?

Reading/writing Excel files

```
read.xlsx, write.xlsx, or read.xlsx2, write.xlsx2 (faster, but unstable)
```

```
# Install the xlsx library
> install.packages('xlsx')
# Load the library
> library(xlsx)
# Now you can Read the Excel file
> titanic data <- read.xlsx("titanic3.xls", sheetIndex=1)</pre>
```



Connection interfaces

In practice, we don't need to deal with connection interface directly. Connections can be made to files or to other, more exotic channels:

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



Connection interfaces

Simple example

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Reading XML/HTML files

```
> library(XML) # you need to install this library
> url <- "http://www.w3schools.com/xml/simple.xml"</pre>
> doc <- xmlTreeParse(url, useInternal=TRUE) # also works for html
> rootNode <- xmlRoot(doc)</pre>
> rootNode[[1]]
<food>
  <name>Belgian Waffles
  <price>$5.95</price>
  <description>Two of our famous Belgian Waffles with plenty of
real maple syrup</description>
  <calories>650</calories>
                                                        datasciencedoio
</food>
```

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Reading XML/HTML files

```
> rootNode[[1]][[1]]
<name>Belgian Waffles</name>
> xpathSApply(rootNode, "//name", xmlValue)
[1] "Belgian Waffles" "Strawberry Belgian Waffles"
"Berry-Berry Belgian Waffles" "French Toast" "Homestyle
Breakfast"
```

xpath: /node: top level node; //node: node at any level;
node[@attr-name]: node with an attribute name;
node[@attr-name = 'bob']: node with an attribute name = 'bob'



Reading/writing JSON

JSON: Javascript object notation.

Common format for data from application programming interfaces (APIs). An alternative to XML

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Reading/writing JSON



Connect to a data base

JSONPackages: RmySQL, RpostresSQL, RODBC, RMONGO

```
> library(RMySQL) # load the library
> ucscDb <- dbConnect(MySQL(), user="genome", host="genome-
mysql.cse.ucsc.edu")
> data <- dbGetQuery(ucscDb, "show databases;") # get the output of SQL query
as data frame in R
> head(data)
            Database
1 information schema
             ailMel1
             allMis1
             anoCar1
             anoCar2
             anoGam1
> dbDisconnect(ucscDb) # don't forget to close the connection
                                                                    datasciencedojo
```

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Textual format

- 1. With the metadata
- 2. Editable in the case of corruption, potentially recoverable
- 3. Adhere to the "Unix philosophy" (*Eric Raymond's 17 Unix Rules*)
- 4. Not space-efficient

Functions to read/write texual format

dput vs. dget dump vs. source save vs. load



Textual format

Example:

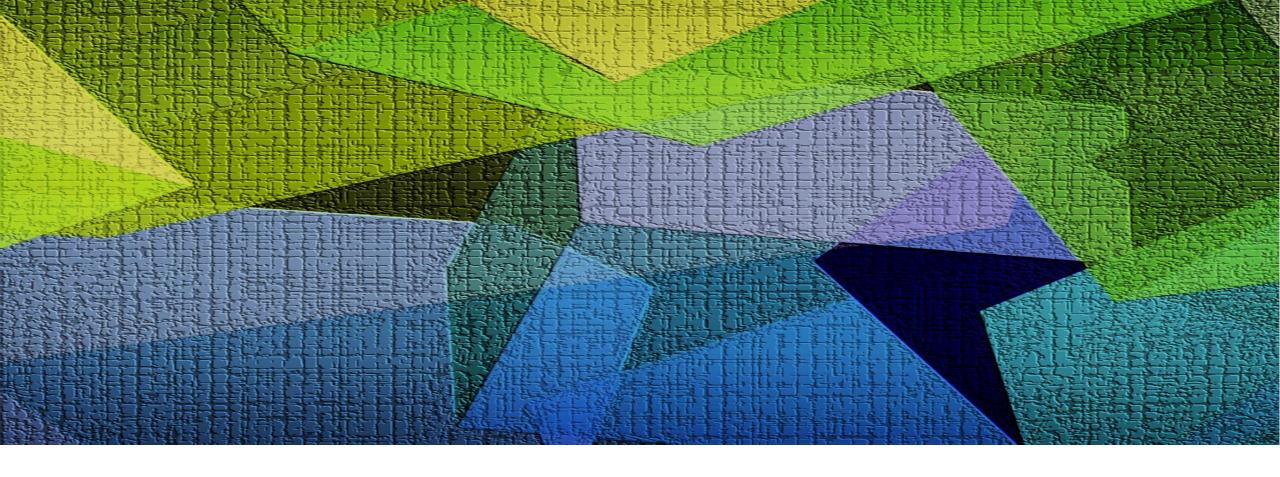
```
save(R_object1, R_object2, file="R_objects.RData")
load(file="R objects.RData")
```



Summary – R/W Data

- 1. R/W local flat files
- 2. R/W local Excel files
- 3. Connection interfaces
- 4. Reading XML/HTML files
- 5. R/W to JSON
- 6. Connect to a database
- 7. Textual format





R Tutorial - Statistical Simulation (optional)

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Statistical Simulation

Probability distribution functions usualy have four functions associated with them. The functions are prefixed with:

- d for density, like dnorm()
- r for random number generation, like rnorm()
- p for cumulative distribution, like pnorm()
- q for quantile function, like qnorm()



Statistical Simulation

Example of normal distribution:

```
> dnorm(0, mean = 0, sd = 1)
[1] 0.3989423
> dnorm(10, mean = 0, sd = 1)
[1] 7.694599e-23
> pnorm(0, mean = 0, sd = 1)
[1] 0.5
> pnorm(1, mean = 0, sd = 1)
[1] 0.8413447
> pnorm(100, mean = 0, sd = 1)
[1] 1
```

```
> qnorm(0.5, mean = 0, sd = 1)
[1] 0
> qnorm(0, mean = 0, sd = 1)
[1] -Inf
> qnorm(0.2, mean = 0, sd = 1)
[1] -0.8416212
> rnorm(4, mean = 0, sd = 1)
[1] -0.80938783 -0.07203091
0.99059330  0.69783570
```



Statistical Simulation

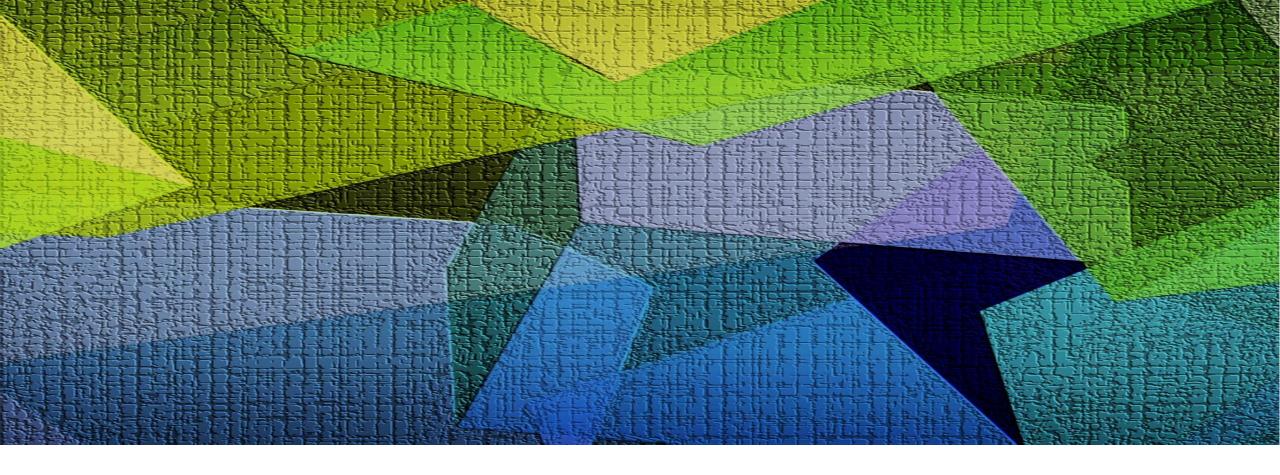
Build-in standard distributions:

Normal (*norm), Poisson (*pois), Binomial (*binom), Exponential (*exp), Gamma (*gamma), Uniform (*unif)

Reproducible random number: set set.seed() in advance

```
> rnorm(3, mean = 0, sd = 1)
[1] -1.1991719 -0.3227133  0.4802463
> set.seed(1)
> rnorm(3, mean = 0, sd = 1)
[1] -0.6264538  0.1836433 -0.8356286
> set.seed(1)
> rnorm(3, mean = 0, sd = 1)
[1] -0.6264538  0.1836433 -0.8356286
```





R Tutorial - Basic Plotting Systems (optional)

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- 1. Base graphics: constructed piecemeal. Conceptually simpler and allows plotting to mirror the thought process.
- 2. Lattice graphics: entire plots created in a simple function call.
- 3. ggplot2 graphics: an implementation of the Grammar of Graphics by Leland Wikinson. Combines concepts from both base and lattice graphics. (Need to install ggplot2 library)
- 4. Fancier and more telling ones: wait for the bootcamp!

A list of interactive visualization in R at:

http://ouzor.github.io/blog/2014/11/21/interactive-visualizations.html



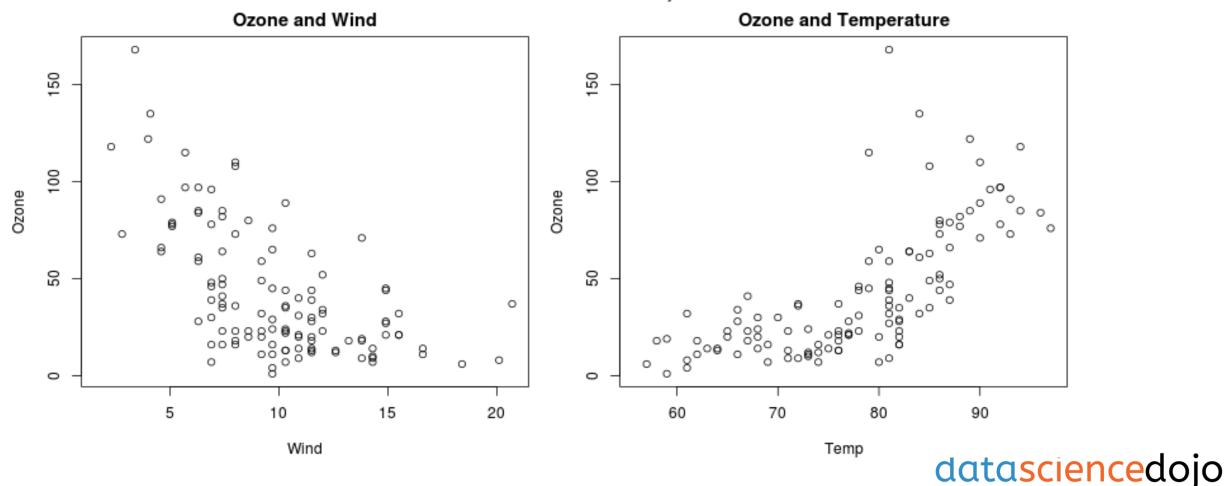
```
0
  library(datasets)
                                      150
> names(airquality)
[1] "Ozone" "Solar.R"
                                   airquality$Ozone
            "Temp"
                         "Month"
"Wind"
                                      9
 "Day"
> plot(x = airquality$Temp,
y = airquality$Ozone)
                                                   70
                                            60
                                                         80
                                                                90
                                                   airquality$Temp
```



```
# par() function is used to specify global graphics
parameters that affect all plots in an R session. Type ?
par to see all parameters
> par(mfrow = c(1, 2), mar = c(4, 4, 2, 1), oma = c(0, 0, 2, 0))
> with(airquality, {
+ plot(Wind, Ozone, main="Ozone and Wind")
+ plot(Temp, Ozone, main="Ozone and Temperature")
+ mtext("Ozone and Weather in New York City", outer=TRUE)
+ })
```



Ozone and Weather in New York City



unleash the data scientist in you

Plotting functions

lines: adds liens to a plot, given a vector of x values and

corresponding vector of y values

points: adds a point to the plot

text: add text labels to a plot using specified x,y coordinates

title: add annotations to x,y axis labels, title, subtitles, outer margin

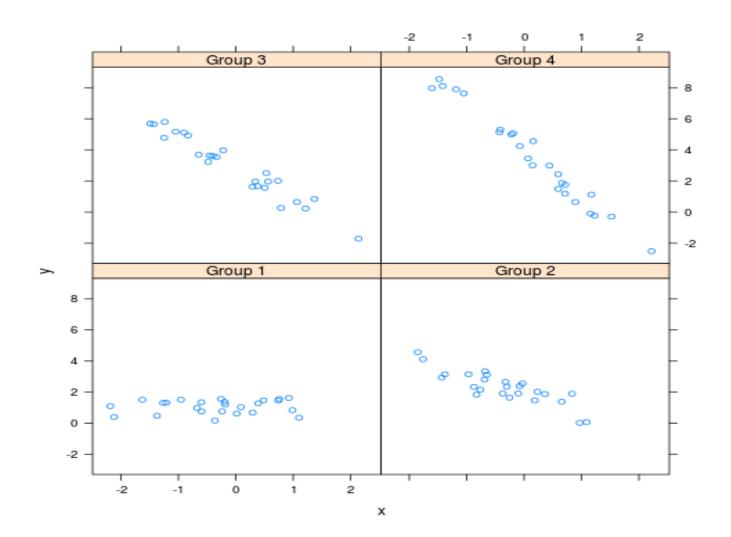
mtext: add arbitrary text to margins (inner or outer) of plot

axis: specify axis ticks



```
> library(lattice) # need to load the lattice library
> set.seed(10) # set the seed so our plots are the same
> x <- rnorm(100)
> f <- rep(1:4, each = 25) # first 25 elements are 1,
second 25 elements are 2, ...
> y <- x + f - f * x+ rnorm(100, sd = 0.5)
> f <- factor(f, labels = c("Group 1", "Group 2", "Group 3", "Group 4"))
> xyplot(y ~ x | f)
```



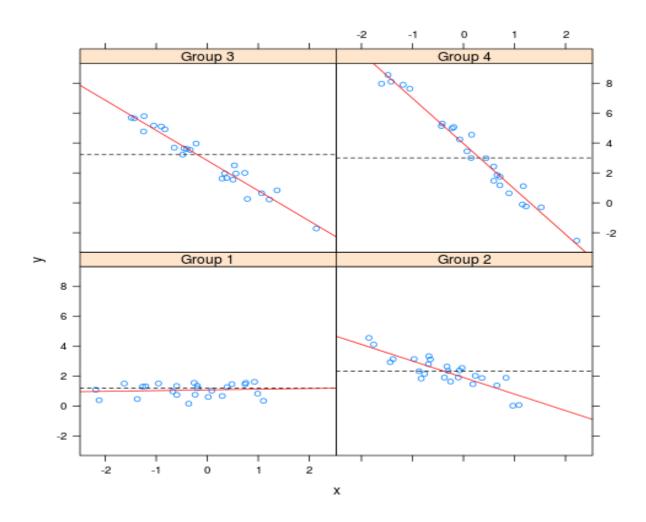




What more on the plot? Customize the panel funciton:

```
> xyplot(y ~ x | f, panel = function(x, y, ...) {
    # call the default panel function for xyplot
    panel.xyplot(x, y, ...)
    # adds a horizontal line at the median
    panel.abline(h = median(y), lty = 2)
    # overlays a simple linear regression line
    panel.lmline(x, y, col = 2)
})
```







Plotting functions

```
xyplot() -> main function for creating scatterplots
bwplot() -> box and whiskers plots (box plots)
```

```
histogram() -> histograms
```

stripplot() -> box plot with actual points

dotplot() -> plot dots on "violin strings"

splom() -> scatterplot matrix (like pairs() in base plotting system)

levelplot()/contourplot() -> plotting image data

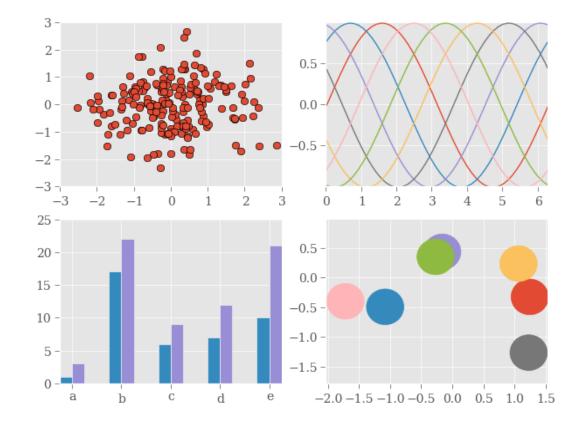


ggplot2 plotting systems

Need to install ggplot2 library

Mix elements of base and lattice

Good tutorial (3 basic plotting systems): https://sux13.github.io/ DataScienceSpCourseN otes/4_EXDATA/Explora tory_Data_Analysis_Course Notes.html





End

But actually it's a Start!

