Introduction to R Programming

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)

Introduction to R Programming

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
```

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)

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

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

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"   "gmtoff"
> p$sec
[1] 10.89086
```

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Dates and times

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] "POSIXlt" "POSIXt"
> x
[1] "2015-03-26 12:30:00 PDT"
```

For the **formatting strings**, check **?strptime** for details

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 0 0
```

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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
```

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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
```

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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",  "yes",
"no",  "yes",  "no"))
> x
[1] yes yes no  yes no
Levels: no yes
> table(x)
x
 no yes
  2   3
```

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
```

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

```
> 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
> 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]
```

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Matrix - cbind() and rbind()

Matrix 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
```

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Matrix - naming matrix

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

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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  =  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
```

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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)
[1] "0" "1" "2" "3" "4" "5" "6"

> 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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Missing values

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

NaN: Not a Number
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"`

`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`

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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

```
> x <- c(1, 2, 3)
> y <- c(4, 5, 6)
> rbind(x, y)
  [,1] [,2] [,3]
x    1    2    3
y    4    5    6
```

```
> cbind(x, y)
     x y
[1,] 1 4
[2,] 2 5
[3,] 3 6
> a = cbind(x, y)
> colnames(a) <- c("x", "y")
```

Introduction to R Programming

Basic Operations

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
```

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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,]
[1] 1 3 5
```

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"
```

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)
}
```

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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.

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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
...

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Build-in functions

Statistical Functions:
rnorm(), dunif(), mean(), sum()...

More complete list:
http://www.statmethods.net/management/functions.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
```

The three dots allows:
1 .an arbitrary number and variety of arguments
2. passing arguments on to 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

lapply: loop over a list and evaluate a function on each element
sapply: same as lapply and try to simplify the result

```
> lapply(c( -1, -5), abs)
[[1]]
[1] 1

[[2]]
[1] 5
```

```
> sapply(c( -1, -5), abs)
[1] 1 5
```

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*apply

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
```

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*apply

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
```

*apply

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"))
> splitted <- split(score, gender)
> splitted
$Female
[1] 79 94
$Male
[1] 90 85
> lapply(splitted, mean)
$Female
[1] 86.5
$Male
[1] 87.5
```

*apply

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
```

*apply

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:

```
setwd("C:\\MyWorkingDirectory")
setwd("C:/MyWorkingDirectory") # can use forward slash
setwd(choose.dir()) # opens a file browser

getwd()  # returns a string with
        # the current working directory
```

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
```

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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

Introduction to R Programming

Reading and Writing Data

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")
```

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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)
```

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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

```
> con <- file("Titanic.csv", "r")
> titanic_data <- read.csv(con)
> close(con)

> con <-
url("http://vincentarelbundock.github.io/Rdatasets/csv/datasets/Titanic.csv
")
> another_data <- read.csv(con)
```

Reading XML/HTML files

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

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

```
> library(jsonlite)
> jsonData <- fromJSON("http://citibikenyc.com/stations/json")
> names(jsonData)
[1] "executionTime"   "stationBeanList"
> jsonData$stationBeanList[1,1:3]
  id      stationName availableDocks
1 72 W 52 St & 11 Ave             31
```

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Reading/writing JSON

```
> head(iris, 3)
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
1          5.1         3.5          1.4         0.2  setosa
2          4.9         3.0          1.4         0.2  setosa
3          4.7         3.2          1.3         0.2  setosa

> iris2 <- toJSON(iris, pretty=TRUE)
```

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
2             ailMel1
3             allMis1
4             anoCar1
5             anoCar2
6             anoGam1
> dbDisconnect(ucscDb) # don't forget to close the connection
```

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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

Introduction to R Programming

Statistical Simulation

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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 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
```

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Introduction to R Programming

Basic Plotting Systems (optional)

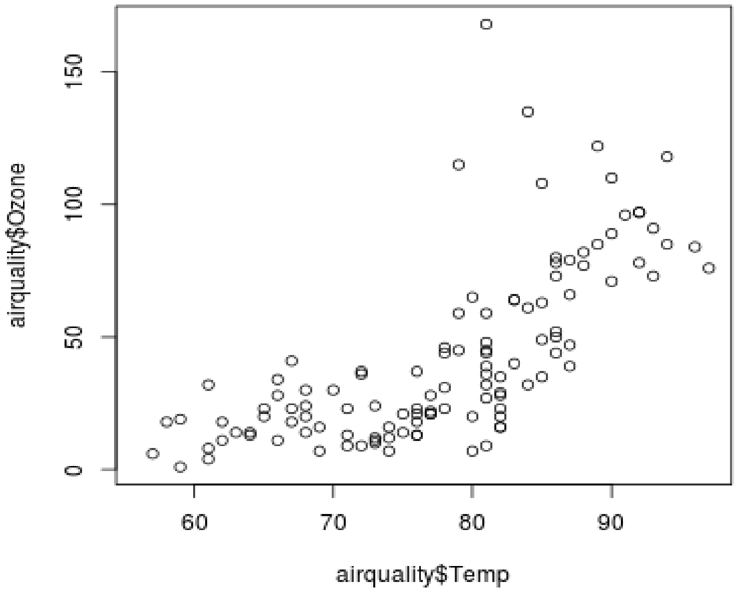
Basic plotting systems

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

Basic plotting systems

```
> library(datasets)
> names(airquality)
[1] "Ozone"   "Solar.R" "Wind"
"Temp"    "Month"   "Day"
> plot(x = airquality$Temp, y =
airquality$Ozone)
```



Basic plotting systems

```
# 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)
+ })
```

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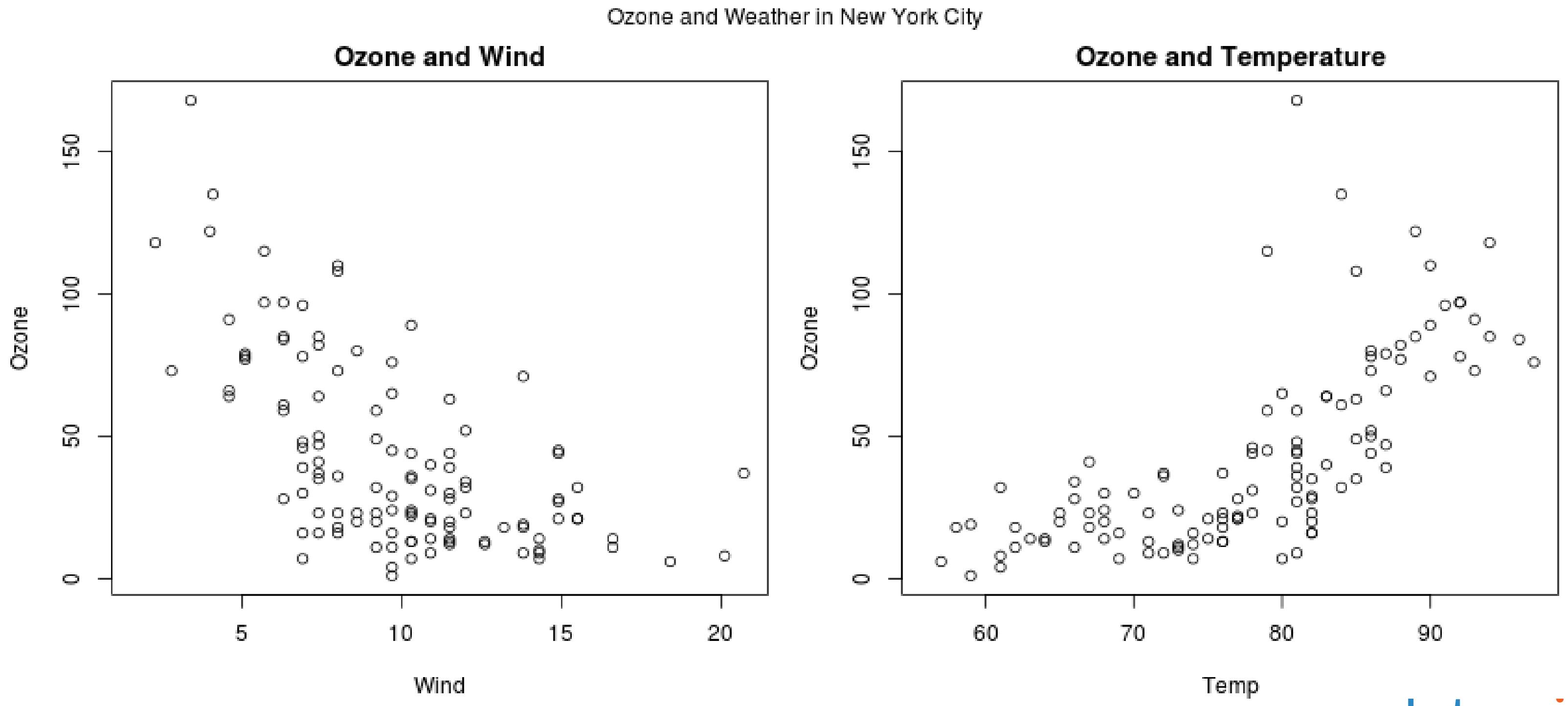
Basic plotting systems



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Basic plotting systems

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

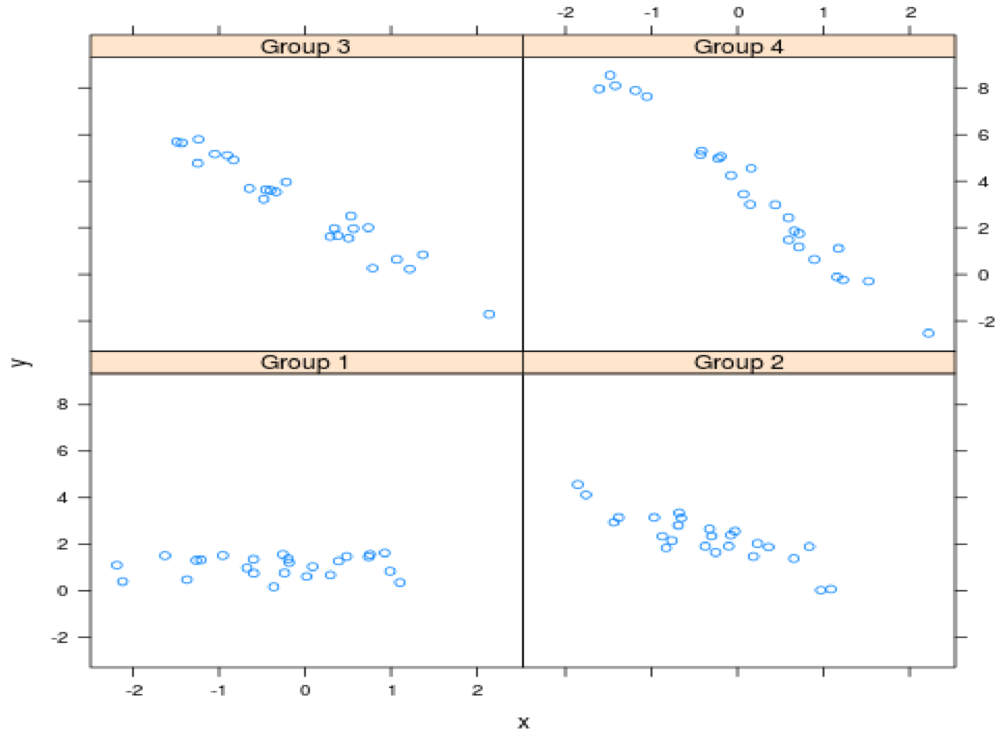
mtext: add arbitrary text to margins (inner or outer) of plot

axis: specify axis ticks

Lattice plotting systems

```
> 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)
```

Lattice plotting systems

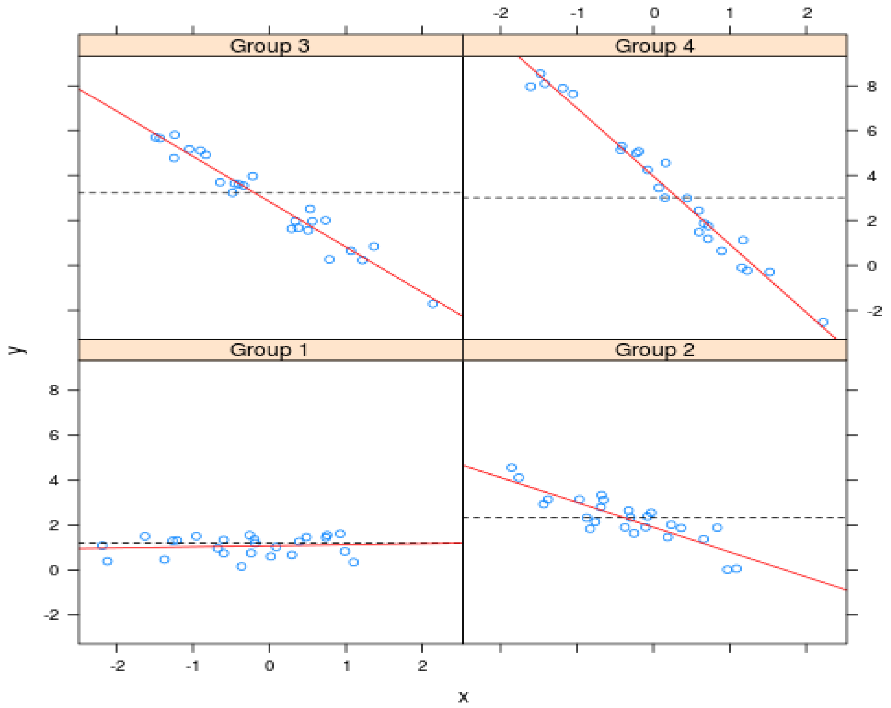


Lattice plotting systems

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)
})
```

Lattice plotting systems



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Lattice plotting systems

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)

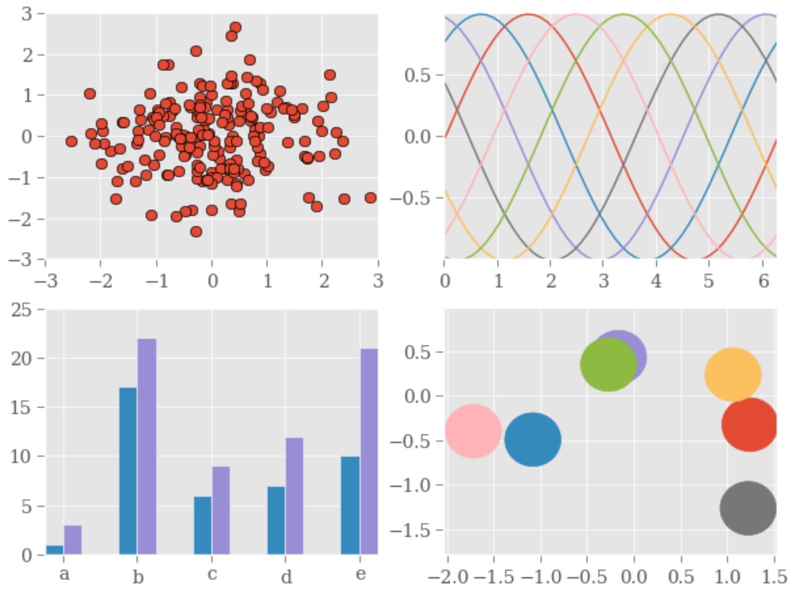
levelplot()/contourplot() –> plotting image data

ggplot2 plotting systems

Need to install ggplot2 library

Mix elements of base and lattice

Good tutorial (3 basic plotting systems): https://sux13.github.io/DataScienceSpCourseNotes/4_EXDATA/Exploratory_Data_Analysis_Course_Notes.html



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End

But it's also a start!

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