LECTURE 2: A CRASH COURSE IN R

STAT 545: Introduction to computational statistics

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August 19, 2019

The R programming language

From the manual,

- R is a system for statistical computation and graphics
- R provides a programming language, high level graphics, interfaces to other languages and debugging facilities

It is possible to go far using R interactively

Better:

- Organize code for debugging/reproducibility/homework

John Chambers:

- Everything that exists is an object
- Everything that happens is a function call

- `typeof()` gives the type or internal storage mode of an object
- `str()` provides a summary of the R object
- `class()` returns the object's class

Atomic vectors

Collections of objects of the same type

Common types include: “`logical`”, “`integer`”, “`double`”, “`complex`”, “`character`”, “`raw`”

`R` has no scalars, just vectors of length 1

Creating vectors

One-dimensional vectors:

```
age <- 25        # 1-dimensional vector
name <- "Alice";  undergrad <- FALSE
```

```
typeof(age)  # Note: age is a double
#> [1] "double"
class(age)
#> [1] "numeric"
```

```
age <- 15L       # L for long integer
typeof(age)
#> [1] "integer"
```

Creating vectors

```r
people <- c('Alice', 'Bob', 'Carol') # c() concatenates
years <- 1991:2000  # but not years <- 2000:1991, use seq()
even_years  <- (years %% 2) ==  0
```

```r
typeof(people)
#> [1] "character"
length(years)
#> [1] 10
is.vector(even_years)
#> [1] TRUE
```

Indexing elements of a vector

Use brackets `[]` to index subelements of a vector

```
people[1]   # First element is indexed by 1
#> [1] "Alice"
years[1:5]  # Index with a subvector of integers
#> [1] 1991 1992 1993 1994 1995
years[c(1, 3, length(years))]
#> [1] 1991 1993 2000
```

Negative numbers exclude elements

```
people[-1]
#> [1] "Bob"   "Carol"  # All but the first element
years[-c(1, length(years))] # All but first and last elements
#> [1] 1991 1992 1993 1994 1995
```

Index with logical vectors

```
even_years  <- (years %% 2) ==  0
#> [1] FALSE TRUE FALSE TRUE FALSE TRUE FALSE TRUE FALSE TRUE
years[even_years]   # Index with a logical vector
#> [1] 1992 1994 1996 1998 2000
```

Indexing elements of a vector

Example: sample 100 Gaussian random variables and find the mean of the positive elements

```
xx <- rnorm(100, 0, 1)          # Sample 100 Gaussians
indx_xx_pos <- (xx > 0)         # Is this element positive
xx_pos <- xx[indx_xx_pos]       # Extract positive elements
xx_pos_mean <- mean(xx_pos)     # calculate mean
```

Example: sample 100 Gaussian random variables and find the mean of the positive elements

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indx_xx_pos <- (xx > 0)         # Is this element positive
xx_pos <- xx[indx_xx_pos]       # Extract positive elements
xx_pos_mean <- mean(xx_pos)     # calculate mean
```

More terse

```
xx <- rnorm(100, 0, 1)              # Sample 100 Gaussians
xx_pos_mean <- mean(xx[xx > 0])     # calc. mean of positives
```

Replacing elements of a vector

Can assign single elements

```r
people[1] <- "Dave"; print(people)
#> [1] "Dave"  "Bob"   "Carol"
```

Replacing elements of a vector

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```
people[1] <- "Dave"; print(people)
#> [1] "Dave"  "Bob"   "Carol"
```

or multiple elements

```
years[even_years] <- years[even_years] + 1
#> [1] 1991 1993 1993 1995 1995 1997 1997 1999 1999 2001
```

Replacing elements of a vector

Can assign single elements

```
people[1] <- "Dave"; print(people)
#> [1] "Dave"  "Bob"   "Carol"
```

or multiple elements

```
years[even_years] <- years[even_years] + 1
#> [1] 1991 1993 1993 1995 1995 1997 1997 1999 1999 2001
```

or assign multiple elements a single value
(more on this when we look at recycling)

```
years[-c(1,length(years)] <- 0
#> [1] 1991 0 0 0 0 0 0 0 0 2001
```

What if we assign to an element outside the vector?

```
years[length(years) + 1] <- 2015
years
#> [1] 1991    0    0    0    0    0    0    0    0 2001 2015
length(years)
#> [1] 11
```

We have increased the vector length by 1

In general, this is an inefficient way to go about things

Much more efficient is to first allocate the entire vector

Recycling

```r
vals <- 1:6
#> [1] 1  2  3  4  5  6
vals + 1
#> [1] 2  3  4  5  6  7
```

Recycling

```
vals <- 1:6
#> [1] 1  2  3  4  5  6
vals + 1
#> [1] 2  3  4  5  6  7
```

```
vals + c(1, 2)
#> [1] 2  4  4  6  6  8
```

Can repeat explicitly too

Recycling

```
vals <- 1:6
#> [1] 1  2  3  4  5  6
vals + 1
#> [1] 2  3  4  5  6  7
```

```
vals + c(1, 2)
#> [1] 2  4  4  6  6  8
```

Can repeat explicitly too

```
rep(c(1, 2),3)
#> [1] 1  2  1  2  1  2
rep(c(1, 2),each=3)
#> [1] 1  1  1  2  2  2
```

SOME USEFUL R FUNCTIONS

`seq()`, `min()`, `max()`, `length()`, `range()`, `any()`, `all()`,

Comparison operators: `<`, `<=`, `>`, `>=`, `==`, `!=`

Logical operators: `&&`, `||`, `!`, `&`, `|`, `xor()`

`is.logical()`, `is.integer()`, `is.double()`, `is.character()`

`as.logical()`, `as.integer()`, `as.double()`, `as.character()`

'Coercion' often happens implicitly in function calls:

```
sum(rnorm(10) > 0)
```

Lists (generic vectors) in R

Elements of a list can be any `R` object (including other lists)

Lists are created using `list()`:

```
> car <- list("Ford", "Mustang", 1999, TRUE)
> length(car)
```

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> length(car)
```

Can have nested lists:

```
# car, house, cat and sofa are other lists
> possessions <- list(car, house, cat, sofa, "3000USD")
```

Indexing elements of a list

Use brackets `[]` and double brackets `[[]]`

Brackets `[]` return a sublist of indexed elements

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Brackets `[]` return a sublist of indexed elements

```
> car[1]
[[1]]
[1] "Ford"

> typeof(car[1])
[1] "list"
```

Indexing elements of a list

Use brackets [] and double brackets [[]]

Double brackets [[]] return element of list

```
> car[[1]]
[1] "Ford"

> typeof(car[[1]])
[1] "character"
```

Named lists

Can assign names to elements of a list

```
> names(car) <- c("Manufacturer", "Make", "Year",
+ "Mileage", "Gasoline")
# Or
> car <- list("Manufacturer" = "Ford", "Make" = "Mustang",
+ "Year" = 1999, "Mileage" = 120021.3, "Gasoline" = TRUE)
```

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> names(car) <- c("Manufacturer", "Make", "Year",
+ "Mileage", "Gasoline")
# Or
> car <- list("Manufacturer" = "Ford", "Make" = "Mustang",
+ "Year" = 1999, "Mileage" = 120021.3, "Gasoline" = TRUE)
```

```
> car[["Year"]]   # A length-one vector
[1] 1999
# Or
> car$Year   # Shorthand notation
[1] 1999
```

Object attributes

`names()` is an instance of an object attribute

These store useful information about the object

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These store useful information about the object

Other common attributes: `class`, `dim` and `dimnames`.

Many have specific accessor functions e.g. `class()` or `dim()`

You can create your own

Matrices and arrays

Are two- and higher-dimensional collections of objects

These have an appropriate `dim` attribute

```
> my_mat <- 1:6    # vector
[1] 1 2 3 4 5 6
> dim(my_mat) <- c(3,2)  # 3 rows and 2 columns
> my_mat
     [,1] [,2]
[1,]    1    4
[2,]    2    5
[3,]    3    6
```

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[1] 1 2 3 4 5 6
> dim(my_mat) <- c(3,2)  # 3 rows and 2 columns
> my_mat
     [,1] [,2]
[1,]    1    4
[2,]    2    5
[3,]    3    6
```

Equivalently (and better)

```
> my_mat <- matrix(1:6, nrow = 3, ncol = 2) # ncol is redundant
```

Are two- and higher-dimensional collections of objects

These have an appropriate `dim` attribute

```
> my_arr <- array(1:8, c(2,2,2))
, , 1
     [,1] [,2]
[1,]    1    3
[2,]    2    4

, , 2
     [,1] [,2]
[1,]    5    7
[2,]    6    8
```

Matrices and arrays

Useful functions include

- `typeof()`, `class()`, `str()`
- `dim()`, `nrow()`, `ncol()`
- `is.matrix()`, `as.matrix()`, …

Matrix multiplication is carried out with the %*% operator

Simple * is elementwise multiplication

A vector/list is NOT an 1-d matrix (no `dim` attribute)

```
> is.matrix(1:6)
[1] FALSE
```

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```
> is.matrix(1:6)
[1] FALSE
```

Use `drop()` to eliminate empty dimensions

```
> my_mat <- array(1:6, c(2,3,1))  # dim(my_mat) is (2,3,1)
, , 1
     [,1] [,2] [,3]
[1,]    1    3    5
[2,]    2    4    6
```

Matrices and arrays

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[1] FALSE
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, , 1
     [,1] [,2] [,3]
[1,]    1    3    5
[2,]    2    4    6
> my_mat <- drop(my_mat)      # dim is now (2,3)
     [,1] [,2] [,3]
[1,]    1    3    5
[2,]    2    4    6
```

Indexing matrices and arrays

```
> my_mat[2,1]  #  Again, use square brackets
[1] 2
```

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Excluding an index returns the entire dimension

```
 > my_mat[2,]
[1] 2 4 6
> my_arr[1,,1]  # slice along dim 2, with dims 1, 3 equal to 1
[1] 6 8
```

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[1] 2 4 6
> my_arr[1,,1]  # slice along dim 2, with dims 1, 3 equal to 1
[1] 6 8
```

Usual ideas from indexing vectors still apply

```
> my_mat[c(2,3),]
     [,1] [,2]
[1,]    2    5
[2,]    3    6
```

Column-major order

We saw how to create a matrix from an array

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

Column-major order

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```
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     [,1] [,2]
[1,]    1    4
[2,]    2    5
[3,]    3    6
```

In `R` matrices are stored in column-major order (like `Fortran`, and unlike `C` and `Python`)

```
> my_mat[1:6]
[1]   1  2  3  4  5  6
```

Recycling

Column-major order explains recycling to fill larger matrices

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```
> ones <- matrix(1, nrow=3, ncol = 3)
     [,1] [,2] [,3]
[1,]    1    1    1
[2,]    1    1    1
[3,]    1    1    1
```

Recycling

Column-major order explains recycling to fill larger matrices

```
> ones <- matrix(1, nrow=3, ncol = 3)
     [,1] [,2] [,3]
[1,]    1    1    1
[2,]    1    1    1
[3,]    1    1    1
```

```
> my_seq <- matrix(c(1,2,3), nrow=3, ncol = 3)
     [,1] [,2] [,3]
[1,]    1    1    1
[2,]    2    2    2
[3,]    3    3    3
```

Data frames

Very common and convenient data structures

Used to store tables:

Columns are variables and rows are observations

	Age	PhD	GPA
Alice	25	TRUE	3.6
Bob	24	TRUE	3.4
Carol	21	FALSE	3.8

An R data frame is a list of equal length vectors and special convenience syntax

Data frames

```
> df <- data.frame(age = c(25L,24L,21L),
                   PhD = c(T,T,F),
                   GPA = c(3.6,2.4,2.8))
```

```
> df
  age  PhD   GPA
1 25   TRUE  3.6
2 24   TRUE  2.4
3 21   FALSE 2.8
> typeof(df)
[1] "list"
> class(df)
[1] "data.frame"
```

```
> str(df)  # Try yourself
```

Data frames

Since data frames are lists, we can use list indexing

Can also use matrix indexing (more convenient)

```
> df[2,3]
[1] 2.4
> df[2,]
  age  PhD GPA
2  24 TRUE 2.4
> df$GPA
[1] 3.6 2.4 2.8
```

- list functions apply as usual
- matrix functions are also interpreted intuitively

Data frames

Many datasets are data frames and many packages expect dataframes

```
> library("datasets")
> class(mtcars)
[1] "data.frame"
```

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

if statements

Allow conditional execution of statements

```
if( condition1 ) {
    statement1
} else if( condition2 ) {
    statement2
} else {
    statement3
}
```

`!`: logical negation

`&` and `&&`: logical 'and'

`|` and `||`: logical 'or'

`&` and `|` perform elementwise comparisons on vectors

`&&` and `||`:

- evaluate from left to right
- look at first element of each vector
- evaluation proceeds **only** until the result is determined

EXPLICIT LOOPING: for(), while() AND repeat()

```
for(elem in vect) {    # Can be atomic vector or list
  Do_stuff_with_elem   # over successive elements of vect
}
```

EXPLICIT LOOPING: `for()`, `while()` AND `repeat()`

```
for(elem in vect) {     # Can be atomic vector or list
  Do_stuff_with_elem    # over successive elements of vect
}
```

```
x <- 0
for(ii in 1:50000) x <- x + log(ii)    # Horrible
```

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x <- 0
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```r
x <- sum(log(1:50000))    # Much more simple and efficient!
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```

```r
x <- sum(log(1:50000))    # Much more simple and efficient!
```

```r
> system.time({x<-0; for(i in 1:50000) x[i] <- i})
  user  system elapsed
 0.048   0.000   0.048
> system.time(x <- log(sum(1:50000)))
  user  system elapsed
  0.001    0     0.002
```

Vectorization

Vectorization allows concise and fast loop-free code

Example: Entropy $H(p) = -\sum_{i=1}^{|p|} p_i \log p_i$ of a prob. distrib.

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```
H <- -sum( p * log(p) )  # Vectorized but wrong (p[i] ==  0?)
```

Vectorization allows concise and fast loop-free code

Example: Entropy $H(p) = -\sum_{i=1}^{|p|} p_i \log p_i$ of a prob. distrib.

```
H <- -sum( p * log(p) )  # Vectorized but wrong (p[i] ==  0?)
```

```
H <- 0                  # Correct but slow
for(i in 1:length(p))
  if(p[i] > 0) H <- H - p[i] * log(p[i])
```

Vectorization

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Example: Entropy $H(p) = -\sum_{i=1}^{|p|} p_i \log p_i$ of a prob. distrib.

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H <- -sum( p * log(p) )  # Vectorized but wrong (p[i] ==  0?)
```

```
H <- 0                  # Correct but slow
for(i in 1:length(p))
  if(p[i] > 0) H <- H - p[i] * log(p[i])
```

```
pos <- p > 0
H   <- - sum( p[pos] * log(p[pos]) )
```

While loops

```
while( condition ) {
  stuff   # Repeat stuff while condition evaluates to TRUE
}
```

If `stuff` doesn't affect `condition`, we loop forever.

Then, we need a `break` statement. Useful if many conditions

```
while( TRUE ) {  # Or use `repeat { ... }'
  stuff1
  if( condition1 ) break
  stuff2
  if( condition2 ) break
}
```

The *apply family

Useful functions for repeated operations on vectors, lists etc.

Sample usage:

```r
# Calc. mean of each element of my_list
rslt_list <- lapply(my_list, FUN = mean)
```

Stackexchange has a nice summary: [url]

Note (Circle 4 of the *R inferno*):

- These are not vectorized operations but are loop-hiding
- Cleaner code, but comparable speeds to explicit `for` loops

`R` comes with its own suite of built-in functions

- An important part of learning `R` is learning the vocabulary
  See e.g. `http://adv-r.had.co.nz/Vocabulary.html`

Non-trivial applications require you build your own functions

- Reuse the same set of commands
- Apply the same commands to different inputs
- Cleaner, more modular code
- Easier testing/debugging

Creating functions

Create functions using `function`:

```
my_func <- function( formal_arguments ) body
```

The above statement creates a function called `my_func`

formal_arguments comma separated names
describes inputs `my_func` expects

function_body a statement or a block
describes what `my_func` does with inputs

An example function

```
normalize_mtrx <- function( ip_mat, row = TRUE ) {
# Normalizes columns to add up to one if row = FALSE
# If row = TRUE or row not specified, normalizes columns
  if(!is.mat(ip_mat)) {
    warning("Expecting a matrix as input");
    return(NULL)
  }
  # You can define objects inside a function
  # You can even define other functions
  rslt <- if(row) ip_mat / rowSums(ip_mat) else
                  t( t(ip_mat) / colSums(ip_mat))
}
```

```
n_mtrx <- normalize_mtrx(mtrx)
```

Argument matching

Proceeds by a three-pass process

- Exact matching on tags
- Partial matching on tags: multiple matches gives an error
- Positional matching

Any remaining unmatched arguments triggers an error

Plotting in base R

```
> str(diamonds)
'data.frame': 53940 obs. of  10 variables:
 $ carat  : num  0.23 0.21 0.23 0.29 0.31 0.24 0.24 0.26 ...
 $ cut    : Ord.factor w/ 5 levels "Fair"<"Good"<..: 5 4 2 ...
 $ color  : Ord.factor w/ 7 levels "D"<"E"<"F"<"G"<..: 2 2 ...
 $ clarity: Ord.factor w/ 8 levels "I1"<"SI2"<"SI1"<..: 2 3 ...
 $ depth  : num  61.5 59.8 56.9 62.4 63.3 62.8 62.3 61.9 ...
 $ table  : num  55 61 65 58 58 57 57 55 61 61 ...
 $ price  : int  326 326 327 334 335 336 336 337 337 338 ...
 $ x      : num  3.95 3.89 4.05 4.2 4.34 3.94 3.95 4.07 ...
 $ y      : num  3.98 3.84 4.07 4.23 4.35 3.96 3.98 4.11 ...
 $ z      : num  2.43 2.31 2.31 2.63 2.75 2.48 2.47 2.53 ...
```

```
plot(diamonds$carat, diamonds$price)  # plot(x,y)
```

Plotting in ggplot

```
ggplot() +
  layer(
    data = diamonds,
    mapping = aes(x = carat, y = price),
    geom = "point",
    stat = "identity",
    position = "identity" ) +
  scale_y_continuous() + scale_x_continuous() +
  coord_cartesian()
```

Plotting in ggplot

```
ggplot() +
  layer(
    data = diamonds,
    mapping = aes(x = carat, y = price),
    geom = "point",
    stat = "identity",
    position = "identity" ) +
  scale_y_continuous() + scale_x_continuous() +
  coord_cartesian()
```

Of course, `ggplot` has intelligent defaults

```
ggplot(diamonds, aes(carat, price)) + geom_point()
```

Plotting in ggplot

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ggplot() +
  layer(
    data = diamonds,
    mapping = aes(x = carat, y = price),
    geom = "point",
    stat = "identity",
    position = "identity" ) +
  scale_y_continuous() + scale_x_continuous() +
  coord_cartesian()
```

Of course, `ggplot` has intelligent defaults

```
ggplot(diamonds, aes(carat, price)) + geom_point()
```

There's also further abbreviations via `qplot` (I find it confusing)

Layers

ggplot produces an object that is rendered into a plot

This object consists of a number of layers

Each layer can get own inputs or share arguments to `ggplot()`

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ggplot produces an object that is rendered into a plot

This object consists of a number of layers

Each layer can get own inputs or share arguments to `ggplot()`

Add another layer to previous plot:

```
ggplot(diamonds, aes(x=carat, y = price)) + geom_point()
  + geom_line(stat= "smooth", color="blue", size=5, alpha=0.7)
```

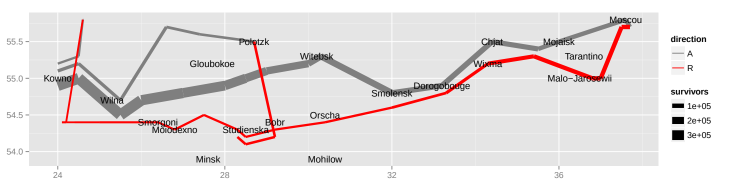
More Examples

```
ggplot(diamonds, aes(x=carat, y = price,colour=cut)) +
  geom_point() +
  geom_line(stat= "smooth", size=5, alpha= 0.7)
```

```
ggplot(diamonds, aes(x=carat, y = price,colour=cut)) +
  geom_point() +
  geom_line(stat= "smooth", method=lm, size=5, alpha= 0.7) +
   scale_x_log10()+ scale_y_log10()
```

```
ggplot(diamonds, aes(x=carat, fill=cut)) +
 geom_histogram(alpha=0.7, binwidth=.4, color="black",
 position="dodge") + xlim(0,2) + coord_cartesian(xlim=c(.1,5))
```

A MORE COMPLICATED EXAMPLE



'*A Layered Grammar of Graphics*', Hadlay Wickham, Journal of Computational and Graphical Statistics, 2010

`ggplot` documentation: `http://docs.ggplot2.org/current/`

Search 'ggplot' on Google Images for inspiration

Play around to make your own figures