R Objects & Programmatic Data Manipulation

Fundamental Techniques in Data Science

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Outline

R Objects & Data Types

Vectors

Vectors are the simplest kind of R object.

- There is no concept of a “scalar” in R.

Vectors come in one of six “atomic modes”:

- numeric/double
- logical
- character
- integer
- complex
- raw

Vectors

```
(v1 <- vector("numeric", 3))

[1] 0 0 0

(v2 <- vector("logical", 3))

[1] FALSE FALSE FALSE

(v3 <- vector("character", 3))

[1] "" "" ""

(v4 <- vector("integer", 3))

[1] 0 0 0

(v5 <- vector("complex", 3))

[1] 0+0i 0+0i 0+0i

(v6 <- vector("raw", 3))

[1] 00 00 00
```

Generating Vectors

We have many ways of generating vectors.

```
(y1 <- c(1, 2, 3))

[1] 1 2 3

(y2 <- c(TRUE, FALSE, TRUE, TRUE))

[1]  TRUE FALSE  TRUE  TRUE

(y3 <- c("bob", "suzy", "danny"))

[1] "bob"   "suzy"  "danny"

1:5

[1] 1 2 3 4 5

1.2:5.3

[1] 1.2 2.2 3.2 4.2 5.2
```

Generating Vectors

```
rep(33, 4)

[1] 33 33 33 33

rep(1:3, 3)

[1] 1 2 3 1 2 3 1 2 3

rep(y3, each = 2)

[1] "bob"   "bob"   "suzy"  "suzy"  "danny" "danny"

seq(0, 1, 0.25)

[1] 0.00 0.25 0.50 0.75 1.00
```

The Three Most Useful Data Types

Numeric

```r
(a <- 1:5)
```

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

Character

```r
(b <- c("foo", "bar"))
```

```
[1] "foo" "bar"
```

Logical

```r
(c <- c(TRUE, FALSE))
```

```
[1]  TRUE FALSE
```

Combining Data Types in Vectors

What happens if we try to concatenate different data types?

```
c(a, b)

[1] "1"   "2"   "3"   "4"   "5"   "foo" "bar"

c(b, c)

[1] "foo"   "bar"   "TRUE"  "FALSE"

c(a, c)

[1] 1 2 3 4 5 1 0
```

Matrices

Matrices generalize vectors by adding a dimension attribute.

```
(m1 <- matrix(a, nrow = 5, ncol = 2))

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

attributes(v1)

NULL

attributes(m1)

$dim
[1] 5 2
```

Matrices

Matrices are populated in column-major order, by default.

```
(m2 <- matrix(1:9, 3, 3))

     [,1] [,2] [,3]
[1,]    1    4    7
[2,]    2    5    8
[3,]    3    6    9
```

The `byrow = TRUE` option allows us to fill by row-major order.

```
(m3 <- matrix(1:9, 3, 3, byrow = TRUE))

     [,1] [,2] [,3]
[1,]    1    2    3
[2,]    4    5    6
[3,]    7    8    9
```

Mixing Data Types in Matrices

Like vectors, matrices can only hold one type of data.

```
cbind(c, letters[1:5])

     c
[1,] "TRUE"  "a"
[2,] "FALSE" "b"
[3,] "TRUE"  "c"
[4,] "FALSE" "d"
[5,] "TRUE"  "e"

cbind(c, c(TRUE, TRUE, FALSE, FALSE, TRUE))

         c
[1,]  TRUE  TRUE
[2,] FALSE  TRUE
[3,]  TRUE FALSE
[4,] FALSE FALSE
[5,]  TRUE  TRUE
```

Lists

Lists are the workhorse of R data objects.

- An R list can hold an arbitrary set of other R objects.

We create lists using the `list()` function

```
(l1 <- list(1, 2, 3))

[[1]]
[1] 1

[[2]]
[1] 2

[[3]]
[1] 3
```

Lists

```
(l2 <- list("bob", TRUE, 33, 42+3i))

[[1]]
[1] "bob"

[[2]]
[1] TRUE

[[3]]
[1] 33

[[4]]
[1] 42+3i
```

Lists

List elements have no defualt names, but we can define our own

```
(l3 <- list(name = "bob",
            alive = TRUE,
            age = 33,
            relationshipStatus = 42+3i)
)

$name
[1] "bob"

$alive
[1] TRUE

$age
[1] 33

$relationshipStatus
[1] 42+3i
```

Lists

We can also assign post hoc names via the ’names()’ function

```
names(l1) <- c("first", "second", "third")
l1

$first
[1] 1

$second
[1] 2

$third
[1] 3
```

Lists

We can append new elements onto an existing list:

```
(l4 <- list())

list()

l4$grass <- "green"
l4$money <- 0
l4$logical <- FALSE
l4

$grass
[1] "green"

$money
[1] 0

$logical
[1] FALSE
```

Lists

The elements inside a list don't really know that they live in a list; they'll pretty much behave as normal

```
l4$money - 42

[1] -42
```

Data Frames

Data frames are R's way of storing rectangular data sets.

- Each column of a data frame is a vector.
- Each of these vectors can have a different type.

We create data frames using the `data.frame()` function

```
(d1 <- data.frame(1:10, c(-1, 1), seq(0.1, 1, 0.1)))

   X1.10 c..1..1. seq.0.1..1..0.1.
1      1       -1              0.1
2      2        1              0.2
3      3       -1              0.3
4      4        1              0.4
5      5       -1              0.5
6      6        1              0.6
7      7       -1              0.7
8      8        1              0.8
9      9       -1              0.9
10    10        1              1.0
```

Data Frames

```
(d2 <- data.frame(x = 1:10, y = c(-1, 1), z = seq(0.1, 1, 0.1)))

    x  y   z
1   1 -1 0.1
2   2  1 0.2
3   3 -1 0.3
4   4  1 0.4
5   5 -1 0.5
6   6  1 0.6
7   7 -1 0.7
8   8  1 0.8
9   9 -1 0.9
10 10  1 1.0
```

Data Frames

```
(d3 <- data.frame(a = sample(c(TRUE, FALSE), 10, replace = TRUE),
                  b = sample(c("foo", "bar"), 10, replace = TRUE),
                  c = runif(10)
                  )
)

       a   b         c
1  FALSE foo 0.4708232
2   TRUE foo 0.2701596
3   TRUE bar 0.6199154
4  FALSE bar 0.2078104
5   TRUE bar 0.4912943
6  FALSE bar 0.1840306
7  FALSE bar 0.5438698
8   TRUE bar 0.5755350
9  FALSE bar 0.7557042
10 FALSE bar 0.8405729
```

Data Frames

```
(d4 <- data.frame(matrix(NA, 10, 3)))

   X1 X2 X3
1  NA NA NA
2  NA NA NA
3  NA NA NA
4  NA NA NA
5  NA NA NA
6  NA NA NA
7  NA NA NA
8  NA NA NA
9  NA NA NA
10 NA NA NA
```

Data Frames

Data frames are actually lists of vectors (representing the columns)

```
is.data.frame(d3)

[1] TRUE

is.list(d3)

[1] TRUE
```

Although they look like rectangular ”matrices”, from R’s perspective a data frame IS NOT a matrix

```
is.matrix(d3)

[1] FALSE
```

We cannot treat a data frame like a matrix. E.g., matrix algebra doesn’t work with data frames

```
d1 %*% t(d2)

Error in d1 %*% t(d2):  requires numeric/complex matrix/vector arguments

as.matrix(d1
```

Factors

Factors are R's way of repesenting nominal variables.

- We can create a factor using the `factor()` function

```
(f1 <- factor(sample(1:3, 10, TRUE), labels = c("red", "yellow", "blue")))

 [1] red    yellow blue   red    blue   blue   yellow red
 [9] red    red
Levels: red yellow blue
```

Factors are stored as integer vectors with a *levels* attribute and a special *factor* class.

```
typeof(f1)

[1] "integer"

attributes(f1)

$levels
[1] "red"    "yellow" "blue"

$class
[1] "factor"
```

Factors

Even though a factor's data are represented by an integer vector, R does not consider factors to be interger/numeric data.

```
is.numeric(f1)

[1] FALSE

is.integer(f1)

[1] FALSE
```

Since factors represent nominal variables, we cannot do math with factors

```
f1 + 1

 [1] NA NA NA NA NA NA NA NA NA NA

mean(f1)

[1] NA
```

Programmatic Data Manipulation

Tidyverse Solutions: **dplyr**

The **dplyr** package provides two principle subsetting functions

- `select()` : subset columns
- `filter()` : subset rows

```r
library(dplyr)
```

What are pipes?

The %>% symbol epresents the *pipe* operator.

- We use the pipe operator to compose functions into a *pipeline*.

The following code represents a pipeline.

```
firstBoys <-
  read_sav("../data/boys.sav") %>%
  head()
```

This pipeline replaces the following code.

```
firstBoys <- head(read_sav("../data/boys.sav"))
```

Why are pipes useful?

Let’s assume that we want to:

1. Load data
2. Transform a variable
3. Filter cases
4. Select columns

Without a pipe, we may do something like this:

```
boys <- read_sav("../data/boys.sav")

Error in read_sav("../data/boys.sav"):  could not find function "read_sav"

boys <- transform(boys, hgt = hgt / 100)

Error in transform(boys, hgt = hgt/100):  object 'boys' not found

boys <- filter(boys, age > 15)

Error in filter(boys, age > 15):  object 'boys' not found

boys <- subset(boys, select = c(hgt, wgt, bmi))

Error in subset(boys, select = c(hgt, wgt, bmi)):  object 'boys' not found
```

Why are pipes useful?

Let's assume that we want to:

1. Load data
2. Transform a variable
3. Filter cases
4. Select columns

With the pipe, we could do something like this:

```
library(magrittr)

boys <-
  read_sav("../data/boys.sav") %>%
  transform(hgt = hgt / 100) %>%
  filter(age > 15) %>%
  subset(select = c(hgt, wgt, bmi))

Error in read_sav("../data/boys.sav"):  could not find function "read_sav"
```

With a pipeline, our code more clearly represents the sequence of steps in our analysis.

Benefits of Pipes

When you use pipes, your code becomes more readable.

- Operations are structured from left-to-right and not from in-to-out
- You can avoid many nested function calls
- You don't have to keep track of intermediate objects
- It's easy to add steps to the sequence

In RStudio, you can use a keyboard shortcut to insert the %>% symbol.

- Windows/Linux: *ctrl* + *shift* + *m*
- Mac: *cmd* + *shift* + *m*

What do pipes do?

Pipes compose R functions without nesting.

- `f(x)` becomes `x` %>% `f()`

```
mean(rnorm(10))

[1] -0.4294987

rnorm(10) %>% mean()

[1] -0.04373715
```

What do pipes do?

Multiple function arguments are fine.

- `f(x, y)` becomes `x` %>% `f(y)`

```
cor(boys, use = "pairwise.complete.obs")

Error in is.data.frame(x):  object 'boys' not found

boys %>% cor(use = "pairwise.complete.obs")

Error in is.data.frame(x):  object 'boys' not found
```

What do pipes do?

Composing more than two functions is easy, too.

- `h(g(f(x)))` becomes `x` %>% `f` %>% `g` %>% `h`

```
max(na.omit(subset(boys, select = wgt)))

Error in subset(boys, select = wgt):  object 'boys' not found

boys %>%
  subset(select = wgt) %>%
  na.omit() %>%
  max()

Error in subset(., select = wgt):  object 'boys' not found
```

The Role of `.` in a Pipeline

In the expression `a` %>% `f(arg1, arg2, arg3)`, `a` will be "piped into" `f()` as `arg1`.

```
data(cats, package = "mice")
cats %>% plot(Hwt ~ Bwt)

Error in plot(., Hwt ~ Bwt):  object 'cats' not found
```

Clearly, we have a problem if we pipe our data into the wrong argument.

- We can change this behavior with the `.` symbol.
- The `.` symbol acts as a placeholder for the data in a pipeline.

The Role of `.` in a Pipeline

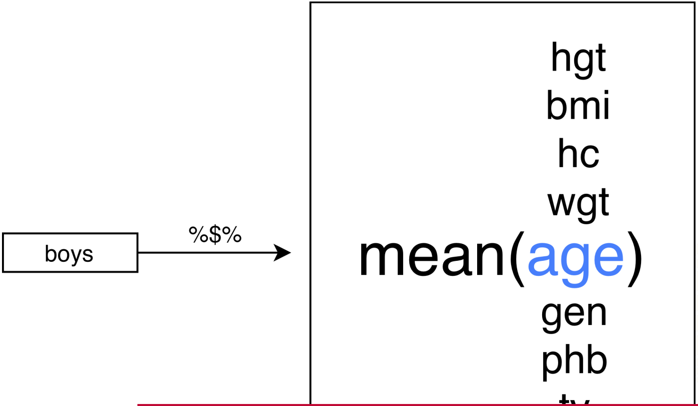
```
cats %>% plot(Hwt ~ Bwt, data = .)

Error in eval(m$data, eframe):  object 'cats' not found
```

Different Flavors of Pipe

The standard pipe (%>%)

The exposition pipe (%$%)



Using the Exposition Pipe: %$%

The exposition pipe offers a more elegant way to solve our earlier problem.

```
cats %$% plot(Hwt ~ Bwt)

Error in base::with(., plot(Hwt ~ Bwt)):  object 'cats' not found
```

Performing a T-Test in a Pipeline

```
cats %$% t.test(Hwt ~ Sex)

Error in base::with(., t.test(Hwt ~ Sex)):  object 'cats' not found
```

The above is equivalent to either of the following.

```
cats %>% t.test(Hwt ~ Sex, data = .)
t.test(Hwt ~ Sex, data = cats)
```

Storing the Results

```
catsTest <- cats %$% t.test(Bwt ~ Sex)

Error in base::with(., t.test(Bwt ~ Sex)):  object 'cats' not found

catsTest

Error in eval(expr, envir, enclos):  object 'catsTest' not found
```

References