Functional Programming in R

So far, you've been using *for* and *while* loops in R for iteration. There are, however, benefits to a functional programming approach.

In an iterative style, we *loop* through values and successively manipulate each value, whereas in a functional style we *apply* some function to every value independently. It's easiest to illustrate with an example.

Suppose that I have the following dataframe:

```
> df = data.frame(matrix(1:100, nrow=10))
> df
        X1       X2       X3       X4       X5       X6       X7       X8       X9       X10
1        1       11       21       31       41       51       61       71       81       91
2        2       12       22       32       42       52       62       72       82       92
3        3       13       23       33       43       53       63       73       83       93
4        4       14       24       34       44       54       64       74       84       94
5        5       15       25       35       45       55        65       75       85       95
6        6       16       26       36       46       56       66       76       86       96
7        7       17       27       37       47       57       67       77       87       97
8        8       18       28       38       48       58       68       78       88       98
9        9       19       29       39       49       59       69       79       89       99
10        10       20       30       40       50       60       70       80       90       100
```

Now, perhaps I would like to calculate the mean of every column.

One way to do this is to loop through the columns and use the mean() function:

```
> means = c()
> for (i in 1:ncol(df)) {
+    means = c(means, mean(df[[i]]))
+ }
> means
[1] 5.5 15.5 25.5 35.5 45.5 55.5 65.5 75.5 85.5 95.5
```

However, I can do this in a somewhat more compact fashion by using R's sapply() function:

```
> means = sapply(1:ncol(df), function(i) mean(df[[i]]))
> means
[1] 5.5 15.5 25.5 35.5 45.5 55.5 65.5 75.5 85.5 95.5
```

In general, the family of *apply() functions in R all facilitate programming in a functional paradigm.

Using lapply() with anonymous functions

We'll first learn about functional programming by using lapply(). The other *apply() functions are mainly extensions of lapply(), and we'll cover them later.

A picture is worth a thousand words:

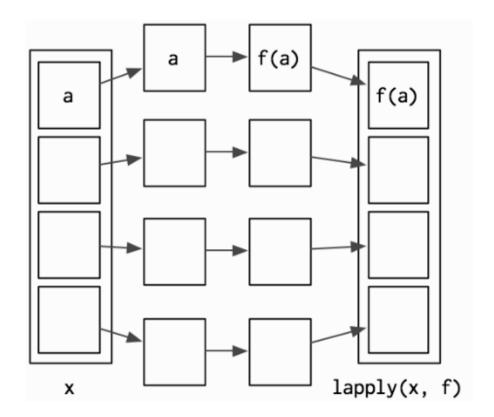


Figure 1: A visual illustration of lapply() from *Advanced R*.

Here's an example of using lapply() to double every number in a vector. Run the following code:

```
double = function(x) {
   2*x
}
lapply(1:10, double)
```

We first create a function double(x) and then we lapply() the double() function onto the vector 1:10, with the result of each computation returned in a

list. In general, when calling lapply(values, func), each value of values is supplied as an unnamed first argument to func().

Exercise. Why might we want to return the output of lapply() in a *list* by default instead of just unlist()ing the values automatically?¹

We can write this more compactly using an *anonymous function*, which is an unnamed function defined for use in a local context only. Run the following code:

```
> lapply(1:10, function(x) 2*x)
[1] 2 4 6 8 10 12 14 16 18 20
```

If we anticipate that we won't be using a function often enough to give it a name, we can define it within sapply() like we did with function(x) 2*x. (Recall that a function doesn't need an explicit return() statement – it returns the last expression evaluated by default – and that it only needs curly braces if the body of the function has multiple expressions.)

Exercise. Write a function using lapply() and class() to print out the class of each column in the built-in mtcars dataset. Run unlist() at the end so it prints in a more human-readable format. (*Hint:* Remember that data frames are built on top of lists.)

Exercise. Write a function using lapply() to standardize each column of mtcars by (1) subtracting off its mean and (2) dividing it by its standard deviation (given by sd()). Be sure to check that your function returns a data frame.

Exercise. Write a function using lapply() that standardizes every numeric column of an input data frame and leaves the others unchanged. Test your function on the dataframe defined by df = data.frame(matrix(1:100, nrow=10)); df[1:5] = lapply(df[1:5], as.character) (understand what this code is doing as well).

Looping patterns

We'll pause for a moment to discuss, at a higher level, the operation of looping. In general, there are three main ways to loop through a list-based data structure:

- Looping through the elements: for (col in df)
- Looping through the indices: for (i in 1:length(df))
- Looping through the names: for (n in names(df))

¹Functions in R don't have a return type, so we don't know in advance what they'll return. Although the double() function only returns numerics, that isn't always the case, so it's best to return results in a list(), which allows for multiple types in its entries.

(Remember that a data frame is just a list, so the first loop iterates through each column individually and the second loop iterates from 1 to the number of columns in df.)

Exercise. Write a function that takes a data frame as input and modifies each column to be equal to itself minus the *previous* column, with the first column remaining unchanged. Test your function on df = data.frame(matrix(rnorm(100), nrow=10)) - aside from 9 entries in the first column, every entry should be equal to 10.

The first form of iteration is the simplest, but you don't get the name or index of each item, just the item itself. The second and the third are more complex, but provide you with more information, so keep them in mind – they may be helpful for more complex problems.

vapply() and sapply()

lapply() is in fact not the most basic of the *apply() functions; lapply() is. Here's a brief description of two more functions to give you a sense for the overall landscape:

- lapply() maps a function onto a list and *returns a list*.
- vapply() is an extension of lapply() that maps a function onto a list and *returns an atomic vector*. It takes an additional argument specifying the *type* and *length* of each element of the return vector, throwing an error if they don't match.
- sapply() is an extension of lapply() which will unlist() the results. If appropriate, it will also assign dimensions to the output, turning it into a matrix.

Let's look at vapply(). It's used as such (run this code):

```
vapply(mtcars, class, character(1))
vapply(list(matrix(1:9, nrow=3), matrix(1:20, nrow=5)), dim, numeric(2))
```

In general, when calling vapply(args, func, example), each time func() is called on an element of args, the output must have the same type and length as example. Otherwise, vapply() stops with an error. Also, when returning multiple numeric vectors, vapply() will add appropriate dimensions to the output.

Exercise. Using any inputs you like, write valid vapply(args, func, example) calls which have each of the following values for example: logical(3), numeric(10), character(2).

Exercise. With a variety of different functions, test the behavior of vapply() and sapply() when the list of arguments is an empty list (list()). How would

the behavior of vapply() help you write code robust to errors and bugs?²

Exercise. What happens when sapply(args, func) is called in a situation where func() returns vectors of different lengths for different elements of args? How can vapply() be used to detect unexpected instances of this situation?

Exercise. Experiment with lists containing Sys.time(). In particular, what happens when you use an *apply() function to determine the class of every element in a list containing Sys.time() for one of its entries?

It's dangerous to use sapply() when writing functions you'll use elsewhere, because you won't know if your output is an unexpected type or has an unexpected length until your program exhibits strange behavior elsewhere. It's better to use vapply(), which throws an error when the output isn't of the specified type and length and enforces type consistency in various edge cases. However, it's fine to use sapply() when working interactively in the console, where you'll be able to visually notice any strange behavior.

Passing in named arguments

If you have sapply(df, func) and want to pass in named arguments to every call of func(), you can do so by passing in named arguments into sapply() directly, e.g., sapply(df, func, param=TRUE) will call func(c, param=TRUE) for every column c of df.

Remark. The same syntax works for lapply(). For vapply(), the named arguments go after the example return value.

Exercise. Write a function using sapply() to find the mean of every vector in a list of numeric vectors, ignoring NA values. Test your function on the list L = lapply(1:5, function(x) sample(c(1:4, NA))).

Exercise. Let trims = seq(0, 0.5, 0.1) and x = rnorm(100). Rewrite the expression lapply(trims, function(trim) mean(x, trim=trim)) to not need an anonymous function.

Why use *apply() instead of loops?

Exercise. Write a function that takes a data frame as input and returns it with its column names modified, where the name of the nth column has _n appended to the end.

At times, the usage of loops is inevitable and the most natural way to program something. Don't get caught up in trying to code something functionally if a

²Since vapply() will return the correct type of 0-length vector in the case where the list of arguments is empty, it helps guard against errors from various edge cases.

loop seems intuitive. In particular, these three use cases are more suitable for loops than for functional programming:

- Modifying a data structure in place (changing it without making a new copy)
 - This is because you have to use the <<- operator to modify the object while situated in the scope of a function call.
- Recursive functionality
- While loops

Moreover, people will sometimes say say that you should use the *apply() functions instead of loops because loops are slow. This is not true.

As we saw earlier with the n-dominoes problem, loops can be sped up significantly by *preallocating memory* for the data structures which you access. In general, loops can be made approximately as fast as writing equivalent code for a function to be used with *apply() if you follow these guidelines³:

- Initialize new objects to full length before the loop, rather than increasing their size within the loop.
 - Every time you increase the size of an object within a loop, you
 actually copy the whole structure over to a different part of memory every
 single time.
- Do not do things in a loop that can be done outside the loop.
- Do not avoid loops simply for the sake of avoiding loops (see the above criteria).

Given that loops don't actually have performance issues in R, why should we use *apply() functions at all? For these three reasons:⁴

- Using the *apply() functions can make it clearer what you're doing.
 - The notion of applying the same function to every element of a list is in general very intuitive. Code clarity is important, both for yourself and for others.
- The *apply() functions have no unwanted side effects.
 - That is to say, their functionality is *isolated* from the rest of your code, so it's harder for you to make accidental modifications to variables you've defined elsewhere.

³From a 2008 issue of R News.

 $^{^4}$ See the answers to Is R's apply family more than syntactic sugar, including the comments on the first one.

- Two caveats are that this isn't true if you use assign() or the <<-operator, which are seldom used and only show up in very specific situations.
- Multi-core processing packages for R implement parallelization by over-writing the built-in *apply() functions with their own versions. As such, liberal usage of *apply() in your code means that you'll be able to easily parallelize it without much rewriting.
 - It's precisely because the *apply() functions have no side effects that they're often used for parallelization purposes. Otherwise, it can be very difficult to ensure correct program behavior.
 - More importantly, when calling, say, sapply(args, func), each call
 of func() is completely independent of the other ones. This allows
 them to easily be dispatched to different processor cores.

Improving old code

Exercise. Go back to your old code for various R exercises. Find five functions which could be written more easily or clearly using functional programming (*e.g.*, using the *apply() functions instead of a for loop) and rewrite them. Check the difference in runtime.

Exercise. If you remember writing any R code in the past for exercises where you kept adding values to a vector or list on every iteration of a loop, rewrite the code here using a preallocated data structure (if possible). Check the difference in runtime using the timeit package.

Supplemental exercises

(coming soon)