Intermediate R

June, 2024

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# 1 About this Course

## 1.1 Curriculum

The course continues building programming fundamentals in R programming and data analysis. You will learn how to make use of complex data structures, use custom functions built by other R users, creating your own functions, and how to iterate repeated tasks that scales naturally. You will also learn how to clean messy data to a Tidy form for analysis, and conduct an end-to-end data science workflow.

## 1.2 Target Audience

The course is intended for researchers who want to continue learning the fundamentals of R programming and how to deal with messy datasets. The audience should know how to subset dataframes and vectors and conduct basic analysis, and/or have taken our [Intro to R course](https://github.com/fhdsl/Intro_to_R).

## 1.3 Offerings

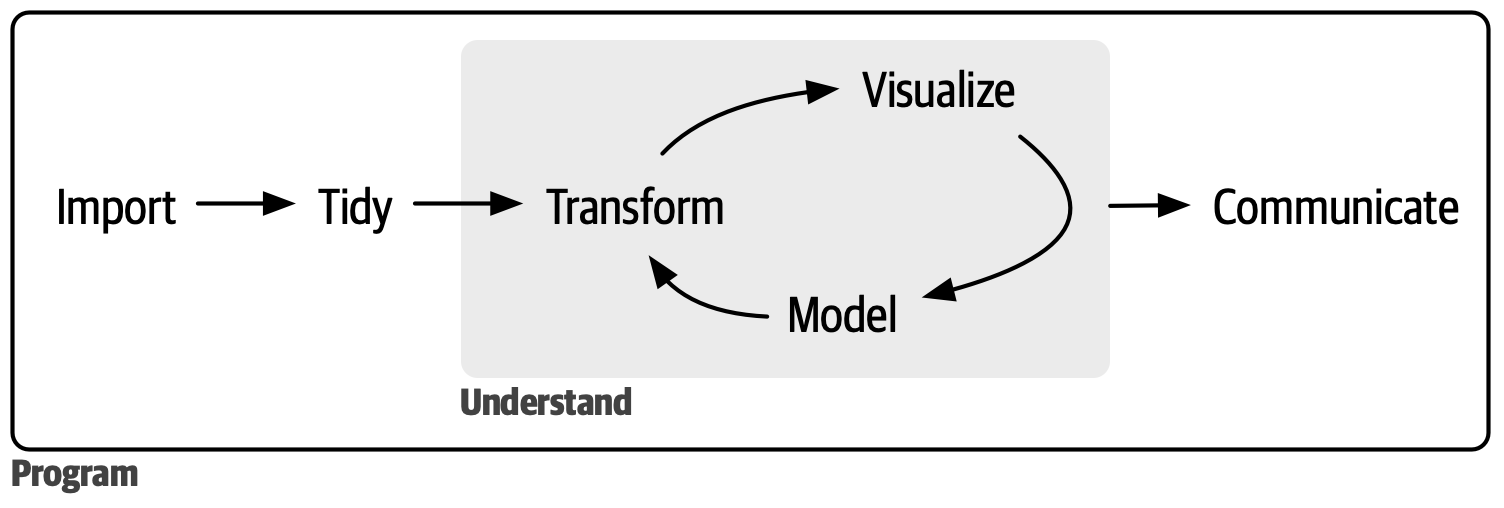
This course is taught on a regular basis at Fred Hutch Cancer Center through the Data Science Lab. Announcements of course offering can be found [here](https://hutchdatascience.org/training/). If you wish to follow the course content asynchronously, you may access the course content on this website and [exercises and solutions on Posit Cloud](https://posit.cloud/content/8236252). The Posit Cloud compute space can be copied to your own workspace for personal use, and you can get started via this [introduction](https://hutchdatascience.org/Intro_to_R/intro-to-computing.html#posit-cloud-setup). Or, you can access the [exercises and solutions on GitHub](https://github.com/fhdsl/Intermediate_R_Exercises).

# 2 Fundamentals

Welcome to Intermediate R! Each week, we cover a chapter, which consists of a lesson and exercise. In the first week, we go over the goals of the course, and review data structures and data types that you have seen before from [Intro to R](https://hutchdatascience.org/Intro_to_R/). We also look at some new data structures and more properties of data structures.

In [Intro to R](https://hutchdatascience.org/Intro_to_R/), you learned how to do basic data analysis such as subsetting a dataframe, looking at summary statistics, and visualizing your data. This was done in the context of a clean, Tidy dataframe. In this course, we focus on working with data “from the wild”, in which the data comes in a more messy, un-Tidy form. Let’s see what we will learn in the next 6 weeks together:

## 2.1 Goals of this course

* Continue building *programming fundamentals*: How to use complex data structures, use and create custom functions, and how to iterate repeated tasks.
* Continue exploration of *data science fundamentals*: how to clean messy data to a Tidy form for analysis.
* At the end of the course, you will be able to: conduct a full analysis in the data science workflow (minus model).
* 

To get started, let’s recall the fundamental data types in R:

## 2.2 Data types in R

* Numeric: 18, -21, 65, 1.25
* Character: “ATCG”, “Whatever”, “948-293-0000”
* Logical: TRUE, FALSE
* Missing values: NA

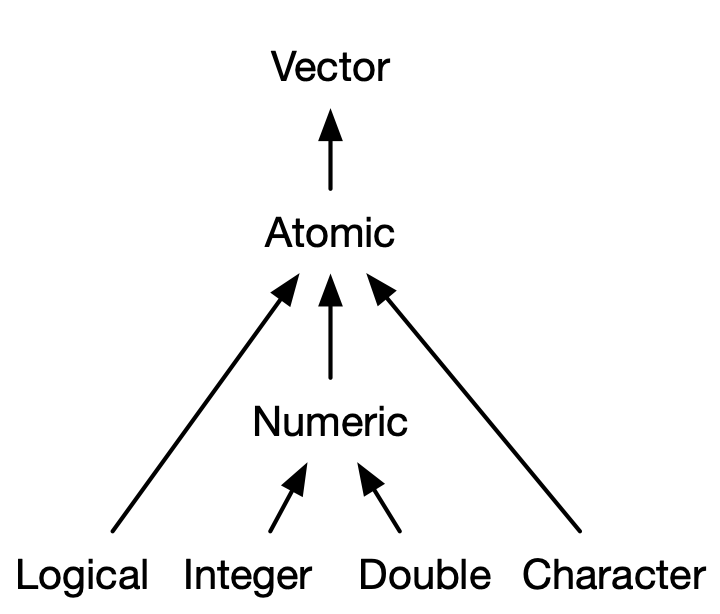
And the fundamental data structures: in this course, we will learn more about a new, flexible data structure called a **List**. We also lightly introduce *Factor* and *Matrix*, but they will not be used for the rest of the course.

## 2.3 Data structures

* Vector
* *Factor*
* Dataframe
* **List**
* *Matrix*

## 2.4 Vector

We know what an **(atomic) vector** is: it can contains a data type, and all elements must be the same data type. If a vector consists of only numeric data, then it is a Numeric Vector, etc. We organize vector subtypes by the following graphic:



Organization of Vectors. Image Source: [Advanced R](https://adv-r.hadley.nz/vectors-chap.html).

Within the Numeric type that we are familiar with, there are more specific types: *Integer* consists of whole number values, and *Double* consists of decimal values. Most of the time we only need to consider Numeric types, but once in a while we need to be more specific.

Now that we have distinguished vector subtypes, it is important to examine what a vector is by inspection:

* We can test whether a vector is a certain type with is.\_\_\_() functions, such as is.character().
* is.character(c("hello", "there"))
* ## [1] TRUE
* is.character(c(1, 3, 5, 7))
* ## [1] FALSE
* We can also test for missing data NA for any types of vector: The test will return a vector testing each element, because NA can be mixed into other values:
* is.na(c(34, NA))
* ## [1] FALSE TRUE

We can **coerce** vectors from one type to the other with as.\_\_\_() functions, such as as.numeric().

as.numeric(c("23", "45"))

## [1] 23 45

as.numeric(c(TRUE, FALSE))

## [1] 1 0

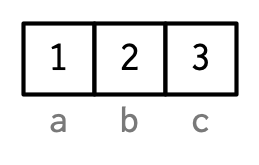
This is very common in data cleaning, when we load in data and they assigned to the wrong data type.

Sometimes, a data structure may have metadata **attributes** associated with them. This gives us more information about the data structure, but doesn’t contain the important data.

For instance, a common attribute is **names,** which can attached to vectors.

x = c(1, 2, 3)  
names(x) = c("a", "b", "c")  
x

## a b c   
## 1 2 3



Names as an attribute for a Vector. Image Source: [Advanced R.](https://adv-r.hadley.nz/vectors-chap.html)

We can look for more general attributes beyond names via the attributes() function:

attributes(x)

## $names  
## [1] "a" "b" "c"

Now, let’s review the ways one can subset a vector. Here are three ways:

1. Positive numeric vector

* data = c(2, 4, -1, -3, 2, -1, 10)  
  data[c(1, 3, 5)]
* ## [1] 2 -1 2

1. Negative numeric vector performs *exclusion*

data[c(-1, -2)]

## [1] -1 -3 2 -1 10

1. Logical vector

data[c(TRUE, FALSE, TRUE, FALSE, TRUE, FALSE, FALSE)]

## [1] 2 -1 2

In practice, we often subset a vector implicitly, via some kind of criteria. Here is a [review of implicit subsetting from Intro to R](https://hutchdatascience.org/Intro_to_R/working-with-data-structures.html#subsetting-vectors-implicitly). Let’s review implicit vector subsetting below:

1. How do you subset the following vector so that it only has positive values?

data = c(2, 4, -1, -3, 2, -1, 10)

data[data > 0]

## [1] 2 4 2 10

1. How do you subset the following vector so that it has doesn’t have the character “temp”?

chars = c("temp", "object", "temp", "wish", "bumblebee", "temp")

chars[chars != "temp"]

## [1] "object" "wish" "bumblebee"

1. How do you subset the following vector so that it has no NA values?

vec\_with\_NA = c(2, 4, NA, NA, 3, NA)

vec\_with\_NA[!is.na(vec\_with\_NA)]

## [1] 2 4 3

## 2.5 Factors

Factors are a type of vector that holds categorical information, such as sex, gender, or cancer subtype. They are useful for:

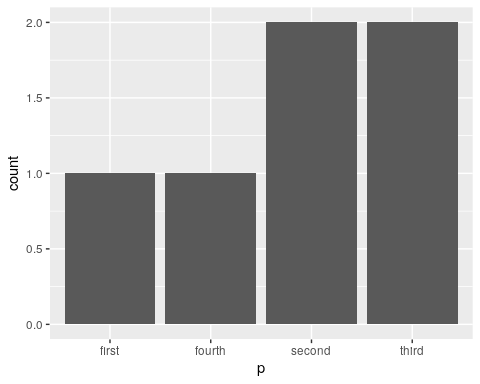
* When you know you have a fixed number of categories.
* When you want to display character vectors in a non-alphabetical order, which is common in plotting.
* Inputs for statistical models, as factors are a special type of numerical vectors.

Let’s take a look at Factors in practice:

place = factor(c("first", "third", "third", "second", "second", "fourth"))  
place

## [1] first third third second second fourth  
## Levels: first fourth second third

df = data.frame(p = place)  
ggplot(df) + geom\_bar(aes(x = p))

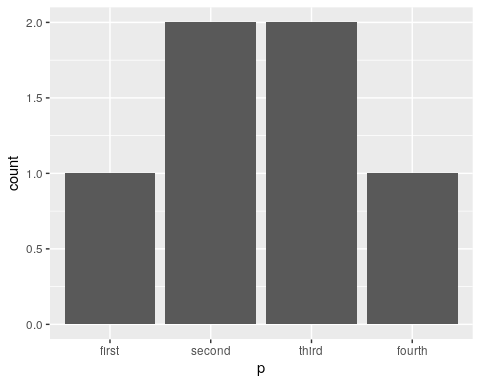


We can construct Ordered Factors:

place = ordered(c("first", "third", "third", "second","second", "fourth"), levels = c("first", "second", "third", "fourth"))  
place

## [1] first third third second second fourth  
## Levels: first < second < third < fourth

df = data.frame(p = place)  
ggplot(df) + geom\_bar(aes(x = p))



## 2.6 Dataframes

Usually, we load in a Dataframe from a spreadsheet or a package, but we can create a new dataframe by using vectors of the same length via the data.frame() function:

df = data.frame(x = 1:3, y = c("cup", "mug", "jar"))  
df

## x y  
## 1 1 cup  
## 2 2 mug  
## 3 3 jar

We have attributes for Dataframes. The most important attribute is names, which correspond to the column names of a Dataframe. You have been using it for a while already!

attributes(df)

## $names  
## [1] "x" "y"  
##   
## $class  
## [1] "data.frame"  
##   
## $row.names  
## [1] 1 2 3

We can directly access the names attribute via names() or colnames():

names(df)

## [1] "x" "y"

Here is another example:

library(palmerpenguins)  
attributes(penguins)

## $class  
## [1] "tbl\_df" "tbl" "data.frame"  
##   
## $row.names  
## [1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18  
## [19] 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36  
## [37] 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54  
## [55] 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72  
## [73] 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90  
## [91] 91 92 93 94 95 96 97 98 99 100 101 102 103 104 105 106 107 108  
## [109] 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126  
## [127] 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144  
## [145] 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160 161 162  
## [163] 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180  
## [181] 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197 198  
## [199] 199 200 201 202 203 204 205 206 207 208 209 210 211 212 213 214 215 216  
## [217] 217 218 219 220 221 222 223 224 225 226 227 228 229 230 231 232 233 234  
## [235] 235 236 237 238 239 240 241 242 243 244 245 246 247 248 249 250 251 252  
## [253] 253 254 255 256 257 258 259 260 261 262 263 264 265 266 267 268 269 270  
## [271] 271 272 273 274 275 276 277 278 279 280 281 282 283 284 285 286 287 288  
## [289] 289 290 291 292 293 294 295 296 297 298 299 300 301 302 303 304 305 306  
## [307] 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323 324  
## [325] 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340 341 342  
## [343] 343 344  
##   
## $names  
## [1] "species" "island" "bill\_length\_mm"   
## [4] "bill\_depth\_mm" "flipper\_length\_mm" "body\_mass\_g"   
## [7] "sex" "year"

Some notes about the other attributes:

* Sometimes, Dataframes will be in a format called “[tibble](https://tibble.tidyverse.org/)”, as shown in the penguins class names as “tbl\_df”, and “tbl”.
* Row names are not commonly used. Here is a [reason](https://adv-r.hadley.nz/vectors-chap.html#rownames).

Let’s review how to subset Dataframes. There are many ways to do it, and here are just some opinionated ways of doing it for this class.

*Getting one single column:*

penguins$bill\_length\_mm

## [1] 39.1 39.5 40.3 NA 36.7 39.3 38.9 39.2 34.1 42.0 37.8 37.8 41.1 38.6 34.6  
## [16] 36.6 38.7 42.5 34.4 46.0 37.8 37.7 35.9 38.2 38.8 35.3 40.6 40.5 37.9 40.5  
## [31] 39.5 37.2 39.5 40.9 36.4 39.2 38.8 42.2 37.6 39.8 36.5 40.8 36.0 44.1 37.0  
## [46] 39.6 41.1 37.5 36.0 42.3 39.6 40.1 35.0 42.0 34.5 41.4 39.0 40.6 36.5 37.6  
## [61] 35.7 41.3 37.6 41.1 36.4 41.6 35.5 41.1 35.9 41.8 33.5 39.7 39.6 45.8 35.5  
## [76] 42.8 40.9 37.2 36.2 42.1 34.6 42.9 36.7 35.1 37.3 41.3 36.3 36.9 38.3 38.9  
## [91] 35.7 41.1 34.0 39.6 36.2 40.8 38.1 40.3 33.1 43.2 35.0 41.0 37.7 37.8 37.9  
## [106] 39.7 38.6 38.2 38.1 43.2 38.1 45.6 39.7 42.2 39.6 42.7 38.6 37.3 35.7 41.1  
## [121] 36.2 37.7 40.2 41.4 35.2 40.6 38.8 41.5 39.0 44.1 38.5 43.1 36.8 37.5 38.1  
## [136] 41.1 35.6 40.2 37.0 39.7 40.2 40.6 32.1 40.7 37.3 39.0 39.2 36.6 36.0 37.8  
## [151] 36.0 41.5 46.1 50.0 48.7 50.0 47.6 46.5 45.4 46.7 43.3 46.8 40.9 49.0 45.5  
## [166] 48.4 45.8 49.3 42.0 49.2 46.2 48.7 50.2 45.1 46.5 46.3 42.9 46.1 44.5 47.8  
## [181] 48.2 50.0 47.3 42.8 45.1 59.6 49.1 48.4 42.6 44.4 44.0 48.7 42.7 49.6 45.3  
## [196] 49.6 50.5 43.6 45.5 50.5 44.9 45.2 46.6 48.5 45.1 50.1 46.5 45.0 43.8 45.5  
## [211] 43.2 50.4 45.3 46.2 45.7 54.3 45.8 49.8 46.2 49.5 43.5 50.7 47.7 46.4 48.2  
## [226] 46.5 46.4 48.6 47.5 51.1 45.2 45.2 49.1 52.5 47.4 50.0 44.9 50.8 43.4 51.3  
## [241] 47.5 52.1 47.5 52.2 45.5 49.5 44.5 50.8 49.4 46.9 48.4 51.1 48.5 55.9 47.2  
## [256] 49.1 47.3 46.8 41.7 53.4 43.3 48.1 50.5 49.8 43.5 51.5 46.2 55.1 44.5 48.8  
## [271] 47.2 NA 46.8 50.4 45.2 49.9 46.5 50.0 51.3 45.4 52.7 45.2 46.1 51.3 46.0  
## [286] 51.3 46.6 51.7 47.0 52.0 45.9 50.5 50.3 58.0 46.4 49.2 42.4 48.5 43.2 50.6  
## [301] 46.7 52.0 50.5 49.5 46.4 52.8 40.9 54.2 42.5 51.0 49.7 47.5 47.6 52.0 46.9  
## [316] 53.5 49.0 46.2 50.9 45.5 50.9 50.8 50.1 49.0 51.5 49.8 48.1 51.4 45.7 50.7  
## [331] 42.5 52.2 45.2 49.3 50.2 45.6 51.9 46.8 45.7 55.8 43.5 49.6 50.8 50.2

*I want to select columns bill\_length\_mm, bill\_depth\_mm, species, and filter for species that are “Gentoo”:*

penguins\_select = select(penguins, bill\_length\_mm, bill\_depth\_mm, species)  
penguins\_gentoo = filter(penguins\_select, species == "Gentoo")

or

penguins\_select\_2 = penguins[, c("bill\_length\_mm", "bill\_depth\_mm", "species")]  
penguins\_gentoo\_2 = penguins\_select\_2[penguins$species == "Gentoo" ,]

or

penguins\_gentoo\_2 = penguins\_select\_2[penguins$species == "Gentoo", c("bill\_length\_mm", "bill\_depth\_mm", "species")]

*I want to filter out rows that have NAs in the column bill\_length\_mm:*

penguins\_clean = filter(penguins, !is.na(bill\_length\_mm))

or

penguins\_clean = penguins[!is.na(penguins$bill\_depth\_mm) ,]

## 2.7 Lists

Lists are the most flexible data structure in R, as they can contain a flexible amount and type of information. They operate similarly as vectors as they group data into one dimension, but each element of a list can be any data type *or data structure*!

l1 = list(  
 1:3,   
 "a",   
 c(TRUE, FALSE, TRUE),   
 c(2.3, 5.9)  
)

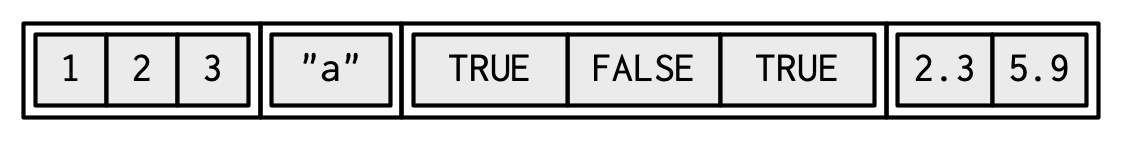


Illustration of a List. Image Source: [Advanced R.](https://adv-r.hadley.nz/vectors-chap.html)

Unlike vectors, you access the elements of a list via the double bracket [[]]. You access a smaller list with single bracket []. (More discussion on the different uses of the bracket [here](https://adv-r.hadley.nz/subsetting.html#subset-single) and [here](https://stackoverflow.com/questions/1169456/the-difference-between-bracket-and-double-bracket-for-accessing-the-el).)

Use unlist() to coerce a list into a vector. Notice all the automatic coersion that happened for the elements.

unlist(l1)

## [1] "1" "2" "3" "a" "TRUE" "FALSE" "TRUE" "2.3" "5.9"

We can give the attribute **names** to lists:

l1 = list(  
 ranking = 1:3,   
 name = "a",   
 success = c(TRUE, FALSE, TRUE),   
 score = c(2.3, 5.9)  
)  
#or  
names(l1) = c("ranking", "name", "success", "score")

And access named elements of lists via the $ operation:

l1$score

## [1] 2.3 5.9

Therefore, l1$score is the same as l1[[4]] and is the same as l1[["score"]].

Here’s an interesting connection between Lists and Dataframes that we will make use of later on in this course: A Dataframe is just a named list of vectors of same length with additional **attributes** of (column) names and row.names!

## 2.8 Matrix

A matrix holds information of the same data type in two dimensions - it’s like a two dimensional vector. Matricies are most often used in statistical computing and matrix algebra, such as creating a design matrix. They are often created by taking a vector and reshaping it with a set number of rows and columns, or converting from a dataframe with only one data type.

my\_matrix = matrix(1:10, nrow = 2)  
my\_matrix

## [,1] [,2] [,3] [,4] [,5]  
## [1,] 1 3 5 7 9  
## [2,] 2 4 6 8 10

You access elements of a matrix similar to that of a dataframe’s indexing:

#column 3  
my\_matrix[, 3]

## [1] 5 6

#row 2  
my\_matrix[2 ,]

## [1] 2 4 6 8 10

#column 3, row 2  
my\_matrix[2, 3]

## [1] 6

## 2.9 Exercises

You can find [exercises and solutions on Posit Cloud](https://posit.cloud/content/8236252), or on [GitHub](https://github.com/fhdsl/Intermediate_R_Exercises).

# 3 Data Cleaning, Part 1

It is often said that 80% of data analysis is spent on the cleaning and preparing data *for* the analysis. Today we will start looking at common data cleaning tasks, in particular data recoding.

In the process, we will be learning a handful of new functions. You already use functions on a regular basis, but for this course, you will be learning how to use other people’s custom functions more independently. Therefore, we start with a review and deeper dive on how to use other people’s custom functions, then we will look at new functions for recoding.

## 3.1 Interpreting functions, carefully

As you become more independent R programmers, you will spend time learning about new functions on your own. We have gone over the basic anatomy of a function call back in Intro to R, but now let’s go a bit deeper to understand how a function is built and how to call them.

Recall that a function has a **function name**, **input arguments**, and a **return value**.

*Function definition consists of assigning a* ***function name*** *with a “function” statement that has a comma-separated list of named* ***function arguments****, and a* ***return expression****. The function name is stored as a variable in the global environment.*

In order to use the function, one defines or import it, then one calls it.

Example:

addFunction = function(num1, num2) {  
 result = num1 + num2   
 return(result)  
}  
result = addFunction(3, 4)

When the function is called in line 5, the variables for the arguments are reassigned to function arguments to be used within the function and helps with the modular form.

*What do you think are some valid inputs for this function?*

To see why we need the variables of the arguments to be reassigned, consider the following function that is *not* modular:

x = 3  
y = 4  
addFunction = function(num1, num2) {  
 result = x + y   
 return(result)  
}  
result = addFunction(10, -10)

Some syntax equivalents on calling the function:

addFunction(3, 4)  
addFunction(num1 = 3, num2 = 4)  
addFunction(num2 = 4, num1 = 3)

but this *could* be different:

addFunction(4, 3)

With a deeper knowledge of how functions are built, when you encounter a foreign function, you can look up its help page to understand how to use it. For example, let’s look at mean():

?mean  
  
Arithmetic Mean  
  
Description:  
  
 Generic function for the (trimmed) arithmetic mean.  
  
Usage:  
  
 mean(x, ...)  
   
 ## Default S3 method:  
 mean(x, trim = 0, na.rm = FALSE, ...)  
   
Arguments:  
  
 x: An R object. Currently there are methods for numeric/logical  
 vectors and date, date-time and time interval objects.  
 Complex vectors are allowed for ‘trim = 0’, only.  
  
 trim: the fraction (0 to 0.5) of observations to be trimmed from  
 each end of ‘x’ before the mean is computed. Values of trim  
 outside that range are taken as the nearest endpoint.  
  
 na.rm: a logical evaluating to ‘TRUE’ or ‘FALSE’ indicating whether  
 ‘NA’ values should be stripped before the computation  
 proceeds.  
  
 ...: further arguments passed to or from other methods.

Notice that the arguments trim = 0, na.rm = FALSE have default values. This means that these arguments are *optional* - you should provide it only if you want to. With this understanding, you can use mean() in a new way:

numbers = c(1, 2, NA, 4)  
mean(x = numbers, na.rm = TRUE)

## [1] 2.333333

The use of . . . (dot-dot-dot): This is a special argument that allows a function to *take any number of arguments*. This isn’t very useful for the mean() function, but it makes sense for function such as select() and filter(), and mutate(). For instance, in select(), once you provide your dataframe for the argument .data, you can pile on as many columns to select in the rest of the argument.

Usage:  
  
 select(.data, ...)  
   
Arguments:  
  
 .data: A data frame, data frame extension (e.g. a tibble), or a lazy  
 data frame (e.g. from dbplyr or dtplyr). See \_Methods\_,  
 below, for more details.  
  
 ...: <‘tidy-select’> One or more unquoted expressions separated by  
 commas. Variable names can be used as if they were positions  
 in the data frame, so expressions like ‘x:y’ can be used to  
 select a range of variables.

You will look at the function documentation on your own to see how to deal with more complex cases.

## 3.2 Recoding Data / Conditionals

Suppose that you have a column in your data that needs to be recoded. Since a dataframe’s column, when selected via $, is a vector, let’s start talking about recoding vectors. If we have a numeric vector, then maybe you want to have certain values to be out of bounds, or assign a range of values to a character category. If we have a character vector, then maybe you want to reassign it to a different value.

Here are popular recoding logical scenarios:

1. If: “If elements of the vector meets *condition*, then they are assigned *value*.”
2. If-else: “If elements of the vector meets *condition*, then they are assigned *value X*. Otherwise, they are assigned *value Y*.”
3. If-else\_if-else: “If elements of the vector meets *condition A*, then they are assigned *value X*. Else, if the elements of the vector meets *condition B*, they are assigned *value Y*. Otherwise, they are assigned *value Z*.”

Let’s look at a vector of grade values, as an example:

grade = c(90, 78, 95, 74, 56, 81, 102)

1. If

Instead of having the bracket [ ] notation on the right hand side of the equation, if it is on the left hand side of the equation, then we can modify a subset of the vector.

grade1 = grade  
grade1[grade1 > 100] = 100

1. If-else

grade2 = if\_else(grade > 60, TRUE, FALSE)

1. If-else\_if-else

grade3 = case\_when(grade >= 90 ~ "A",  
 grade >= 80 ~ "B",  
 grade >= 70 ~ "C",   
 grade >= 60 ~ "D",  
 .default = "F")

Let’s do it for dataframes now.

simple\_df = data.frame(grade = c(90, 78, 95, 74, 56, 81, 102),  
 status = c("case", " ", "Control", "control", "Control", "Case", "case"))

1. If

simple\_df1 = simple\_df  
simple\_df1$grade[simple\_df1$grade > 100] = 100

1. If-else

simple\_df2 = simple\_df  
simple\_df2$grade = ifelse(simple\_df2$grade > 60, TRUE, FALSE)

or

simple\_df2 = mutate(simple\_df, grade = ifelse(grade > 60, TRUE, FALSE))

1. If-else\_if-else

simple\_df3 = simple\_df  
  
simple\_df3$grade = case\_when(simple\_df3$grade >= 90 ~ "A",  
 simple\_df3$grade >= 80 ~ "B",  
 simple\_df3$grade >= 70 ~ "C",   
 simple\_df3$grade >= 60 ~ "D",  
 .default = "F")

or

simple\_df3 = simple\_df  
  
simple\_df3 = mutate(simple\_df3, grade = case\_when(grade >= 90 ~ "A",  
 grade >= 80 ~ "B",  
 grade >= 70 ~ "C",   
 grade >= 60 ~ "D",  
 .default = "F"))

## 3.3 Conditionals

The 3 common scenarios we looked at for recoding data is closely tied to the concept of **conditionals** in programming: *given certain conditions, you run a specific code chunk.* Given a vector’s value, assign it a different value. Or, given a value, run the following hundred lines of code. Here is what it looks like:

1. If:

if(expression\_is\_TRUE) {  
 #code goes here  
}

1. If-else:

if(expression\_is\_TRUE) {  
 #code goes here  
}else {  
 #other code goes here  
}

1. If-else\_if-else:

if(expression\_A\_is\_TRUE) {  
 #code goes here  
}else if(expression\_B\_is\_TRUE) {  
 #other code goes here  
}else {  
 #some other code goes here  
}

The expression that is being tested whether it is TRUE **must be a singular logical value**, and not a logical vector. If the latter, see the recoding section for now.

Example:

nuc = "A"  
  
if(nuc == "A") {  
 nuc = "T"  
}else if(nuc == "T") {  
 nuc = "A"  
}else if(nuc == "C") {  
 nuc = "C"  
}else if(nuc == "G") {  
 nuc = "C"  
}else {  
 nuc = NA  
}  
  
nuc

## [1] "T"

Example:

my\_input = c(1, 3, 5, 7, 9)  
#my\_input = c("e", "e", "a", "i", "o")  
  
if(is.numeric(my\_input)) {  
 result = mean(my\_input)  
}else if(is.character(my\_input)) {  
 result = table(my\_input)  
}  
  
result

## [1] 5

This introduction to conditionals will be more useful when we start writing our functions.

## 3.4 Exercises

You can find [exercises and solutions on Posit Cloud](https://posit.cloud/content/8236252), or on [GitHub](https://github.com/fhdsl/Intermediate_R_Exercises).

# 4 Data Cleaning, Part 2

Another important data cleaning step is to make sure that the shape of the data is useful for the analysis. Today, we will learn about a data organizing standard called Tidy Data, and some common transformations of making a dataframe *longer* and *wider* to get there.

## 4.1 Tidy Data

It is important to have standard of organizing data, as it facilitates a consistent way of thinking about data organization and building tools (functions) that make use of that standard. The [principles of **Tidy data**](https://vita.had.co.nz/papers/tidy-data.html), developed by Hadley Wickham:

1. Each variable must have its own column.
2. Each observation must have its own row.
3. Each value must have its own cell.

If we want to be technical about what variables and observations are, Hadley Wickham describes:

A dataset is a collection of **values**, usually either numbers (if quantitative) or strings (if qualitative). Every value belongs to a **variable** and an **observation**. A **variable** contains all values that measure the same underlying attribute (like height, temperature, duration) across units. An **observation** contains all values measured on the same unit (like a person, or a day, or a race) across attributes.



A Tidy dataframe. Image source: [R for Data Science](https://r4ds.hadley.nz/data-tidy).

Besides a standard, Tidy data is useful because many tools in R are most effective when your data is in a Tidy format. This includes data visualization with ggplot, regression models, databases, and more.

At first glance, it seems hard to go wrong with these simple criteria of Tidy data! However, in reality, many dataframes we load in aren’t Tidy, and it’s easiest seen through counterexamples and how to fix it. Here are some common ways that data becomes un-Tidy:

1. Columns contain values of variables, rather than variables
2. Variables are stored in rows
3. Multiple variables are stored in a single column

After some clear examples, we emphasize that “Tidy” data is *subjective* to what kind of analysis you want to do with the dataframe.

### 4.1.1 1. Columns contain values, rather than variables (Long is tidy)

df = data.frame(Store = c("A", "B"),  
 Year = c(2018, 2018),  
 Q1\_Sales = c(55, 98),  
 Q2\_Sales = c(45, 70),  
 Q3\_Sales = c(22, 60),  
 Q4\_Sales = c(50, 60))  
df

## Store Year Q1\_Sales Q2\_Sales Q3\_Sales Q4\_Sales  
## 1 A 2018 55 45 22 50  
## 2 B 2018 98 70 60 60

Each observation is a store, and each observation has its own row. That looks good.

The columns “Q1\_Sales”, …, “Q4\_Sales” seem to be *values of a single variable “quarter”* of our observation. The values of “quarter” are not in a single column, but are instead in the columns.

df\_long = pivot\_longer(df, c("Q1\_Sales", "Q2\_Sales", "Q3\_Sales", "Q4\_Sales"), names\_to = "quarter", values\_to = "sales")  
df\_long

## # A tibble: 8 × 4  
## Store Year quarter sales  
## <chr> <dbl> <chr> <dbl>  
## 1 A 2018 Q1\_Sales 55  
## 2 A 2018 Q2\_Sales 45  
## 3 A 2018 Q3\_Sales 22  
## 4 A 2018 Q4\_Sales 50  
## 5 B 2018 Q1\_Sales 98  
## 6 B 2018 Q2\_Sales 70  
## 7 B 2018 Q3\_Sales 60  
## 8 B 2018 Q4\_Sales 60

Now, each observation is a store’s quarter, and each observation has its own row.

The new columns “quarter” and “sales” are variables that describes our observation, and describes our values. We’re in a tidy state!

We have transformed our data to a “**longer**” format, as our observation represents something more granular or detailed than before. Often, the original variables values will repeat itself in a “longer format”. We call the previous state of our dataframe is a “**wider**” format.

### 4.1.2 2. Variables are stored in rows (Wide is tidy)

Are all tidy dataframes Tidy in a “longer” format?

df2 = data.frame(Sample = c("A", "B"),  
 KRAS\_mutation = c(TRUE, FALSE),  
 KRAS\_expression = c(2.3, 3.9))  
df2

## Sample KRAS\_mutation KRAS\_expression  
## 1 A TRUE 2.3  
## 2 B FALSE 3.9

Each observation is a sample, and each observation has its own row. Looks good. Each variable has its own column, and no values are in columns.

What happens if we make it longer?

df2\_long = pivot\_longer(df2, c("KRAS\_mutation", "KRAS\_expression"), names\_to = "gene", values\_to = "values")  
df2\_long

## # A tibble: 4 × 3  
## Sample gene values  
## <chr> <chr> <dbl>  
## 1 A KRAS\_mutation 1   
## 2 A KRAS\_expression 2.3  
## 3 B KRAS\_mutation 0   
## 4 B KRAS\_expression 3.9

Here, each observation is a sample’s gene…type? The observation feels awkward because variables are stored in rows. Also, the column “values” contains multiple variable types: gene expression and mutation values that got coerced to numeric!

To make this dataframe wider,

df2\_long\_wide = pivot\_wider(df2\_long, names\_from = "gene", values\_from = "values")   
df2\_long\_wide$KRAS\_mutation = as.logical(df2\_long\_wide$KRAS\_mutation)  
df2\_long\_wide

## # A tibble: 2 × 3  
## Sample KRAS\_mutation KRAS\_expression  
## <chr> <lgl> <dbl>  
## 1 A TRUE 2.3  
## 2 B FALSE 3.9

We are back to our orignal form, and it was already Tidy.

### 4.1.3 3. Multiple variables are stored in a single column

table3

## # A tibble: 6 × 3  
## country year rate   
## <chr> <dbl> <chr>   
## 1 Afghanistan 1999 745/19987071   
## 2 Afghanistan 2000 2666/20595360   
## 3 Brazil 1999 37737/172006362   
## 4 Brazil 2000 80488/174504898   
## 5 China 1999 212258/1272915272  
## 6 China 2000 213766/1280428583

There seems to be two variables in the numerator and denominator of “rate” column. Let’s separate it.

separate(table3, col = "rate", into = c("count", "population"), sep = "/")

## # A tibble: 6 × 4  
## country year count population  
## <chr> <dbl> <chr> <chr>   
## 1 Afghanistan 1999 745 19987071   
## 2 Afghanistan 2000 2666 20595360   
## 3 Brazil 1999 37737 172006362   
## 4 Brazil 2000 80488 174504898   
## 5 China 1999 212258 1272915272  
## 6 China 2000 213766 1280428583

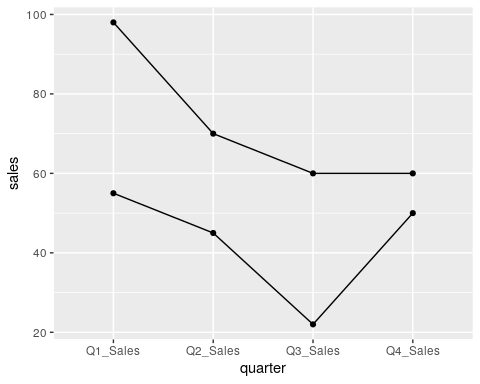
## 4.2 Uses of Tidy data

In general, many functions for analysis and visualization in R assumes that the input dataframe is Tidy. These tools assumes the values of each variable fall in their own column vector. For instance, from our first example, we can compare sales across quarters and stores.

df\_long

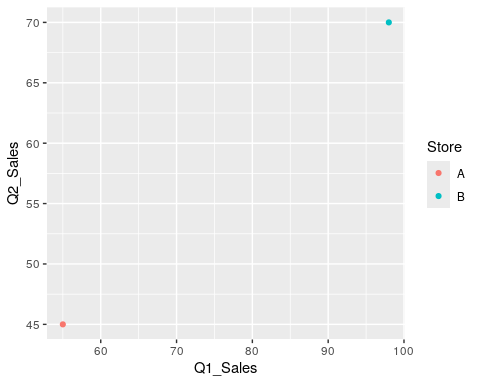
## # A tibble: 8 × 4  
## Store Year quarter sales  
## <chr> <dbl> <chr> <dbl>  
## 1 A 2018 Q1\_Sales 55  
## 2 A 2018 Q2\_Sales 45  
## 3 A 2018 Q3\_Sales 22  
## 4 A 2018 Q4\_Sales 50  
## 5 B 2018 Q1\_Sales 98  
## 6 B 2018 Q2\_Sales 70  
## 7 B 2018 Q3\_Sales 60  
## 8 B 2018 Q4\_Sales 60

ggplot(df\_long) + aes(x = quarter, y = sales, group = Store) + geom\_point() + geom\_line()



Although in its original state we can also look at sales between quarter, we can only look between two quarters at once. Tidy data encourages looking at data in the most granular scale.

ggplot(df) + aes(x = Q1\_Sales, y = Q2\_Sales, color = Store) + geom\_point()



## 4.3 Subjectivity in Tidy Data

We have looked at clear cases of when a dataset is Tidy. In reality, the Tidy state depends on what we call variables and observations. Consider this example, inspired by the following [blog post](https://kiwidamien.github.io/what-is-tidy-data.html) by Damien Martin.

kidney = data.frame(stone\_size = c("Small", "Large"),  
 treatment.A\_recovered = c(81, 192),  
 treatment.A\_failed = c(6, 71),  
 treatment.B\_recovered = c(234, 55),  
 treatment.B\_failed = c(36, 25))  
kidney

## stone\_size treatment.A\_recovered treatment.A\_failed treatment.B\_recovered  
## 1 Small 81 6 234  
## 2 Large 192 71 55  
## treatment.B\_failed  
## 1 36  
## 2 25

Right now, the kidney dataframe clearly has values of a variable in the column. Let’s try to make it Tidy by making it into a longer form and separating out variables that are together in a column.

kidney\_long = pivot\_longer(kidney, c("treatment.A\_recovered", "treatment.A\_failed", "treatment.B\_recovered", "treatment.B\_failed"), names\_to = "treatment\_outcome", values\_to = "count")  
  
kidney\_long = separate(kidney\_long, "treatment\_outcome", c("treatment", "outcome"), "\_")  
  
kidney\_long

## # A tibble: 8 × 4  
## stone\_size treatment outcome count  
## <chr> <chr> <chr> <dbl>  
## 1 Small treatment.A recovered 81  
## 2 Small treatment.A failed 6  
## 3 Small treatment.B recovered 234  
## 4 Small treatment.B failed 36  
## 5 Large treatment.A recovered 192  
## 6 Large treatment.A failed 71  
## 7 Large treatment.B recovered 55  
## 8 Large treatment.B failed 25

Here, each observation is a kidney stone’s treatment’s outcome type, and each observation has its own row.

The column “count” describes our observation, and describes our values. This dataframe seems reasonably Tidy.

How about this?

kidney\_long\_still = pivot\_wider(kidney\_long, names\_from = "outcome", values\_from = "count")  
kidney\_long\_still

## # A tibble: 4 × 4  
## stone\_size treatment recovered failed  
## <chr> <chr> <dbl> <dbl>  
## 1 Small treatment.A 81 6  
## 2 Small treatment.B 234 36  
## 3 Large treatment.A 192 71  
## 4 Large treatment.B 55 25

Here, each observation is a kidney stone’s treatment, and each observation has its own row.

The columns “recovered” and “failed” are variables that describes our observation, and describes its corresponding values. This dataframe seems reasonably Tidy, also.

The reason why both of these versions seem Tidy is that the columns “recovered” and “failed” can be interpreted as independent variables *and* values of the variable “treatment”.

Ultimately, we decide which dataframe we prefer based on the analysis we want to do.

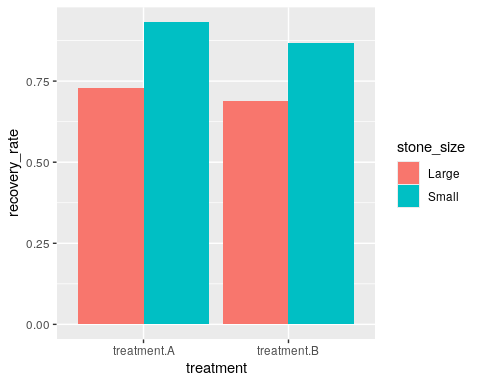
For instance, when our observation is about a kidney stone’s treatment’s outcome type, we compare it between outcome type, treatment, and stone size.

ggplot(kidney\_long) + aes(x = treatment, y = count, fill = outcome) + geom\_bar(position="dodge", stat="identity") + facet\_wrap(~stone\_size)



When our observation is about a kidney stone’s treatment’s, we compare a new variable *recovery rate* ( = recovered / (recovered + failed)) between treatment and stone size.

kidney\_long\_still = mutate(kidney\_long\_still, recovery\_rate = recovered / (recovered + failed))  
ggplot(kidney\_long\_still) + aes(x = treatment, y = recovery\_rate, fill = stone\_size) + geom\_bar(position="dodge", stat="identity")



## 4.4 Exercises

You can find [exercises and solutions on Posit Cloud](https://posit.cloud/content/8236252), or on [GitHub](https://github.com/fhdsl/Intermediate_R_Exercises).

# 5 Writing your first function

After learning how to use other people’s functions, it’s time to write our own! We will look at the anatomy of how a function is constructed, and see bunch of examples in action.



Function machine from algebra class.

First, we remind ourselves why we write functions in the first place. We write functions for two main, often overlapping, reasons:

1. Following DRY (Don’t Repeat Yourself) principle: If you find yourself repeating similar patterns of code, you should write a function that executes that pattern. This saves time and the risk of mistakes.
2. Create modular structure and abstraction: Having all of your code in one place becomes increasingly complicated as your program grows. Think of the function as a mini-program that can perform without the rest of the program. Organizing your code by functions gives modular structure, as well as abstraction: you only need to know the function name, inputs, and output to use it and don’t have to worry how it works.

Some advice on writing functions:

* Code that has a well-defined set of inputs and outputs make a good function.
* A function should do only one, well-defined task.

## 5.1 Anatomy of a function definition

*Function definition consists of assigning a* ***function name*** *with a “function” statement that has a comma-separated list of named* ***function arguments****, and a* ***return expression****. The function name is stored as a variable in the global environment.*

In order to use the function, one defines or import it, then one calls it.

Example:

addFunction = function(argument1, argument2) {  
 result = argument1 + argument2   
 return(result)  
}  
z = addFunction(3, 4)

With function definitions, not all code runs from top to bottom. The first four lines defines the function, but the function is never run. It is called on line 5, and the lines within the function are executed.

When the function is called in line 5, the variables for the arguments are reassigned to function arguments to be used within the function and helps with the modular form. We need to introduce the concept of local and global environments to distinguish variables used only for a function from variables used for the entire program.

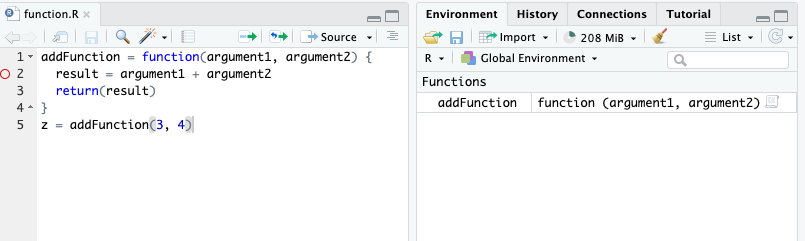
## 5.2 Local and global environments

*{ } represents variable scoping: within each { }, if variables are defined, they are stored in a* ***local environment****, and is only accessible within { }. All function arguments are stored in the local environment. The overall environment of the program is called the* ***global environment*** *and can be also accessed within { }.*

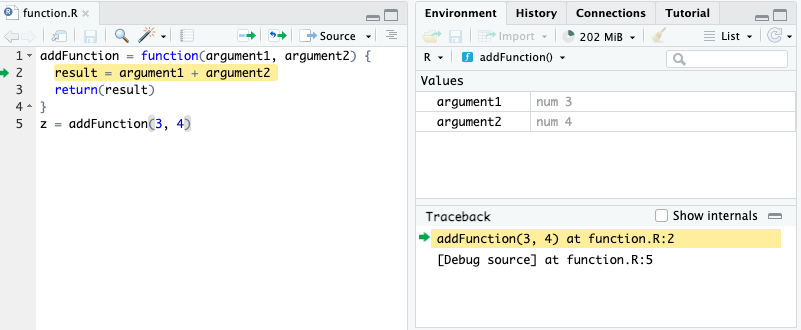
The reason of having some of this “privacy” in the local environment is to make functions modular - they are independent little tools that should not interact with the rest of the global environment. Imagine someone writing a tool that they want to give someone else to use, but the tool depends on your environment, vice versa.

## 5.3 A step-by-step example

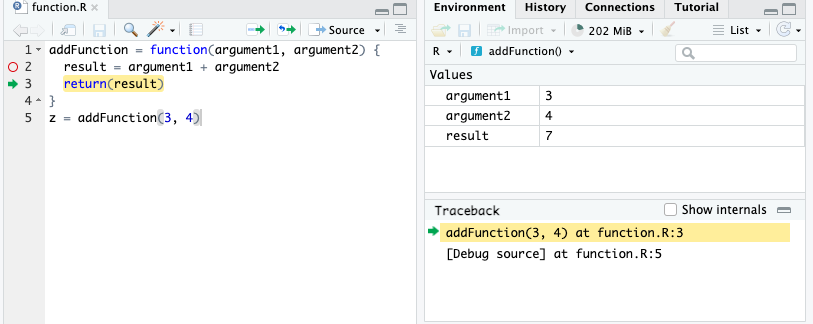
Using the addFunction function, let’s see step-by-step how the R interpreter understands our code:



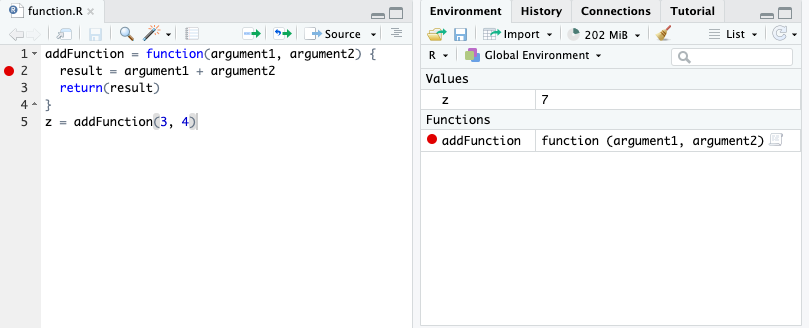
We define the function in the global environment.



We call the function, and the function arguments 3, 4 are assigned to argument1 and argument2, respectively in the function’s local environment.



We run the first line of code in the function body. The new variable “result” is stored in the local environment because it is within { }.



We run the second line of code in the function body to return a value. The return value from the function is assigned to the variable z in the global environment. All local variables for the function are erased now that the function call is over.

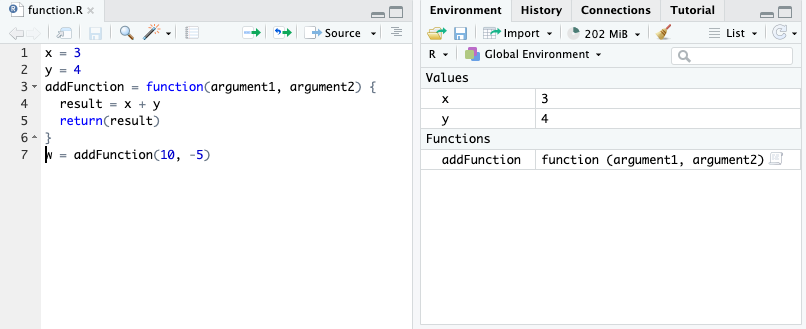
## 5.4 Function arguments create modularity

First time writers of functions might ask: why are variables we use for the arguments of a function *reassigned* for function arguments in the local environment? Here is an example when that process is skipped - what are the consequences?

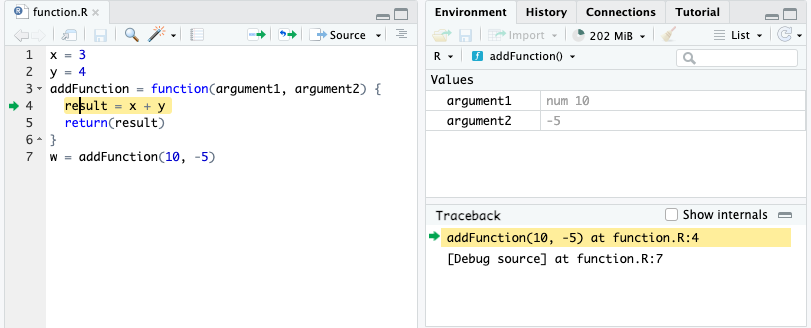
x = 3  
y = 4  
addFunction = function(argument1, argument2) {  
 result = x + y   
 return(result)  
}  
z = addFunction(x, y)  
w = addFunction(10, -5)

What do you expect the value of z to be? How about w?

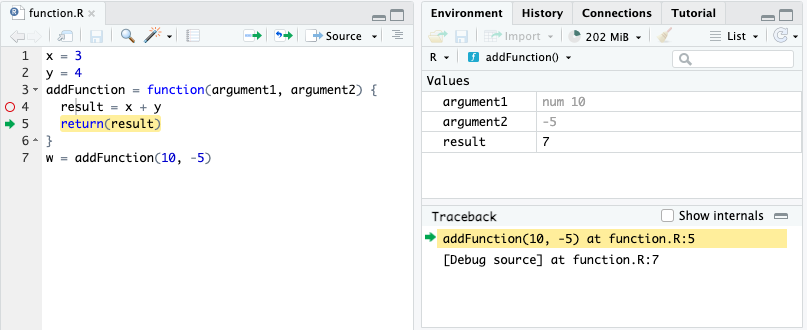
Here is the execution for w:



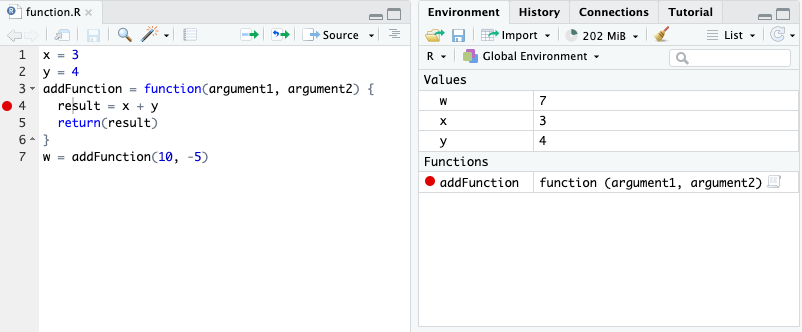
We define the variables and function in the global environment.



We call the function, and the function arguments 10, -5 are assigned to argument1 and argument2, respectively in the function’s local environment.



We run the first line of code in the function body. The new variable “result” is stored in the local environment because it is within { }.



We run the second line of code in the function body to return a value. The return value from the function is assigned to the variable w in the global environment. All local variables for the function are erased now that the function call is over.

The function did not work as expected because we used hard-coded variables from the global environment and not function argument variables unique to the function use!

## 5.5 Examples

* Create a function, called add\_and\_raise\_power in which the function takes in 3 numeric arguments. The function computes the following: the first two arguments are added together and raised to a power determined by the 3rd argument. The function returns the resulting value. Here is a use case: add\_and\_raise\_power(1, 2, 3) = 27 because the function will return this expression: (1 + 2) ^ 3. Another use case: add\_and\_raise\_power(3, 1, 2) = 16 because of the expression (3 + 1) ^ 2. Confirm with that these use cases work. Can this function used for numeric vectors?
* add\_and\_raise\_power = function(x, y, z) {  
   result = (x + y)^z  
   return(result)  
  }  
  add\_and\_raise\_power(1, 2, 3)
* ## [1] 27
* Create a function, called my\_dim in which the function takes in one argument: a dataframe. The function returns the following: a length-2 numeric vector in which the first element is the number of rows in the dataframe, and the second element is the number of columns in the dataframe. Your result should be identical as the dim function. How can you leverage existing functions such as nrow and ncol? Use case: my\_dim(penguins) = c(344, 8)
* library(palmerpenguins)  
  my\_dim = function(df) {  
   result = c(nrow(df), ncol(df))  
   return(result)  
  }  
  my\_dim(penguins)
* ## [1] 344 8
* Create a function, called num\_na in which the function takes in any vector, and then return a single numeric value. This numeric value is the number of NAs in the vector. Use cases: num\_na(c(NA, 2, 3, 4, NA, 5)) = 2 and num\_na(c(2, 3, 4, 5)) = 0. Hint 1: Use is.na() function. Hint 2: Given a logical vector, you can count the number of TRUE values by using sum(), such as sum(c(TRUE, TRUE, FALSE)) = 2.
* num\_na = function(x) {  
   return(sum(is.na(num\_na)))  
  }
* Create a function, called medicaid\_eligible in which the function takes in one argument: a numeric vector called age. The function returns a numeric vector with the same length as age, in which elements are 0 for indicies that are less than 65 in age, and 1 for indicies 65 or higher in age. (Hint: This is a data recoding problem!) Use cases: medicaid\_eligible(c(30, 70)) = c(0, 1)
* medicaid\_eligible = function(age) {  
   result = age  
   result[age < 65] = 0  
   result[age >= 65] = 1  
   return(result)  
  }  
  medicaid\_eligible(c(30, 70))
* ## [1] 0 1

## 5.6 Exercises

You can find [exercises and solutions on Posit Cloud](https://posit.cloud/content/8236252), or on [GitHub](https://github.com/fhdsl/Intermediate_R_Exercises).

# 6 Iteration

Suppose that you want to repeat a chunk of code many times, but changing one variable’s value each time you do it. This could be modifying each element of a vector with the same operation, or analyzing a dataframe with different parameters.

There are three common strategies to go about this:

1. Copy and paste the code chunk, and change that variable’s value. Repeat. *This can be a starting point in your analysis, but will lead to errors easily.*
2. Use a for loop to repeat the chunk of code, and let it loop over the changing variable’s value. *This is popular for many programming languages, but the R programming culture encourages a functional way instead*.
3. **Functionals** allow you to take a function that solves the problem for a single input and generalize it to handle any number of inputs. *This is very popular in R programming culture.*

## 6.1 For loops

A for loop repeats a chunk of code many times, once for each element of an input vector.

for (my\_element in my\_vector) {  
 chunk of code  
}

Most often, the “chunk of code” will make use of my\_element.

#### 6.1.0.1 We can loop through the indicies of a vector

The function seq\_along() creates the indicies of a vector. It has almost the same properties as 1:length(my\_vector), but avoids issues when the vector length is 0.

my\_vector = c(1, 3, 5, 7)  
  
for(i in seq\_along(my\_vector)) {  
 print(my\_vector[i])  
}

## [1] 1  
## [1] 3  
## [1] 5  
## [1] 7

#### 6.1.0.2 Alternatively, we can loop through the elements of a vector

for(vec\_i in my\_vector) {  
 print(vec\_i)  
}

## [1] 1  
## [1] 3  
## [1] 5  
## [1] 7

#### 6.1.0.3 Another example via indicies

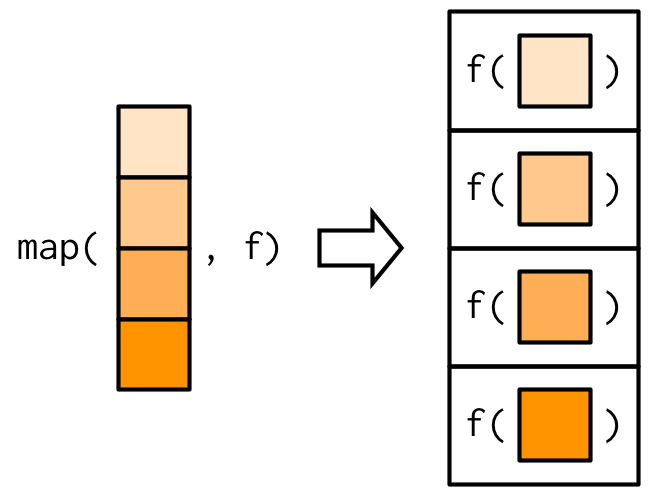
result = rep(NA, length(my\_vector))  
for(i in seq\_along(my\_vector)) {  
 result[i] = log(my\_vector[i])  
}

## 6.2 Functionals

A **functional** is a function that takes in a data structure and function as inputs and applies the function on the data structure, element by element. It *maps* your input data structure to an output data structure based on the function. It encourages the usage of modular functions in your code.

![](data:text/html; charset=utf-8;base64,)

Or,



We will use the purrr package in tidyverse to use functionals. There is another set of functionals in Base-R called the apply family of functions that work very similarly. You can see the comparision of both tools [here](https://purrr.tidyverse.org/articles/base.html) and [here](https://jtr13.github.io/spring19/ss5593&fq2150.html).

map() takes in a vector or a list, and then applies the function on each element of it. The output is *always* a list.

my\_vector = c(1, 3, 5, 7)  
map(my\_vector, log)

## [[1]]  
## [1] 0  
##   
## [[2]]  
## [1] 1.098612  
##   
## [[3]]  
## [1] 1.609438  
##   
## [[4]]  
## [1] 1.94591

Lists are useful if what you are using it on requires a flexible data structure.

To be more specific about the output type, you can do this via the map\_\* function, where \* specifies the output type: map\_lgl(), map\_chr(), and map\_dbl() functions return vectors of logical values, strings, or numbers respectively.

For example, to make sure your output is a double (numeric):

map\_dbl(my\_vector, log)

## [1] 0.000000 1.098612 1.609438 1.945910

All of these are toy examples that gets us familiar with the syntax, but we already have built-in functions to solve these problems, such as log(my\_vector). Let’s see some real-life case studies.

## 6.3 Case studies

### 6.3.1 1. Loading in multiple files.

Suppose that we want to load in a few dataframes, and store them in a list of dataframes for analysis downstream.

We start with the filepaths we want to load in as dataframes.

paths = c("classroom\_data/students.csv", "classroom\_data/CCLE\_metadata.csv")

The function we want to use to load the data in will be read\_csv().

Let’s practice writing out one iteration:

result = read\_csv(paths[1])

#### 6.3.1.1 To do this functionally, we think about:

* What variable we need to loop through: paths
* The repeated task as a function: read\_csv()
* The looping mechanism, and its output: map() outputs lists.

loaded\_dfs = map(paths, read\_csv)

#### 6.3.1.2 To do this with a for loop, we think about:

* What variable we need to loop through: paths.
* Do we need to store the outcome of this loop in a data structure? Yes, a list.
* At each iteration, what are we doing? Use read\_csv() on the current element, and store it in the output list.

paths = c("classroom\_data/students.csv", "classroom\_data/CCLE\_metadata.csv")  
loaded\_dfs = vector(mode = "list", length = length(paths))  
for(i in seq\_along(paths)) {  
 df = read\_csv(paths[i])  
 loaded\_dfs[[i]] = df  
}

### 6.3.2 2. Analyze a dataframe with different parameters.

Suppose you are working with the penguins dataframe:

library(palmerpenguins)  
head(penguins)

## # A tibble: 6 × 8  
## species island bill\_length\_mm bill\_depth\_mm flipper\_length\_mm body\_mass\_g  
## <fct> <fct> <dbl> <dbl> <int> <int>  
## 1 Adelie Torgersen 39.1 18.7 181 3750  
## 2 Adelie Torgersen 39.5 17.4 186 3800  
## 3 Adelie Torgersen 40.3 18 195 3250  
## 4 Adelie Torgersen NA NA NA NA  
## 5 Adelie Torgersen 36.7 19.3 193 3450  
## 6 Adelie Torgersen 39.3 20.6 190 3650  
## # ℹ 2 more variables: sex <fct>, year <int>

and you want to look at the mean bill\_length\_mm for each of the three species (Adelie, Chinstrap, Gentoo).

Let’s practice writing out one iteration:

species\_to\_analyze = c("Adelie", "Chinstrap", "Gentoo")  
penguins\_subset = filter(penguins, species == species\_to\_analyze[1])  
mean(penguins\_subset$bill\_length\_mm, na.rm = TRUE)

## [1] 38.79139

#### 6.3.2.1 To do this functionally, we think about:

* What variable we need to loop through: c("Adelie", "Chinstrap", "Gentoo")
* The repeated task as a function: a custom function that takes in a specie of interest. The function filters the rows of penguins to the species of interest, and compute the mean of bill\_length\_mm.
* The looping mechanism, and its output: map\_dbl() outputs (double) numeric vectors.

analysis = function(current\_species) {  
 penguins\_subset = dplyr::filter(penguins, species == current\_species)  
 return(mean(penguins\_subset$bill\_length\_mm, na.rm=TRUE))  
}  
  
map\_dbl(c("Adelie", "Chinstrap", "Gentoo"), analysis)

## [1] 38.79139 48.83382 47.50488

#### 6.3.2.2 To do this with a for loop, we think about:

* What variable we need to loop through: c("Adelie", "Chinstrap", "Gentoo").
* Do we need to store the outcome of this loop in a data structure? Yes, a numeric vector.
* At each iteration, what are we doing? Filter the rows of penguins to the species of interest, and compute the mean of bill\_length\_mm.

outcome = rep(NA, length(species\_to\_analyze))  
for(i in seq\_along(species\_to\_analyze)) {  
 penguins\_subset = filter(penguins, species == species\_to\_analyze[i])  
 outcome[i] = mean(penguins\_subset$bill\_length\_mm, na.rm=TRUE)  
}  
outcome

## [1] 38.79139 48.83382 47.50488

### 6.3.3 3. Calculate summary statistics on columns of a dataframe.

Suppose that you are interested in the numeric columns of the penguins dataframe.

penguins\_numeric = penguins %>% select(bill\_length\_mm, bill\_depth\_mm, flipper\_length\_mm, body\_mass\_g)

and you are interested to look at the mean of each column. It is very helpful to interpret the dataframe penguins\_numeric as a *list*, iterating through each column as an element of a list.

Let’s practice writing out one iteration:

mean(penguins\_numeric[[1]], na.rm = TRUE)

## [1] 43.92193

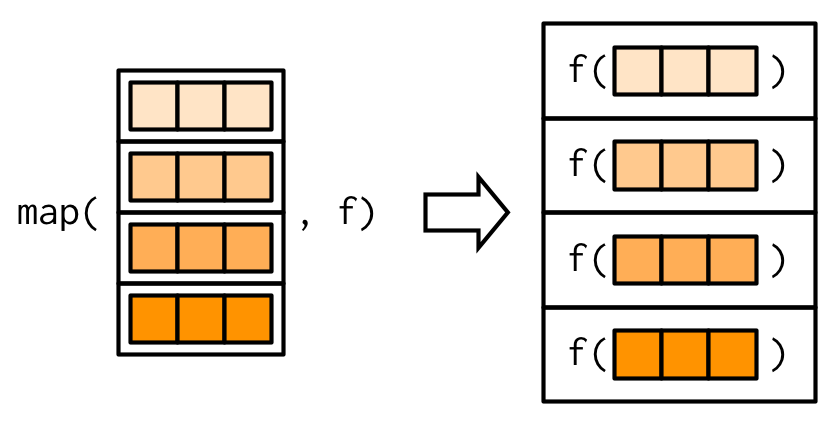
#### 6.3.3.1 To do this functionally, we think about:

* What variable we need to loop through: the list penguins\_numeric
* The repeated task as a function: mean() with the argument na.rm = TRUE.
* The looping mechanism, and its output: map\_dbl() outputs (double) numeric vectors.

map\_dbl(penguins\_numeric, mean, na.rm = TRUE)

## bill\_length\_mm bill\_depth\_mm flipper\_length\_mm body\_mass\_g   
## 43.92193 17.15117 200.91520 4201.75439

Here, R is interpreting the dataframe penguins\_numeric as a *list*, iterating through each column as an element of a list:



#### 6.3.3.2 To do this with a for loop, we think about:

* What variable we need to loop through: the elements of penguins\_numeric as a list.
* Do we need to store the outcome of this loop in a data structure? Yes, a numeric vector.
* At each iteration, what are we doing? Compute the mean of an element of penguins\_numeric.

result = rep(NA, ncol(penguins\_numeric))  
for(i in seq\_along(penguins\_numeric)) {  
 result[i] = mean(penguins\_numeric[[i]], na.rm = TRUE)  
}  
result

## [1] 43.92193 17.15117 200.91520 4201.75439

## 6.4 Exercises

You can find [exercises and solutions on Posit Cloud](https://posit.cloud/content/8236252), or on [GitHub](https://github.com/fhdsl/Intermediate_R_Exercises).

# About the Authors

These credits are based on our [course contributors table guidelines](https://www.ottrproject.org/more_features.html#giving-credits-to-contributors).

| Credits | Names |
| --- | --- |
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| Lead Content Instructor(s) | Chris Lo |
| Lecturer | Chris Lo |
| Content Author(s) (include chapter name/link in parentheses if only for specific chapters) - make new line if more than one chapter involved | If any other authors besides lead instructor |
| Content Contributor(s) (include section name/link in parentheses) - make new line if more than one section involved | Wrote less than a chapter |
| Content Editor(s)/Reviewer(s) | Checked your content |
| Content Director(s) | Helped guide the content direction |
| Content Consultants (include chapter name/link in parentheses or word “General”) - make new line if more than one chapter involved | Gave high level advice on content |
| Acknowledgments | Gave small assistance to content but not to the level of consulting |
| **Production** |  |
| Content Publisher(s) | Helped with publishing platform |
| Content Publishing Reviewer(s) | Reviewed overall content and aesthetics on publishing platform |
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## ─ Session info ───────────────────────────────────────────────────────────────  
## setting value  
## version R version 4.3.2 (2023-10-31)  
## os Ubuntu 22.04.4 LTS  
## system x86\_64, linux-gnu  
## ui X11  
## language (EN)  
## collate en\_US.UTF-8  
## ctype en\_US.UTF-8  
## tz Etc/UTC  
## date 2024-06-17  
## pandoc 3.1.1 @ /usr/local/bin/ (via rmarkdown)  
##   
## ─ Packages ───────────────────────────────────────────────────────────────────  
## package \* version date (UTC) lib source  
## bookdown 0.39.1 2024-06-11 [1] Github (rstudio/bookdown@f244cf1)  
## cachem 1.0.8 2023-05-01 [1] RSPM (R 4.3.0)  
## cli 3.6.2 2023-12-11 [1] RSPM (R 4.3.0)  
## devtools 2.4.5 2022-10-11 [1] RSPM (R 4.3.0)  
## digest 0.6.34 2024-01-11 [1] RSPM (R 4.3.0)  
## ellipsis 0.3.2 2021-04-29 [1] RSPM (R 4.3.0)  
## evaluate 0.23 2023-11-01 [1] RSPM (R 4.3.0)  
## fastmap 1.1.1 2023-02-24 [1] RSPM (R 4.3.0)  
## fs 1.6.3 2023-07-20 [1] RSPM (R 4.3.0)  
## glue 1.7.0 2024-01-09 [1] RSPM (R 4.3.0)  
## htmltools 0.5.7 2023-11-03 [1] RSPM (R 4.3.0)  
## htmlwidgets 1.6.4 2023-12-06 [1] RSPM (R 4.3.0)  
## httpuv 1.6.14 2024-01-26 [1] RSPM (R 4.3.0)  
## knitr 1.47.3 2024-06-11 [1] Github (yihui/knitr@e1edd34)  
## later 1.3.2 2023-12-06 [1] RSPM (R 4.3.0)  
## lifecycle 1.0.4 2023-11-07 [1] RSPM (R 4.3.0)  
## magrittr 2.0.3 2022-03-30 [1] RSPM (R 4.3.0)  
## memoise 2.0.1 2021-11-26 [1] RSPM (R 4.3.0)  
## mime 0.12 2021-09-28 [1] RSPM (R 4.3.0)  
## miniUI 0.1.1.1 2018-05-18 [1] RSPM (R 4.3.0)  
## pkgbuild 1.4.3 2023-12-10 [1] RSPM (R 4.3.0)  
## pkgload 1.3.4 2024-01-16 [1] RSPM (R 4.3.0)  
## profvis 0.3.8 2023-05-02 [1] RSPM (R 4.3.0)  
## promises 1.2.1 2023-08-10 [1] RSPM (R 4.3.0)  
## purrr 1.0.2 2023-08-10 [1] RSPM (R 4.3.0)  
## R6 2.5.1 2021-08-19 [1] RSPM (R 4.3.0)  
## Rcpp 1.0.12 2024-01-09 [1] RSPM (R 4.3.0)  
## remotes 2.4.2.1 2023-07-18 [1] RSPM (R 4.3.0)  
## rlang 1.1.4 2024-06-04 [1] CRAN (R 4.3.2)  
## rmarkdown 2.27.1 2024-06-11 [1] Github (rstudio/rmarkdown@e1c93a9)  
## sessioninfo 1.2.2 2021-12-06 [1] RSPM (R 4.3.0)  
## shiny 1.8.0 2023-11-17 [1] RSPM (R 4.3.0)  
## stringi 1.8.3 2023-12-11 [1] RSPM (R 4.3.0)  
## stringr 1.5.1 2023-11-14 [1] RSPM (R 4.3.0)  
## urlchecker 1.0.1 2021-11-30 [1] RSPM (R 4.3.0)  
## usethis 2.2.3 2024-02-19 [1] RSPM (R 4.3.0)  
## vctrs 0.6.5 2023-12-01 [1] RSPM (R 4.3.0)  
## xfun 0.44.4 2024-06-11 [1] Github (yihui/xfun@9da62cc)  
## xtable 1.8-4 2019-04-21 [1] RSPM (R 4.3.0)  
## yaml 2.3.8 2023-12-11 [1] RSPM (R 4.3.0)  
##   
## [1] /usr/local/lib/R/site-library  
## [2] /usr/local/lib/R/library  
##   
## ──────────────────────────────────────────────────────────────────────────────

# 7 References