Lecture 6: Functions and testing

Contents

Lecture learning objectives:

By then end of this lecture & worksheet 6, students should be able to:

- In R, define and use a named function that accepts parameters and returns values

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- explain the importance of scoping and environments in R as they relate to functions
- Use `testthat` to formulate a test case to prove a function design specification
- Use test-driven development principles to define a function that accepts parameters, returns values and passes all tests
- Handle errors gracefully via exception handling
- Use `roxygen2` friendly function documentation to describe parameters, return values, description and example(s).
- Write comments within a function to improve readability
- Evaluate the readability, complexity and performance of a function
- Source and use functions stored as R code in another file, as well as those in R packages/libraries
- Describe what R packages/libraries are, as well as explain when and why they are useful

```
options(repr.matrix.max.rows = 10)
```

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Which of the following code is not correct for finding sum of all elements in col_1. (*my_t <- tibble(col_1 = c(1.43, 2.21, 3.43, NA), col_2 = c(2.6, 3.4, 5, 6.3)*)

col_1	col_2
1.43	2.6
2.21	3.4
3.43	5.0
NA	6.3

A) my_t |> summarise(sum_val = sum(col_1, na.rm = TRUE))

B) my_t |> summarize(sum_val = sum(col_1, na.rm = TRUE))

C) my_t |> summarise(sum_val = sum(col_1, is.na = TRUE))

D) my_t |> drop_na(col_1) |> summarise(sum_val = sum(col_1))

Answer: C

There is no argument called ***is.na*** that we can pass to ***sum*** function

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Functions

Defining functions in R:

- Use `variable <- function(…arguments…) { …body… }` to create a function and give it a name

Example:

```
add <- function(x, y) {
  x + y
}

add(5, 10)
```

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- As in Python, functions in R are objects. This is referred to as “first-class functions”.
- The last line of the function returns a value, to return a value early use the special word `return`

```
add <- function(x, y) {
    if (!is.numeric(x) | !is.numeric(y)) {
        return(NA)
    }
    x + y
}

add(5, "a")
```

<NA>

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Default function arguments

Same as in Python!

```
repeat_string <- function(x, n = 2) {
    repeated <- ""
    for (i in seq_along(1:n)) {
        repeated <- paste0(repeated, x)
    }
    repeated
}

repeat_string("MDS")
```

'MDSMDS'

Optional - Advanced

Extra arguments via `...`

If we want our function to be able to take extra arguments that we don't specify, we must explicitly convert `...` to a list:

```
add <- function(x, y, ...) {
    total = x + y
    for (value in list(...)) {
        total <- total + value
    }
    total
    print(list(...))
}
add(1, 3, 5, 6)
```

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

[[2]]
[1] 6
```

Lexical scoping in R

R's lexical scoping follows several rules, we will cover the following 3:

- Name masking
- Dynamic lookup
- A fresh start

Name masking

- Names defined inside a function mask names defined outside a function
- If a name isn't defined inside a function, R looks one level up (and then all the way up into the global environment and even loaded packages!)

Talk through the following code with your neighbour and predict the output, then let's confirm the result by running the code.

```
x <- 1
g04 <- function() {
  y <- 2
  i <- function() {
```

Skip to main content

```
  }
  i()
}
g04()
```

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Dynamic lookup

- R looks for values when the function is run, not when the function is created.
- This means that the output of a function can differ depending on the objects outside the function's environment.

Talk through the following code with your neighbour and predict the output, then let's confirm the result by running the code.

```
g12 <- function() x + 1
x <- 15
g12()

x <- 20
g12()
```

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A fresh start

- Every time a function is called a new environment is created to host its execution.

Talk through the following code with your neighbour and predict the output, then let's confirm the result by running the code.

```
g11 <- function() {
  if (!exists("a")) {
    a <- 1
  } else {
    a <- a + 1
  }
  a
}

g11()
g11()
g11()
```

1

1

1

Lazy evaluation

In R, function arguments are lazily evaluated: they're only evaluated if accessed.

Knowing that, now consider the `add_one` function written in both R and Python below:

```
# R code (this would work)
add_one <- function(x, y) {
    x <- x + 1
    return(x)
}
```

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```
# Python code (this would not work)
def add_one(x, y):
    x = x + 1
    return x
```

Why will the above `add_one` function will work in R, but the equivalent version of the function in python would break?

- Python evaluates the function arguments before it evaluates the function and because it doesn't know what `y` is, it will break even though it is not used in the function.
- R performs lazy evaluation, meaning it delays the evaluation of the function arguments until its value is needed within/inside the function. Since `y` is never referenced inside the function, R doesn't complain, or even notice it.

`add_one` in R

```
add_one <- function(x, y) {
    x <- x + 1
    return(x)
}
```

This works:

```
add_one(2, 1)
```

```
3
```

and so does this:

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```
add_one(2)
```

```
3
```

`add_one` in Python

```
def add_one(x, y):
    x = x + 1
    return x`
```

This works:

```
add_one(2, 1)
```

```
3
```

This does not:

```
add_one(2)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-5-f2e542671748> in <module>
----> 1 add_one(2)
```

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The power of lazy evaluation

Let's you have easy to use interactive code like this:

```
head(mtcars, n = 2)
```

A data.frame: 2 × 11

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
Mazda RX4	21	6	160	110	3.9	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21	6	160	110	3.9	2.875	17.02	0	1	4	4

```
dplyr::select(mtcars, mpg, cyl, hp, qsec)
```

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A data.frame: 32 × 4

	mpg	cyl	hp	qsec
	<dbl>	<dbl>	<dbl>	<dbl>
Mazda RX4	21.0	6	110	16.46
Mazda RX4 Wag	21.0	6	110	17.02
Datsun 710	22.8	4	93	18.61
Hornet 4 Drive	21.4	6	110	19.44
Hornet Sportabout	18.7	8	175	17.02
⋮	⋮	⋮	⋮	⋮
Lotus Europa	30.4	4	113	16.9
Ford Pantera L	15.8	8	264	14.5
Ferrari Dino	19.7	6	175	15.5
Maserati Bora	15.0	8	335	14.6
Volvo 142E	21.4	4	109	18.6

Notes:

- There's more than just lazy evaluation happening in the code above, but lazy evaluation is part of it.
- `package::function()` is a way to use a function from an R package without loading the entire library.

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What will be the output of following

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```r
x <- 1
y <- 1

exp_masking <- function(x, name, z) {
  x <- 3
  paste0("Hello ", name, " ", x, y)
  }

x <- 2
y <- 2
name <- "Huang"

try({exp_masking(name = "Elisa")})

try({exp_masking("Elisa")})

try({paste0("Hello ", name, " ", x, y)})
```

```
## OPTION A
[1] "Hello Elisa 32"
Error in exp_masking() : argument "name" is missing, with no default
[1] "Hello Huang 22"

## OPTION B
[1] "Hello Elisa 31"
Error in exp_masking() : argument "name" is missing, with no default
[1] "Hello Elisa 32"

## OPTION C
[1] ""
[1] ""
[1] "Hello Huang 22"

## OPTION D
```

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```
[1] "Hello Elisa 22"
```

Answer: A Clear concepts on

- Name masking
- Dynamic lookup
- A fresh start
- Lazy evaluation
- return statement
- Positional & keyword arguments
- Why we use try

Writing tests with {testthat}

- Industry standard tool for writing tests in R is the {testthat} package.
- To use an R package, we typically load the package into R using the `library` function:

```
library(testthat)
```

How to write a test with {testthat}

```
test_that("Message to print if test fails", expect_*(...))
```

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Often our `test_that` function calls are longer than 80 characters, so we use `{` to split the code across multiple lines, for example:

```
x <- c(3.5, 3.5, 3.5)
y <- c(3.5, 3.5, 3.5)
test_that("x and y should contain the same values", {
    expect_equal(x, y)
})
```

```
Test passed 🌈
```

Are you starting to see a pattern with `{` yet...

Common `expect_*` statements for use with `test_that`

Is the object equal to a value?

- `expect_identical` - test two objects for being exactly equal
- `expect_equal` - compare R objects x and y testing 'near equality' (can set a tolerance)
- `expect_equivalent` - compare R objects x and y testing 'near equality' (can set a tolerance) and does not assess attributes

Does code produce an output/message/warning/error?

- `expect_error` - tests if an expression throws an error

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- `expect_output` - tests that print output matches a specified value

Is the object true/false?

These are fall-back expectations that you can use when none of the other more specific expectations apply. The disadvantage is that you may get a less informative error message.

- `expect_true` - tests if the object returns `TRUE`
- `expect_false` - tests if the object returns `FALSE`

Tolerance and tests:

Below we add a tolerance arguement to the `expect_equal` statement such that the observed difference between these very similar vectors doesn't cause the test to fail.

```
x <- c(3.5, 3.5, 3.5)
y <- c(3.5, 3.5, 3.49999)
test_that("x and y should contain the same values", {
    expect_equal(x, y)
})
```

```
Error: Test failed: 'x and y should contain the same values'
* <text>:4: `x` not equal to `y`.
1/3 mismatches
[3] 3.5 - 3.5 == 1e-05
Traceback:

1. test_that("x and y should contain the same values", {
 .     expect_equal(x, y)
```

Skip to main content

```
3. get_reporter()$end_test(context = get_reporter()$.context, test = test)
4. stop(message, call. = FALSE)
```

```r
x <- c(3.5, 3.5, 3.5)
y <- c(3.5, 3.5, 3.49999)
test_that("x and y should contain the same values", {
    expect_equal(x, y, tolerance = 0.00001)
})
```

```
Test passed 🎊
```

Unit test example

```r
celsius_to_fahr <- function(temp) {
  (temp * (9 / 5)) + 32
}
```

```r
test_that("Temperature should be the same in Celcius and Fahrenheit at -40", {
        expect_identical(celsius_to_fahr(-40), -40)
    })
test_that("Room temperature should be about 23 degrees in Celcius and 73 degrees Fahrenheit", {
        expect_equal(celsius_to_fahr(23), 73, tolerance = 1)
    })
```

```
Test passed 🌈
```

```
Test passed 🥇
```

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Test-driven development (TDD) review

1. Write your tests first (that call the function you haven't yet written), based on edge cases you expect or can calculate by hand
2. If necessary, create some "helper" data to test your function with (this might be done in conjunction with step 1)
3. Write your function to make the tests pass (in this process you might think of more tests that you want to add)

Toy example of how TDD can be helpful

Let's create a function called `fahr_to_celsius` that converts temperatures from Fahrenheit to Celsius.

First we'll write the tests (which will fail):

```
test_fahr_to_celsius <- function() {
    test_that("Temperature should be the same in Celcius and Fahrenheit at -40", {
        expect_identical(fahr_to_celsius(-40), -40)
    })
    test_that("Room temperature should be about 73 degrees Fahrenheit and 23 degrees in Celcius", {
        expect_equal(fahr_to_celsius(73), 23, tolerance = 1)
    })
}
```

Then we write our function to pass the tests:

```
fahr_to_celsius <- function(temp) {
    (temp + 32) * 5/9
}
```

Then we call our tests to check it:

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```
test_fahr_to_celsius()
```

```
Error: Test failed: 'Temperature should be the same in Celcius and Fahrenheit at -40'
* <text>:3: fahr_to_celsius(-40) not identical to -40.
1/1 mismatches
[1] -4.44 - -40 == 35.6
Traceback:

1. test_fahr_to_celsius()
2. test_that("Temperature should be the same in Celcius and Fahrenheit at -40",
 .     {
 .         expect_identical(fahr_to_celsius(-40), -40)
 .     })   # at line 2-4 of file <text>
3. test_code(desc, code, env = parent.frame())
4. get_reporter()$end_test(context = get_reporter()$.context, test = test)
5. stop(message, call. = FALSE)
```

We found an error - so we go back and edit our function:

```
fahr_to_celsius <- function(temp) {
    (temp - 32) * 5/9
}
```

And then call our tests again to see if we got it right!

```
test_fahr_to_celsius()
```

```
Test passed 🥇
Test passed 🎊
```

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Exception handling

How to check type and throw an error if not the expected type:

```
if (!is.numeric(c(1, 2, "c")))
  stop("Cannot compute of a vector of characters.")
```

```
Error in eval(expr, envir, enclos): Cannot compute of a vector of characters.
Traceback:

1. stop("Cannot compute of a vector of characters.")
```

Example of defensive programming at the beginning of a function:

```
fahr_to_celsius <- function(temp) {
```

Skip to main content

```
    }
    (temp - 32) * 5/9
}
```

```
fahr_to_celsius("thirty")
```

```
Error in fahr_to_celsius("thirty"): Cannot calculate temperature in Farenheit for non-numerical values
Traceback:

1. fahr_to_celsius("thirty")
2. stop("Cannot calculate temperature in Farenheit for non-numerical values")   # at line 3 of file <te
```

If you wanted to issue a warning instead of an error, you could use `warning` in place of `stop` in the example above. However, in most cases it is better practice to throw an error than to print a warning...

We can test our exceptions using test_that:

```
test_that("Non-numeric values for temp should throw an error", {
    expect_error(fahr_to_celsius("thirty"))
    expect_error(fahr_to_celsius(list(4)))
    })
```

```
Test passed 😸
```

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`try` in R

Similar to Python, R has a `try` function to attempt to run code, and continue running subsequent code even if code in the try block does not work:

```
try({
    # some code
    # that can be
    # split across several
    # lines
})

# code to continue even if error in code
# in try code block above
```

This code normally results in an error that stops following code from running:

```
x <- data.frame(col1 = c(1, 2, 3, 2, 1),
                col2 = c(0, 1, 0, 0 , 1))
x[3]
dim(x)
```

```
Error in `[.data.frame`(x, 3): undefined columns selected
Traceback:

1. x[3]
2. `[.data.frame`(x, 3)
3. stop("undefined columns selected")
```

Try let's the code following the error run:

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```
try({x <- data.frame(col1 = c(1, 2, 3, 2, 1),
                     col2 = c(0, 1, 0, 0 , 1))
    x[3]
})
dim(x)
```

```
Error in `[.data.frame`(x, 3) : undefined columns selected
```

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Sensibly (IMHO) `try` has a default of `silent=FALSE`, which you can change if you find good reason too.

{roxygen2} friendly function documentation

```
#' Converts temperatures from Fahrenheit to Celsius.
#'
#' @param temp a vector of temperatures in Fahrenheit
#'
#' @return a vector of temperatures in Celsius
#'
#' @examples
#' fahr_to_celsius(-20)
fahr_to_celsius <- function(temp) {
    (temp - 32) * 5/9
}
```

Why `roxygen2` documentation? If you document your functions like this, *when* you create an R package to share them they will be set up to have the fancy documentation that we get using `?function_name`.

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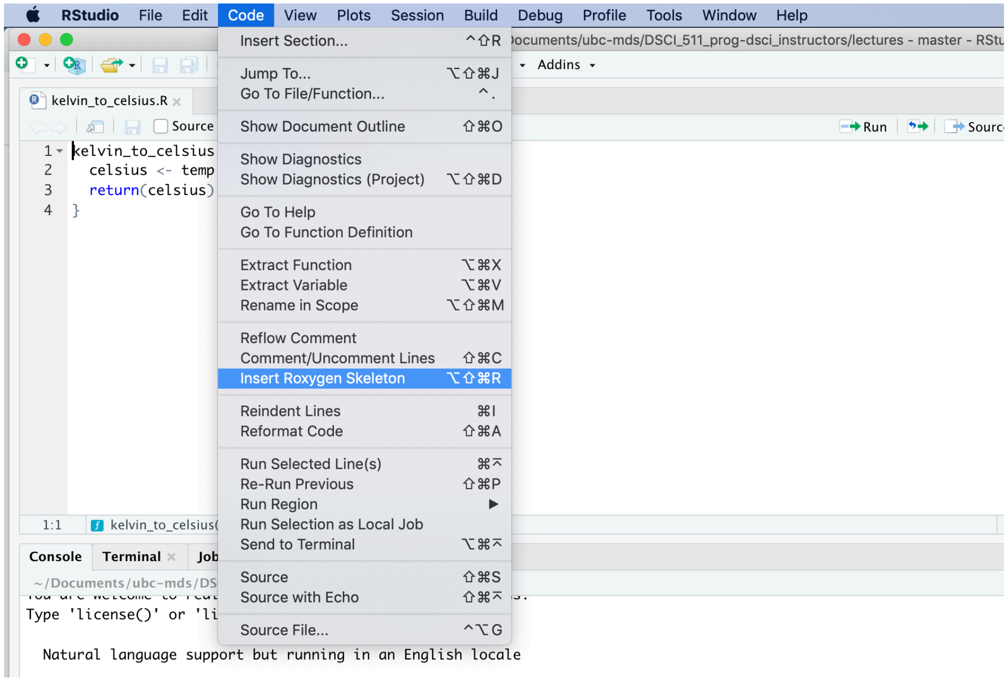
RStudio has template for `roxygen2` documentation



Reading in functions from an R script

Usually the step before packaging your code, is having some functions in another script that you want to read into your analysis. We use the `source` function to do this:

```
source("src/kelvin_to_celsius.R")
```

Once you do this, you have access to all functions contained within that script:

```
kelvin_to_celsius(273.15)
```

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Note - this is how the `test_*` functions are brought into your Jupyter notebooks for the autograding part of your lab3 homework.

Introduction to R packages

- `source("script_with_functions.R")` is useful, but when you start using these functions in different projects you need to keep copying the script, or having overly specific paths…
- The next step is packaging your R code so that it can be installed and then used across multiple projects on your (and others) machines without directly pointing to where the code is stored, but instead accessed using the `library` function.
- You will learn how to do this in Collaborative Software Development (term 2), but for now, let's tour a simple R package to get a better understanding of what they are: https://github.com/ttimbers/convertemp

Install the convertemp R package:

In RStudio, type: `devtools::install_github("ttimbers/convertemp")`

```
library(convertempr)
```

```
Attaching package: 'convertempr'
```

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```
    celsius_to_fahr, fahr_to_celsius, kelvin_to_celsius
```

```
?celsius_to_kelvin
```

celsius_to_kelvin {convertempr} R Documentation

Convert Celsius to Kelvin

Description

Convert a temperature from Celsius to Kelvin

Usage

```
celsius_to_kelvin(temp)
```

Arguments

`temp`	numeric

Value

numeric

Examples

```
celsius_to_kelvin(0)
```

[Package *convertempr* version 0.0.0.9000]

```
celsius_to_kelvin(0)
```

273.15

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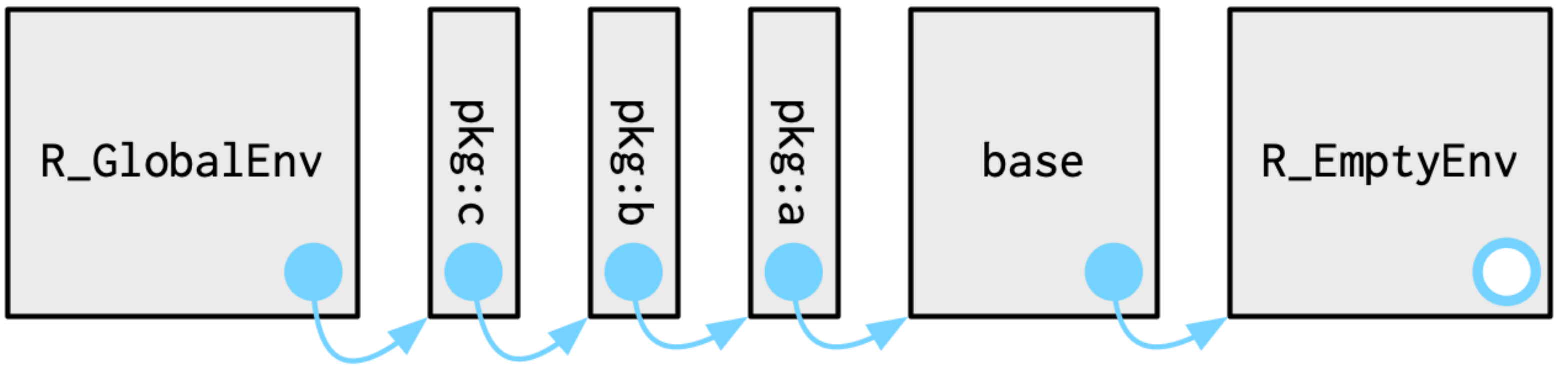
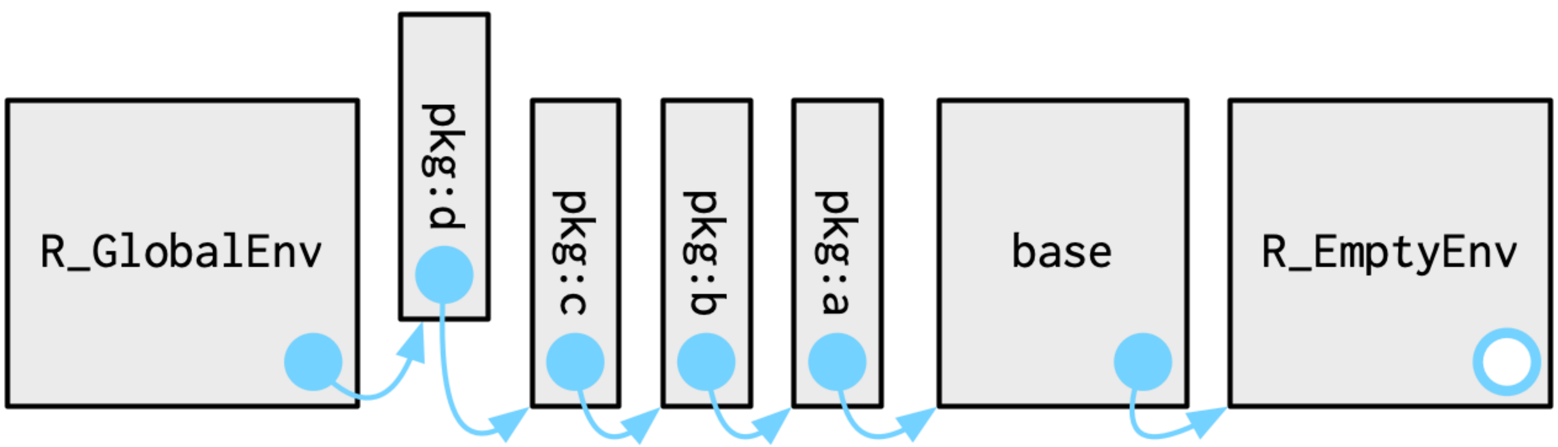
Packages and environments

- Each package attached by library() becomes one of the parents of the global environment
- The immediate parent of the global environment is the last package you attached, the parent of that package is the second to last package you attached, ...



Source: [Advanced R](#) by Hadley Wickham

When you attach another package with library(), the parent environment of the global environment changes:



Source: [Advanced R](#) by Hadley Wickham

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What did we learn today?

- How to write and test functions in R
- How to handle exceptions
- How to source functions from other files
- A little bit about what R packages are

Attribution:

- Advanced R by Hadley Wickham
- The Tidynomicon by Greg Wilson

Previous
Lecture 5 - Tidy control flow in R

Next
Lecture 7: Mapping and nested data frames