Programming in R

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Introduction

Who are we?

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Who are you?

1. Position and research topics?
2. Previous knowledge and experience
   - with R?
   - with other statistical software?
   - with other programming languages?
3. Expectations for this workshop?

Motivation

Why care about R coding?

1. Increase efficiency!
   - Save time and nerves
   - Avoid errors and bugs
   - High transfer effect to other projects (with data analysis)
2. Successful collaborations (including with your future self!)
3. Code as deliverable (i.e., part of research paper)

Agenda

- Loops & iteration
- Functions (part I)
- Functions (part II)
- Functionals & split-apply-combine
- Good programming practices

Quick Recap

"To understand computations in R, two slogans are helpful: Everything that exists is an object. Everything that happens is a function call."

— John Chambers

Basic *Objects* in R

Vectors	
logical	`TRUE`, `FALSE`, `NA`
integer	`1L`, `142`, `-5`, ..., `NA`
double	`1.0`, `1.25784`, `pi`, ..., `NA`
	`NaN`, `-Inf`, `Inf`
character	`"1"`, `"Some other string"`, ..., `NA`

Vectors can have multiple elements **of the same type** $\rightarrow$ `length()` starting from `0`

Basic *Objects* in R

More basic object types	
list	a **list** of vectors `list()`, `as.list()`
matrix	a **vector** with a `"dim"` argument: two dimensions `matrix()`, `as.matrix()` matrix algebra
array	a **vector** with with a `"dim"` argument
data.frame	a **list** with vectors of equal length `data.frame()`, `as.data.frame()`

`data.frame` vs `matrix`

A `data.frame` is a list of vectors → columns can be of different types.

Try!

```
iris_dat <- head(iris)
is.list(iris_dat)
dim(iris_dat)
length(iris_dat)
iris_dat[1:2,]
```

`data.frame` vs `matrix`

A `matrix`/`array` is a vector with dimensions $\rightarrow$ all elements/columns are of the same type.

Try!

```
iris_mat <- as.matrix(head(iris))
dim(iris_mat)
length(iris_mat)
iris_mat[1:2,]
```

Loops & Iteration

Loops & iteration

R has specific tools (functions) that help organize the flow of computations.
You can repeat a similar computation multiple times typically with changing options ("iteration"). The most commonly used tools are:

- loops
  - `for`
  - `while`
  - `repeat`
- `apply` - family

Loops & Iteration - for

`for` statements have the basic form

```
for (element in vector) {
  computation
}
```

For each element in the vector, the computation is executed. Often, the computation depends on the element in that iteration.

Loops & Iteration - for

```r
# iterate over a numeric vector
for (index in 1:3){
  cat(" computation -")
}

>  computation - computation - computation -

# iterate over a character vector
for (name in c("Alice", "Bob", "Casey")){
  if(name == "Bob") cat(" This was Bob -")
  else cat(" Not Bob -")
}

>  Not Bob - This was Bob - Not Bob -
```

Loops & Iteration - while

`while` statements have the basic form

```
while (condition){
  computation
}
```

As long as the condition is TRUE, the computation is executed. Often, the computation depends on something that is related to the condition.

Loops & Iteration - repeat

`repeat` statements have the basic form

```
repeat {
  computation
}
```

Without a `break` the computation is repeated infinite times

Loops & Iteration - next break

- `next` starts next iteration
- `break` ends iteration (of the innermost loop)

```
for(index in 1:8) {
  if (index %in% c(3, 5)) next
  if (index > 6) break
  print(index)
}

> [1] 1
> [1] 2
> [1] 4
> [1] 6
```

Nested loops:

```
for (element in vector_1) {
  computation
  for (element in vector_2) {
    computation
  }
  computation
}
```

Loops & Iteration - nested loops

Nested loops (over the rows and columns of a matrix)

```
matrix <- matrix(NA, nrow = 2, ncol = 3)
for (rowNr in 1:2){
  for (colNr in 1:3){
    matrix[rowNr, colNr] <- rowNr * 10 + colNr
  }
}
matrix

>      [,1] [,2] [,3]
> [1,]   11   12   13
> [2,]   21   22   23
```

Iteration - Good practice

Programming advice

Use `seq()`, `seq_len()`, or `seq_along()`, not `1:length(x)`.

```
x <- numeric()
for (index in 1:length(x)){
  print(index)
}

> [1] 1
> [1] 0

for (index in seq_along(x)){
  print(index)
}
```

Loops & Iteration - Good practice

Programming advice

Don't grow, replace.

```
x <- letters
result1 <- numeric()          # grow
result2 <- numeric(length(x)) # replace
for (index in seq_along(x)){
  result1 <- c(result1, paste(index, x[index]))  # grow
  result2[index] <- paste(index, x[index])       # replace
}
```

Loops & Iteration - apply

`apply` lets you iterate over rows or columns of a matrix or data.frame. You can *apply* a function to all rows/columns

```
apply(matrix,
      MARGIN = 1,        # 1 = iterate over rows
                         # 2 = iterate over columns
      FUN = function)    # function to apply to rows/columns
```

apply

- for objects with dimensions (matrix, array, data.frame)
- apply over (a) chosen dimension(s)

```
my_matrix <- matrix(1:6, nrow = 2)
apply(my_matrix, 1, max)    # apply per row

> [1] 5 6

apply(my_matrix, 2, max)    # apply per column

> [1] 2 4 6
```

apply

```
my_array <- array(1, dim = c(2, 3, 4))
apply(my_array, c(1, 2), sum)  # per row and column

>      [,1] [,2] [,3]
> [1,]    4    4    4
> [2,]    4    4    4

apply(my_array, 3, sum)        # per "third dimension"

> [1] 6 6 6 6
```

Exercises

Functions I

"To understand computations in R, two slogans are helpful: Everything that exists is an object. Everything that happens is a function call."

— John Chambers, Extending R (2016)

Function Calls

Computing in R happens through function calls. A function is applied to one or more objects, and returns an object after the computation.

Figure 1: A function call.

The typical use is:
`function(object1, argument = object2)`

Function Calls

- Computations that seem not to be done using function calls are actually also function calls. Try `` `<-`(a, 5) `` or `` `>`(5, 2) ``
- most functions that seem not to return an object, return it invisibly. Check `(a <- 5)`.

Building Blocks

Functions are the building blocks of R code. Writing functions allows you to organize and optimize the computations that you want to do.
Functions should:

- have a clear purpose
- be well documented
- be portable

Central stepping stone for R users:
Move from solely using functions written by others to writing your own functions.

Function definition

- Name
- Arguments/Formals (input)
- Body (what happens inside, R-code with the computations)
- Output

Function definition

```
                                       # Name
countNA <- function(x) {               # Arguments/Formals
  out <- sum(is.na(x))                 # Body
  out                                  # Output
}
```

Function Names

Every function needs a (meaningful) name!

- Usually **a verb** (what does the function do?)
- Avoid existing names
- Better longer than unclear
- CamelCase vs snake_case

Function Names

Good

- `computeAIC()`
- `removeNAs()`
- `drop_NA_rows()`
- `factor_to_dummies()`

Bad

- `myFun()`
- `foo()`
- `statistics()`
- `data_preparation()`

Arguments

Most functions take one or multiple inputs.
These are usually:

- One or two data arguments
- Additional Options

Arguments

Functions with zero arguments

- `getwd()`
- `Sys.time()`
- ...

Arguments

Functions with one argument

- `dim()`
- `names()`
- …

Arguments

Functions with multiple arguments

- `mean()`
- `median()`
- `lm()`
- ...

Arguments

Programming advice

Less arguments = better!

Arguments

Often arguments have to be objects of a specific type.

```
sum(c("a", "b", "c"))  # gives an error

> Error in sum(c("a", "b", "c")): invalid 'type'
(character) of argument
```

The documentation typically gives (or should give) information about what objects the arguments should be. Check `?sum`

Default arguments

What happens if the user omits an argument?

```
countNA <- function(x, percent) {
  out <- sum(is.na(x))
  if(percent) out/length(x)
  out
}
x <- c(1, 5, NA, 3)
countNA(x = x)

> Error in countNA(x = x): argument "percent" is
missing, with no default
```

Default arguments

Default arguments are made for such instances!

```
countNA <- function(x, percent = FALSE) {
  out <- sum(is.na(x))
  if(percent) out/length(x)
  out
}
x <- c(1, 5, NA, 3)
countNA(x = x)

> [1] 1
```

Default arguments

Additional arguments give (the user) flexibility. Default arguments keep the function easy to use.

Try `?lm`

Programming advice

- Think about which arguments to include, and which should (not) have defaults
- Choose sensible defaults

Single return object

Pure functions return a single object.

- (Standard) The last evaluated object
- Object defined by return()

Figure 2: A pure function.

Return object

`return()` stops the computation, and returns the object.

```
return_early <- function(x, early) {
  x2 <- x*2
  if(early) (return(x2))
  out <- x + x2 # not executed
  out
}
return_early(2, early = TRUE)

> [1] 4

return_early(2, early = FALSE)

> [1] 6
```

Return object

Multiple return objects can be combined in a list!

```
                                                    # Name
do_this <- function(vector, other_vector) { # Arguments
  # many computations                               # Body
  return(list(output1 = this,
              output2 = that))                      # Output
}
```

Return Object

The return object as a list with multiple objects.

```r
get_info <- function(x){
  mean_x <- mean(x)
  median_x <- median(x)
  n_obs_x <- length(x)
  range_x <- range(x)
  return(list(mean = mean_x, median = median_x,
              n_obs = n_obs_x, range = range_x))
}
str(get_info(airquality$Wind))

> List of 4
>  $ mean  : num 9.96
>  $ median: num 9.7
>  $ n_obs : int 153
>  $ range : num [1:2] 1.7 20.7
```

Debugging

- browser()
- traceback()
- options(error = recover)
- options(warn = 2)

browser()

Inspecting a function interactively

```
some_function <- function(x, y) {
  z <- x + y
  browser()
  z
}
some_function(x = 1, y = 5)
```

browser()

```
> some_function <- function(x, y) {
+   z <- x + y
+   browser()
+   z
+ }
> some_function(x = 1, y = 5)
Called from: some_function(x = 1, y = 5)
Browse[1]>
```

browser()

Navigating within a browser:

ls()	Show existing objects in the current environment
c	Exit the browser and continue execution
Q	Exit the browser, return to top level
where	Show call stack

Recover

Being able to chose an environment from the call stack:

```r
# on
options(error = recover)

# off
options(error = NULL)
```

Recover

Being able to choose an environment from a call stack:

```
Error in pretty_table(x, x_label = x_label) : length(x) > 1 is not TRUE

Enter a frame number, or 0 to exit

 1: by(mtcars, mtcars$carb, function(sub_dat) {
    pretty_statistics(sub_dat$cyl, x_label = "Cyl
 2: by.data.frame(mtcars, mtcars$carb, function(sub_dat) {
    pretty_statistics(sub_dat$cyl, x_l
 3: structure(eval(substitute(tapply(seq_len(nd), IND, FUNx, simplify = simplify)), data), call =
 4: eval(substitute(tapply(seq_len(nd), IND, FUNx, simplify = simplify)), data)
 5: eval(substitute(tapply(seq_len(nd), IND, FUNx, simplify = simplify)), data)
 6: tapply(seq_len(32), list(`mtcars$carb` = c(4, 4, 1, 1, 2, 1, 4, 2, 2, 4, 4, 3, 3, 3, 4, 4, 4,
 7: lapply(X = ans[index], FUN = FUN, ...)
 8: FUN(X[[i]], ...)
 9: FUN(data[x, , drop = FALSE], ...)
10: #2: pretty_statistics(sub_dat$cyl, x_label = "Cyl")
11: #3: pretty_table(x, x_label = x_label)
12: #2: stopifnot(length(x) > 1)

Selection:
```

Warnings

Turning warnings into errors

```
# on
options(warn = 2)

# off
options(warn = 1)
```

Exercises

Functions II

Reasons

Why write functions?

- They make code …
  - shorter (less repetition)
  - easier to read and understand
- They help avoid copy-paste errors
- They make it easier to change your code
- They increase transfer
  - other use cases
  - other projects
  - other persons
- They keep your work space clean

Readability

Writing a function:

```
RMSE <- get_RMSE(predictions, observations)
```

Not writing a function:

```
diff <- observations - predictions
sq_diff <- diff^2
m_sq_diff <- mean(dif)
RMSE <- sqrt(m_sq_diff)
```

Side Effects

Functions can have **“side effects”**:

- console output
- plots
- write/save on drive
- …

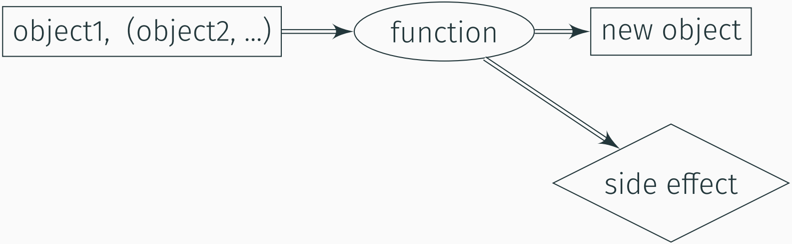


Figure 3: A function with side effect.

Side Effects

Console output: `?cat` and `?print`

```
print_info <- function(x){
  info <- get_info(x)
  cat("There are ", info$n_obs,
      " observed values. \nThe mean is ",
      round(info$mean, 2), ". \nThe median is ",
      round(info$median, 2), ". \n", sep = "")
}
print_info(airquality$Wind)

> There are 153 observed values.
> The mean is 9.96.
> The median is 9.7.
```

Output

Programming advice

- Write pure functions (no-side effects)
- Write separate functions for side effects
- Plotting functions should return `NULL` or the plot as an object

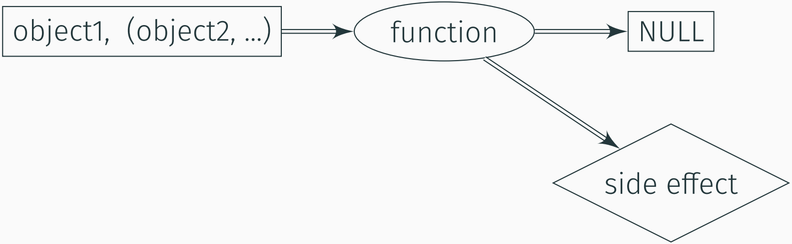


Figure 4: A side effect function.

Error, warning, & message

Error: computation is interrupted without return object!

`?stop`

```
get_log_xtox <- function(x) {
  if(!is.numeric(x)) stop("This does not work!")
  x_x <- x^x
  return(log(x_x))
}
get_log_xtox("a")

> Error in get_log_xtox("a"): This does not work!
```

Error: computation is interrupted without return object!

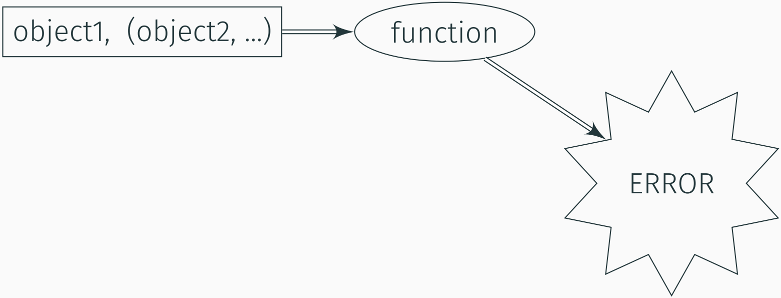


Figure 5: Computation with Error.

Error, warning, & message

`?stopifnot` is an abbreviation for `if(!test) stop()`:

```
get_log_xtox <- function(x) {
  stopifnot(is.numeric(x))
  x_x <- x^x
  return(log(x_x))
}
get_log_xtox("a")

> Error in get_log_xtox("a"): is.numeric(x) is not TRUE
```

Error, warning, & message

Message: To inform the user about something.

?message

```
get_log_xtox <- function(x) {
  x_x <- x^x
  message("Thank you for using this function!")
  return(log(x_x))
}
get_log_xtox(2)

> Thank you for using this function!

> [1] 1.386294
```

Error, warning, & message

Warning: Warn the user that something may be fishy.

```
?warning
```

```
get_log_xtox <- function(x) {
  if(x < 0 && (x %% 2 == 0))
    warning("Not sure you can trust the result.",
            call. = FALSE)
  x_x <- x^x
  return(log(x_x))
}
get_log_xtox(-2)

> Warning: Not sure you can trust the result.

> [1] -1.386294
```

Error, warning, & message

Message & warning: computation is NOT interrupted!

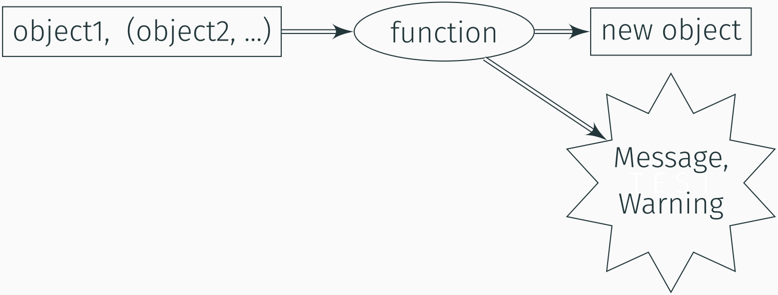


Figure 6: A message or warning.

Output

Programming advice

- Choose carefully when something warrants a message, warning or error
- Write clear and helpful warnings, errors, messages

Where does a function find objects?

R uses specific rules to find objects, which lead to the following:

```
a <- 55
add_a <- function(x){
  return(x + a)
}
add_a(5)

> [1] 60
```

When a function is called, the computations in the body are run line by line. When R cannot find an object inside the function, it looks outside the function.

Where does a function find objects?

Name masking!

Objects inside the function mask objects outside the function with the same name.

```r
a <- 55
add_a <- function(x){
  a <- 5
  return(x + a)
}
add_a(5)

> [1] 10
```

Where does a function find objects?

R uses specific rules to find objects.

1. in the function body
2. in the function call
3. in the function definition
4. outside the function

Watch out with number 4! Frequently restart R: `Ctrl + shift + F10`

Where does a function find objects?

R uses specific rules to find objects.

```
a <- b <- c <- d <- "fourth"
find_object <- function(a, b = "third", c = "third"){
  a <- "first"
  return(c(a = a, b = b, c = c, d = d))
}
find_object(b = "second")

>        a        b        c        d
>  "first" "second"  "third" "fourth"
```

`...` dot-dot-dot

R has a special argument (in the definition of the function):

`...` (dot-dot-dot)

Useful when you don't know how many arguments there will be. **Examples:**

- `?sum`
- `?save`
- `?cbind`
- `?paste`
- ...

... dot-dot-dot

A function that checks for multiple objects if they are character vectors. (A wrapper around (?is.character))

```
is_character <- function(...){
  input <- list(...)
  out <- logical(length(input))
  for(ell_nr in seq_along(input)){
    out[ell_nr] <- is.character(input[[ell_nr]])
  }
  names(out) <- names(input)
  out
}
is_character(a = "Awesome", b = 5, new = "YES")


>     a     b   new
>  TRUE FALSE  TRUE
```

`...` dot-dot-dot

`...` can take *any* number of additional arguments.
Useful for passing arguments to other functions like:

- `apply`-family
- `plot`-family
- ...

... dot-dot-dot

`apply` example:

```
get_quantiles <- function(x, ...){
  if(is.null(dim(x))) return(quantile(x, ...))
  apply(x, 2, quantile, ...)
}
get_quantiles(airquality, na.rm = TRUE,
              probs = c(.2, .8))

>     Ozone Solar.R  Wind Temp Month Day
> 20%    14      92  6.90   69   5.4   7
> 80%    73     266 12.96   86   8.0  25
```

... dot-dot-dot

WARNING!
Watch out with spelling mistakes, arguments can get lost!

```
get_quantiles <- function(x, ...){
  if(is.null(dim(x))) return(quantile(x, ...))
  apply(x, 2, quantile, ...)
}
get_quantiles(airquality, na.rm = TRUE,
              prosb = c(.2, .8))


>        Ozone Solar.R Wind Temp Month Day
> 0%      1.00    7.00  1.7   56     5   1
> 25%    18.00  115.75  7.4   72     6   8
> 50%    31.50  205.00  9.7   79     7  16
> 75%    63.25  258.75 11.5   85     8  23
> 100% 168.00  334.00 20.7   97     9  31
```

Writing Functions

Before creating a function

- What should my function do?
- Which input objects (Arguments)?
- Which additional options (Arguments)?
- What should the output object be?

After creating a function

- Test it
- Add input validation
- Document

Exercises

Functionals

Higher order functions are functions that either **take functions as input** or **return functions as output**.

Functionals

As defined by Hadley Wickham: A **functional** is a function that takes another function as an input. Common argument names are `FUN` or `f`.

Examples

- `apply`-family
- `Reduce`, `Filter`
- `nlm`
- `optimize`
- …

`apply`-family

The `apply`-family *applies* a function repeatedly. This can be seen as an abstraction of a for loop, with the following advantages:

- requires less code to write
- can be easier to read / understand
- does not store intermediate results
- no need to replace / grow

`apply`-family

The members of the `apply`-family in Base R are:

- `lapply` vector / list $\rightarrow$ list
- `sapply` vector / list $\rightarrow$ vector (matrix)
- `apply` matrix / array / data.frame $\rightarrow$ vector (matrix)
- `tapply`, `by`
- `mapply`, `Map`
- `rapply`, `eapply`, `vapply`

`apply`-family

A popular alternative from the tidyverse: `purrr-package`

- `map` vector / list $\rightarrow$ list
- `map2` multiple vectors / lists $\rightarrow$ list
- ...

Our focus: `lapply`

Why?

- Consistent output
- Fast
- No dependencies
- We want to understand R basics

lapply

`lapply` has two main arguments

- `X` the input list/vector
- `FUN` the function that should be repeatedly applied

```
example_list <- list(vec1 = c(1, 3, 4),
                     vec2 = c(4, 2, 10),
                     vec3 = c(2, NA, 1))
lapply(example_list, FUN = mean)

> $vec1
> [1] 2.666667
>
> $vec2
> [1] 5.333333
>
> $vec3
> [1] NA
```

lapply

Other arguments can be passed through `lapply` via '`...`'.

```
example_list <- list(vec1 = c(1, 3, 4),
                     vec2 = c(4, 2, 10),
                     vec3 = c(2, NA, 1))
lapply(example_list, FUN = mean, na.rm = TRUE)

> $vec1
> [1] 2.666667
>
> $vec2
> [1] 5.333333
>
> $vec3
> [1] 1.5
```

lapply

We can use our own functions as input.

```
dropNAs <- function(x) {
  x[!is.na(x)]
}
lapply(example_list, FUN = dropNAs)


> $vec1
> [1] 1 3 4
>
> $vec2
> [1]  4  2 10
>
> $vec3
> [1] 2 1
```

lapply

Anonymous functions can be used as input.

```
lapply(example_list, FUN = function(x) x[!is.na(x)])

> $vec1
> [1] 1 3 4
>
> $vec2
> [1]  4  2 10
>
> $vec3
> [1] 2 1
```

lapply

Data.frames are lists, too.

```
lapply(iris, FUN = class)

> $Sepal.Length
> [1] "numeric"
>
> $Sepal.Width
> [1] "numeric"
>
> $Petal.Length
> [1] "numeric"
>
> $Petal.Width
> [1] "numeric"
>
> $Species
> [1] "factor"
```

lapply

Vectors can be used as input, but often vectorization could be used instead.

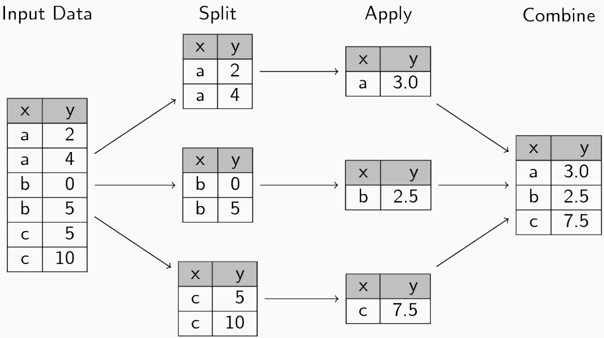
```
lapply(c(1, 2, 3), FUN = function(x) {
  paste0("ID", x)
})


> [[1]]
> [1] "ID1"
>
> [[2]]
> [1] "ID2"
>
> [[3]]
> [1] "ID3"
```

Limitation of `lapply`:
Only a single list/vector can be supplied as input. `Map` is a generalization of `lapply`! It is usually needed less often but a very powerful tool.

A common use case for the `apply`-family is the Split & Apply & Combine paradigm. Here, we want to perform the same analyses for various subgroups in our data set:

- split a data.frame or vector (`?split`)
- apply computations on each split (`?lapply`)
- combine the results (`?do.call`)

Split & Apply & Combine



Split & Apply & Combine

```
head(iris)

>   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
> 1          5.1         3.5          1.4         0.2  setosa
> 2          4.9         3.0          1.4         0.2  setosa
> 3          4.7         3.2          1.3         0.2  setosa
> 4          4.6         3.1          1.5         0.2  setosa
> 5          5.0         3.6          1.4         0.2  setosa
> 6          5.4         3.9          1.7         0.4  setosa

table(iris$Species)

>
>     setosa versicolor  virginica
>         50         50         50
```

Split & Apply & Combine

Splitting the data set via a single (or multiple) grouping variables

```
data_list <- split(iris, f = iris$Species)
class(data_list)

> [1] "list"

length(data_list)

> [1] 3
```

Split & Apply & Combine

Apply the same computation to all data sets

```
out_list <- lapply(data_list, function(subdat) {
  mod <- lm(Sepal.Length ~ Sepal.Width, data = subdat)
  sum_mod <- summary(mod)
  out <- c(Intercept = coef(mod)[[1]],
    Slope = coef(mod)[[2]],
    r2 = sum_mod$r.squared)
  round(out, 3)
})
```

Split & Apply & Combine

```
out_list[["virginica"]]

> Intercept     Slope        r2
>     3.907     0.902     0.209
```

Combine the results

```
do.call(rbind, out_list)

>            Intercept Slope    r2
> setosa         2.639 0.690 0.551
> versicolor     3.540 0.865 0.277
> virginica      3.907 0.902 0.209
```

Exercises

Good programming practices

“Write code for humans, not for machines!”

Code Style

Invest time in writing readable R-code.

- It will make collaborations easier
- It will make debugging easier
- It will make your analyses more reproducible

There is a complete *tidyverse* style-guide.

Go easy on your eyes

- with spaces before and after: `- + / * = <- < == >`
- always use `<-` for assignments
- only use `=` in function calls
- use indentation (largely automatic in RStudio)
- `CamelCaseNames` vs `snake_case_names`
- be consistent!
- wrap long lines at column 70-80 (Rstudio)

White space

```
new_var=(var1*var2/2)-5/(var3+var4)

# versus

new_var <- (var1 * var2 / 2) - 5 / (var3 + var4)
```

Indentation

```r
for(name in names){formula=as.formula(paste0("y~.-",name))
fit<-lm(formula,data=my_data)
coefs[["name"]]=coef(fit)
print(name)
print(summary(fit))}

# versus

for(name in names){
  formula <- as.formula(paste0("y~.-", name))
  fit <- lm(formula, data = my_data)
  coefs[["name"]] <- coef(fit)
  print(name)
  print(summary(fit))
}
```

Wrap long lines

```r
final_results <- data.frame(first_variable =
sqrt(results$mean_squared_error), second_variable =
paste0(results$condition, results$class, sep = ":"),
third_variable = results$bias)

# versus

final_results <- data.frame(
  first_variable = sqrt(results$mean_squared_error),
  second_variable = paste0(results$condition,
                           results$class, sep = ":"),
  third_variable = results$bias)
```

Go easy on your mind

- use meaningful names: “self-explainable”
- always write the formal arguments in function calls (except the first)
- benefit from autocompletion (`<tab>`) => embrace longer names
- use `TRUE` and `FALSE` not `T` and `F`
- comment, comment, comment
    - NOT what (should be clear from the code)
    - but why
    - explain the reasoning, not the code

Use meaningful names

```r
V <- myFun(m1_B)

# versus

RMSE_age_gender <- get_RMSE(lm_age_gender)
```

Programming advice

Use `verbs` for functions and `nouns` for other objects.

Write formal arguments

Benefit from auto completion using `tab`

```
m1_B <- lm(outcome ~ age*gender,
           exp1, condition_1, freq)

# versus

lm_age_gender <- lm(outcome ~ age * gender,
                    data = exp1,
                    subset = condition_1,
                    weigths = freq)
```

Comment, comment, comment

```r
## Start every Rscript with a comment that explains
##  what the code in the script does, why it does
##  this, and to which project it belongs.
##  Your future self will be very thankful!
##
## Mention which packages you are using in this Rscript.

## Use sections to separate chunks ----------------------

## Maybe even subsections ===============================

## Recode variables so that missings are coded as "NA"
dat[dat %in% c(99, 999)] <- NA  # missings coded 99 or 999
```

Keep your code slim

Try to limit your *package-dependencies*.

Only load `library()` the packages that you absolutely need. If you are only using `dplyr`, it does not make sense to load the complete `tidyverse`.

Controversial: when possible, use the `::` operator (and consider not loading the package).

```
<package>::<function>
```

- explicit dependencies
- less name conflicts

Never Attach

Forget about `attach()`!

Don't use it, unless you completely understand what happens (see `?attach`).

Use `with(data.frame, expression)` instead.

```
# using with()
n <- 2e+4
data <- data.frame(x = runif(n),
                   y = runif(n),
                   z = seq_len(n))
result <- with(data, exp(x) / log(z) + 5 * sqrt(y))
```

Testing R code

Writing code is error prone. Incorporate tests and checks in your workflow.

- minimal examples
- write tests and checks
- helpful packages: `testthat`, `RUnit`, `testit`, ...

Speed

Computing speed can become an issue. Avoid common pitfalls:

- don't grow, but replace
- vectorize where possible
- check the computing speed

`?system.time`, microbenchmark or profiling tools

```
n <- 2e+4
data <- data.frame(x = runif(n),
                   y = runif(n),
                   z = seq_len(n))
```

Speed

Don't grow!

```
system.time({
  new_data <- NULL

  for(row_nr in seq_len(NROW(data))){
    new_data <- cbind(
      data[row_nr,],
      result = exp(data$x[row_nr]) /
        log(data$z[row_nr]) +
        5 * sqrt(data$y[row_nr]))
  }
})


>    user  system elapsed
>    2.22    0.01    2.23
```

Speed

Replace!

```
system.time({
  n_rows <- dim(data)[1]
  data$result <- rep(NA, n_rows)

  for(row_nr in seq_len(n_rows)){
    data$result[row_nr] <- exp(data$x[row_nr]) /
      log(data$z[row_nr]) +
      5 * sqrt(data$y[row_nr])
  }
})

>    user  system elapsed
>    0.29    0.55    0.84
```

Speed

Vectorize!

```
system.time({
  data$result <- exp(data$x) / log(data$z) +
    5 * sqrt(data$y)
})

>    user  system elapsed 
>       0       0       0
```

Speed

Compare the speed of different implementations using:

`microbenchmark::microbenchmark`

```
get_mean1 <- function(x){
  weight <- 1/length(x)
  out <- 0
  for(i in seq_along(x)){
    out <- out + x[i] * weight
  }
  return(out)
}

get_mean2 <- function(x){
  sum(x)/length(x)
}
```

Speed

Compare the speed of different implementations using:

`microbenchmark::microbenchmark`

```
x <- rnorm(500)
microbenchmark::microbenchmark(
  mean(x), get_mean1(x), get_mean2(x))

> Error in loadNamespace(x): there is no package called
'microbenchmark'
```

Speed

Programming advice

Don’t worry about speed before it becomes an issue.

Wrap Up

General Advice

- Investing time in learning R pays off
- It's a steady learning curve
- Learn from masters
- Rewrite important code - the first attempt is usually not the best approach

General R Advice

- Document well
- Use a consistent style
- Write functions
- Split long functions in smaller ones
- Write wrappers
- Use Iteration (don't copy paste)
- Use matrix operations and vectorized functions instead of loops
- Use git

Literature Recommendations

R Resources

- Avanced R Ed. 1
- Avanced R Ed. 21
- R Inferno
- R Packages
- Clean Code
- The Pragmatic Programmer

Thank you for your attention!

Thank you for your attention!

Questions? Remarks?