Writing Clean and Efficient Code

An Introduction

Benjamín Muñoz

Massachusetts Institute of Technology

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PML Workshop

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  2. **Organization:** I know where to find the input and where the outputs will be located.
  3. **Abstraction:** Combine basic instructions into more abstract functions or states.

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   - Key point: The more you abstract away, and the better your naming, the fewer comments you will need!

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  - Document the version (number) of the packages you use.

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- R tries to be very compatible with past versions, but that is not necessarily the case for other packages.
- We are in the long-term business, so it might make sense to make sure I can run code from 2013 in 2021 without running into weird hiccups.
- **The reproducibility spectrum:** Snapshot of full operating system > Snapshot of R and all R packages > Code and Data > Nothing.
- `renv`, a hopeful `packrat` replacement fits in the 2nd best spot and should be good enough for most.

★ Reproducibility in the Social Sciences.

★ How to Improve your Relationship with your Future Self

Organization 2.0: Workflow

- We've already discussed file and folder organization. There are a couple of extra tools that are useful.

  ⋆ At a minimum, follow the R4DS recommendations on workflow.

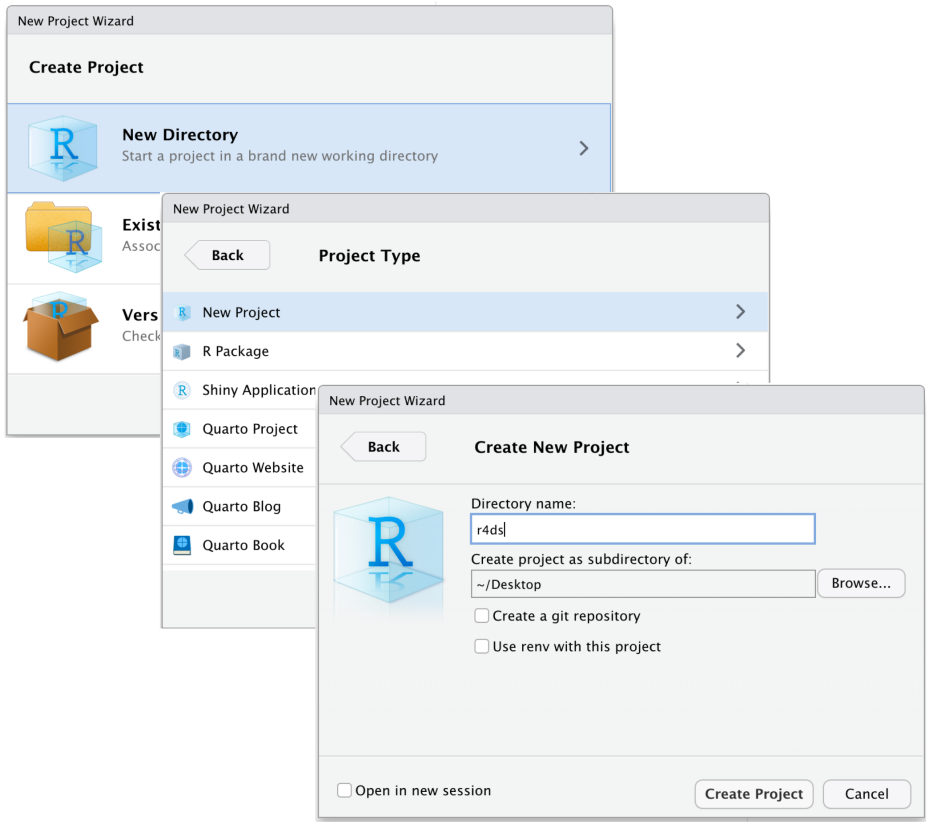
  1. Standardized names for scripts.
  2. Standardized names for outputs (also for formats).
  3. Use `.Rproj` files to set your **working directory**.

  ⋆ Other extreme (maybe too much) use tools as workflowr.

  - Create a website with all the documentation of your project, which helps ensure transparency, reproducibility and shareability.

Organization 2.0: Workflow

- **working directory**. Use the function `getwd()` to check it.
- It is not a good idea to use `setwd(«/path/to/my/CoolProject»)`. Instead, you can use `.Rproj` files. This type of file allows the use of relative paths.



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  - Note that you can always run each line of a function individually and print the output to see if it matches what you expect.
  - When you code, always debug as you go. I.e. don't write 50 functions and then start testing your code. Rather do it, a function or two at a time.
  - Use Generative Intelligence intensively (ChatGPT, Copilot, Deepseek, etc.).

Efficiency in R

- Why is some code «fast» and other code «slow» in R?
- Two main culprits:
  - Bad algorithms.
  - Inefficient memory usage.
- Does not suffice to use and understand `apply()` family of functions.

  ⋆ Need to understand basics of computational complexity and memory allocation.
- **Practical Advice:**
  1. Consider appropriate algorithms (canned functions).
  2. Compartmentalize your code and evaluate its efficiency piece by piece.
  3. Vectorize whenever possible (try to avoid nested loops).
  4. If possible, parallelize.

Computational Complexity Examples

- Good starting point ⟶ measure time from start to end.
  - ⋆ Use the `tictoc` package.
- However, this is not enough. Many other factors impact the speed.

R Code

```
# Block 1: Simple for loop
for (i in 1:n) {
  foo()
}

# Block 2: Sequential for loops
for (i in 1:n) {
  foo()
}
for (i in 1:n) {
  bar()
}

# Block 3: Nested for-loops
for (i in 1:n) {
  foo()
  for (i in 1:n) {
    bar()
  }
}

# Block 4: Simple bootstrap
for (i in 1:b) {
  # Hint: mle with BFGS takes O(n^2)
  estimate <- mle(X_1, ..., X_n, method = BFGS)
}
```

Memory Allocation in R

- Even if the algorithms are efficient, we can lose real-life performance due to inefficient memory usage.
- Will go over basics of memory (in R), data types, and vectorization to motivate efficiency prescriptions.

What is memory?

- Computer consists of three main parts: CPU core(s) (different circuits), Memory (RAM, Hard drive), GPU (can ignore for this session).
- CPU is wicked fast.
- Every R session lives on RAM memory.
- RAM is actually very very fast for memory standards, but painstakingly slow compared to CPUs, particularly saving new things to it (writes).
- To write efficient code, we **need to avoid unnecessary memory writes!**

Memory Usage in R

- What happens when I delete an object with `rm()`?
  - You tell R that this reference to an object is no longer needed.
  - If there are no more, it will be «garbage collected» *automatically*.

  ⋆ **Big Culprit:** Copying of objects.
  - R uses a «copy if modified» framework so if `y <- x`, and `y[1] <- 0`, `y` will no longer point to `x`, but will allocate a new chunk of memory and point to that.
    $\Longrightarrow$ Avoid implicit and explicit copying of objects whenever possible.
    $\Longrightarrow$ «Vectorizing» is mostly faster because it avoids this implicit copying.

Implicit Copying of Objects

R Code

```
# Example from: http://adv-r.had.co.nz/memory.html
library(pryr)
x <- data.frame(matrix(runif(100 * 1e4), ncol = 100))
medians <- vapply(x, median, numeric(1))

for (i in seq_along(medians) |> head(5)) {
  x[, i] <- x[, i] - medians[i]
  print(c(pryr::address(x), pryr::refs(x)))
}

## [1] "0x55ba813f6e80" "1"
## [1] "0x55ba8457d8f0" "1"
## [1] "0x55ba8460eb00" "1"
## [1] "0x55ba8460ee60" "1"
## [1] "0x55ba8493dad0" "1"
```

Explicit Copying of Objects

- Define the size and type of object to avoid copying object.
- Example: creating a vector of ones.

R Code

```
    f1 <- function() { # Adding ones one by one
  x <- 1.0
  for (i in 2:10000) {
    x <- c(x, 1.0)
  }
  return(x)
}
f2 <- function() { # Define length + type of vector
  x <- numeric(10000) # Can be character(), interger() etc
  for (i in 1:10000) {
    x[i] <- 1.0
  }
  return(x)
}
f3 <- function() { # Vectorization
  x <- rep(1.0, 10000)
  return(x)
}
bench::mark( # Sum two columns for each row
  f1(), f2(), f3()
) |> dplyr::select(expression, median)

## # A tibble: 3 x 2
## expression median
## <bch:expr> <bch:tm>
## 1 f1() 162ms
## 2 f2() 452.4us
## 3 f3() 14.4us
```

Functions in R

- From last time, arguments are not copied until modified, yay!
- What if we return a function in a function?
- **Turns out:** Functions save their surrounding environment!
- So what? Imagine you create a large variable (`x <- 1:1e+50`) before you create your function, then your function will also copy the large variable into memory.
- Now on to more applied examples of why data types matter and how to vectorize in R.

Memory Prescription 1: Data Types Matter

- List vs. Matrix vs. Dataframe (or Tibble).
  - Matrix algebra is heavily optimized!
  - Neither lists nor matrices have memory overhead.
  - Dataframes have many specialized functions such as grouping that are much faster than DIY approaches on lists or matrices.

R Code

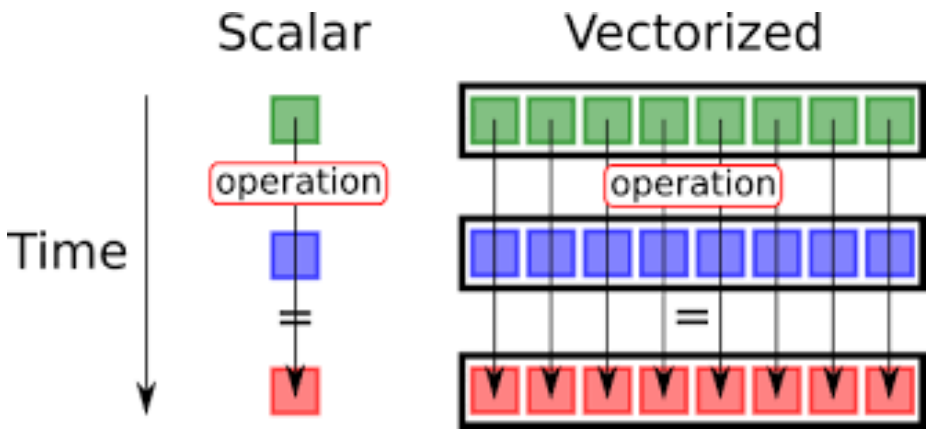
```
x <- runif(10000)
y <- rnorm(10000)
DF <- data.frame(x = x, y = y) # Dataframe
TIB <- tibble::as_tibble(DF) # Tidyverse tibble
MAT <- cbind(x, y) # Matrix

bench::mark( # Sum two columns for each row
  apply(DF, 2, sum),
  apply(TIB, 2, sum),
  apply(MAT, 2, sum),
  colSums(MAT) # Implemented in C
) |> dplyr::select(expression, median)

## # A tibble: 4 x 2
## expression median
## <bch:expr> <bch:tm>
## 1 apply(DF, 2, sum) 271.2us
## 2 apply(TIB, 2, sum) 279.9us
## 3 apply(MAT, 2, sum) 165.2us
## 4 colSums(MAT) 27.9us
```

Memory Prescription 2: Vectorize

- **Vectorize** your codes as much as you can.
- Most R functions allow you to vectorize by default.



★ `apply`, `lapply`, `sapply`, `...` come built-in with R and allow you to apply **any** function in a vectorized way to a matrix/dataframe, list, or vector.

★ `purrr`'s `map`, `map_dbl`, `map_dfc`, `...` are the `tidyverse` equivalents and extensions to the `apply()` family.

Vectorization: apply and purrr

R Code

```
library(purrr)
d <- list(
  data.frame(quant = c("danny", "insong", "teppei")),
  data.frame(schools = c("MIT", "Harvard"))
)
# We want a list as an output
lapply(d, nrow)

# default map returns a list
purrr::map(d, nrow)

# The tidy version
d |> purrr::map(nrow)

## Second Example
v <- 1:10

# We want a vector as an output
sapply(v,                                          (x) x * x)

# The tidy version
v |> purrr::map_dbl(                                    (x) x * x)
```

Vectorization using purrr

- `map_*` return different object type and will fail if it is not appropriate.
- Makes the code more predictable, and thus easier to debug.
- Of particular interest are `map_dfr` and `map_dfc`, which run a function on the input and then row/column bind the outputs together.
- Inspired popular parallelization package `furrr`.

Parallelization: Why and when to parallelize

- Enable multiple computations to take place at the same time.
- Useful when you have time-consuming, unordered tasks.
  - Data cleaning.
  - Bootstrap.
  - Monte Carlo simulations.
  - Any tasks with lots of loops, apply, or maps

Often need two different codes for parallel and non-parallel computing ⟶ Increase potential bugs.

Methods for parallel computing differ across operating systems and different packages implements different methods:

- `mclapply`, `parallel`, `doParallel`, etc.
- Parallelization with `mclapply` (forking) does not work in Windows.
- Your choice of package would decide how to run in parallel.

`future` package

- `future` provides a simple and uniform tool for async. parallel, and distributed processing in R.
- Same coding style between sequential and parallel tasks.
- Users decide how to parallelize: the code does not depend on how to run in parallel.
  - Use the same code for parallel computing in different operating systems

R Code

```
f <- future::future(expr) # Evaluate in parallel
r <- future::resolved(f) # Check if done
v <- future::value(f) # Get result
```