

Benchmarking in R

how to check and compare speed of code execution?

Time efficiency

Benchmarking

- Comparing different ways of solving the same problem
- Same problem can be solved in different ways. Some are more time efficient some are slower.
- We need to identify which part of the program slows down our program/code
- We will discuss also byte coding
- In each body of the function there is information about vbytes

Structure of the class

1. `system.time()` –measure the time needed for execution of the code.
Returns three numbers.
2. `Benchmark()` – relative time of our codes, comparison of time of codes across different option
3. `Microbenchmark()` - repeating code and see the distribution of time
4. Byte compiler - 0101010101001
5. Profiling `profvis()`– identifying which element of our code are the slowest

Sys.time()

```
> system.time(runif(1e7))  
  user  system elapsed  
 0.19   0.03   0.21  
> |
```

Shows time in seconds

User – how long it took to generate the random numbers for the user

System – time needed for memory allocation or disk access

Elapse - sum of user and system

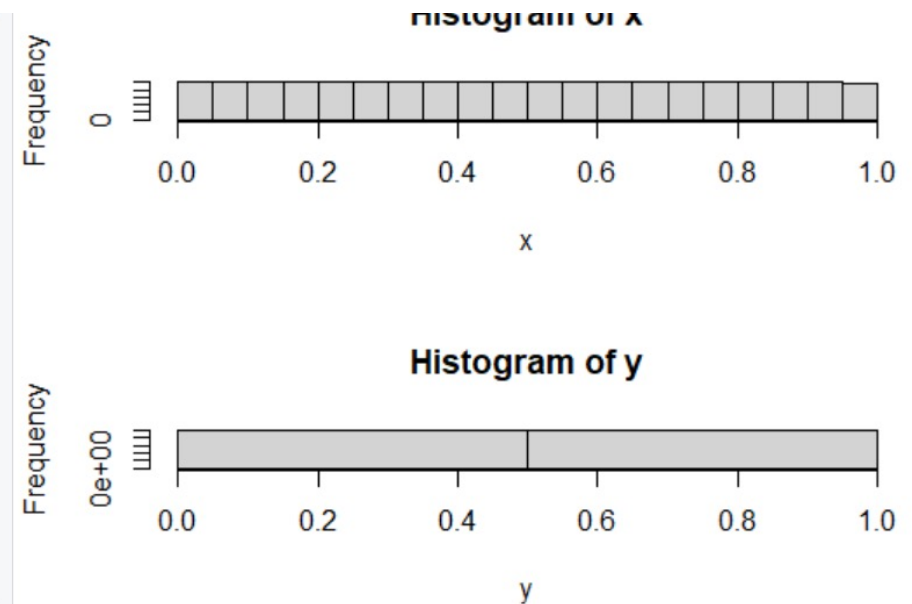
Due to rounding to decimal place might not be seen as the sum.

We see that it took less than half of the second

It may happen that user > elapsed → parallel on several core programming

Speed of execution of longer code with sys.time → use {}

```
Browse[1]>  
> system.time(runif(1e7))  
  user  system elapsed  
  0.19   0.03   0.21  
> system.time({  
+   x <- runif(1e6)  
+   y <- ifelse(x > 0.5, 1, 0)  
+   layout(matrix(1:2, nrow = 2, ncol = 1)) # divides the device up into as  
+   # many rows and columns as there are in matrix mat,  
+   # with the column-widths and the row-heights specified in the respective argumen  
ts.  
+   hist(x)  
+   hist(y, breaks = c(0, 0.5, 1))  
+   layout(matrix(1))  
+   print(summary(as.factor(y)))  
+   rm(x, y)  
+ })  
  0      1  
500762 499238  
  user  system elapsed  
  0.73   0.04   0.86  
> |
```



Which function is more time efficient with sys.time?

```
> system.time(m1 <- my_mean1(myData$x))
  user  system elapsed 
0.02    0.00    0.02 
> system.time(m2 <- my_mean2(myData$x))
  user  system elapsed 
3.12    0.05    3.20 
> system.time(m3 <- mean(myData$x))
  user  system elapsed 
0.02    0.00    0.02 
> system.time(m4 <- mean(as.numeric(myData$x)))
  user  system elapsed 
0.02    0.00    0.02 
_ |
```

We create several functions to calculate mean

1. my_mean1 function is vectorized. Sum of all vectors elements / length of vector
2. my_mean2 – we have loop over elements of vector. We loop over the element of vector . At each iteration we increase the value of sum. Loopover every single element of a vector

Dataframe complex object. Transformation of dataframe to vector is time consuming

Loop is the slowest. It takes almost 3 seconds

Are the result identical?

```
> identical(m1, m3)
[1] FALSE
> identical(m2, m3)
[1] FALSE
> identical(m4, m3)
[1] TRUE
> # lets see the results
> m1
[1] 0.0001645981
> m2
[1] 0.0001645981
> m3
[1] 0.0001645981
> m4
[1] 0.0001645981
```

Are the result identical?

Up to 10 decimal place mean is the same for all functions.

Due to rounding it may seem that there is no difference

Our functions build in mean() is written in C++ our user defined functions written in R → each programming language different rounding policy across programming languages.

Do we care that they are not identical?

Function compiled from different programming languages might give us different precision after the comma.

Do we care? Yes if we work for cern

```
> (m1 == m3)
[1] FALSE
> (abs(m1 - m3) < 1e-15)
[1] TRUE
> |
```

Benchmarking – average time needed to execute the code

- Can we trust `sys.time`?

Benchmarking – average time needed to execute the code

- We run our code 100 times and then we verify the average time of execution.
- We compare codes that return the same outcome.

Benchmark() – how to read the output?

We limit ourselves to 100000 elements in order not to wait too long

```
> benchmark(m1 <- my_mean1(myData$x[1:100000]),  
+          m2 <- my_mean2(myData$x[1:100000]),  
+          m3 <- mean(myData$x[1:100000]),  
+          m4 <- mean(as.numeric(myData$x[1:100000])),  
+          )
```

	test	replications	elapsed	relative	user.self	sys.self	user.child	sys.child
1	m1 <- my_mean1(myData\$x[1:1e+05])	100	0.08	1.000	0.04	0.04	NA	NA
2	m2 <- my_mean2(myData\$x[1:1e+05])	100	4.03	50.375	3.97	0.03	NA	NA
3	m3 <- mean(myData\$x[1:1e+05])	100	0.10	1.250	0.05	0.04	NA	NA
4	m4 <- mean(as.numeric(myData\$x[1:1e+05]))	100	0.08	1.000	0.07	0.02	NA	NA

Says which code. It can be a label

How much time we run it?

Not useful always NA.
Derived processes

Time in seconds

Total time executing 100 repetitions of a particular code

Loop took 4 seconds to run 100 times

Vectorized

1 – fastest code

$4.03/0.08 = 50.375$ – the slowest code loop .

Using loop was 50 times slower than the fastest approach.

$0.1/0.08 = 1.25$

Writing own function faster than base mean() it is strange.
Base mean() is more complex than our function.

Divide the number needed for 100 replications by the fastest time

Time for memory allocation

Time by user

```

> (compare_mean <- benchmark("my_mean1" = {m1 <- my_mean1(myData$x[1:100000])},
+                             "my_mean2" = {m2 <- my_mean2(myData$x[1:100000])},
+                             "mean" = {m3 <- mean(myData$x[1:100000])},
+                             "mean_on_num" = {m4 <- mean(as.numeric(myData$x[1:100000]))}
+                             )
+ )

```

	test	replications	elapsed	relative	user.self	sys.self	user.child	sys.child
3	mean	100	0.06	1.000	0.05	0.01	NA	NA
4	mean_on_num	100	0.08	1.333	0.05	0.04	NA	NA
1	my_mean1	100	0.06	1.000	0.07	0.00	NA	NA
2	my_mean2	100	2.96	49.333	2.95	0.00	NA	NA

Arguments of benchmark

- 1. we can decide which column to print
- 2. Which column to sort result
- 3. change the repetitions – more replication more precision
- Loop

```
> (compare_mean1a <- benchmark("my_mean1" = {m1 <- my_mean1(myData$x[1:10000])},  
+                               "my_mean2" = {m2 <- my_mean2(myData$x[1:10000])},  
+                               "mean" = {m3 <- mean(myData$x[1:10000])},  
+                               "mean_on_num" = {m4 <- mean(as.numeric(myData$x[1:10000]))},  
+                               columns = c("test", "replications", "elapsed", "relative"),  
+                               order = "relative",  
+                               repetitions = 500  
+ )
```

Loop 160 slower than other options

	test	replications	elapsed	relative
3	mean	500	0.01	1
4	mean_on_num	500	0.03	3
1	my_mean1	500	0.05	5
2	my_mean2	500	1.60	160

```
> |
```

Microbenchmark() – not in seconds

```
> (compare_mean2 <- microbenchmark("my_mean1" = {m1 <- my_mean1(myData$x[1:10000])},  
+                               "my_mean2" = {m2 <- my_mean2(myData$x[1:10000])},  
+                               "mean" = {m3 <- mean(myData$x[1:10000])},  
+                               "mean_on_num" = {m4 <- mean(as.numeric(myData$x[1:10000]))}  
+ )
```

Adjust the time units
automatically

Unit: microseconds

expr	min	lq	mean	median	uq	max	neval	clsd
my_mean1	26.001	28.9010	43.27996	32.6515	47.1500	178.701	100	a
my_mean2	2005.600	2614.9010	3308.41698	2925.1010	3374.3500	12472.701	100	b
mean	34.001	36.6505	59.31698	46.8515	66.3020	197.201	100	a
mean_on_num	34.501	39.1010	64.63202	53.3015	81.7515	155.902	100	a

> |
Distribution of time needed to run the particular code

Min time of execution

Max time of execution

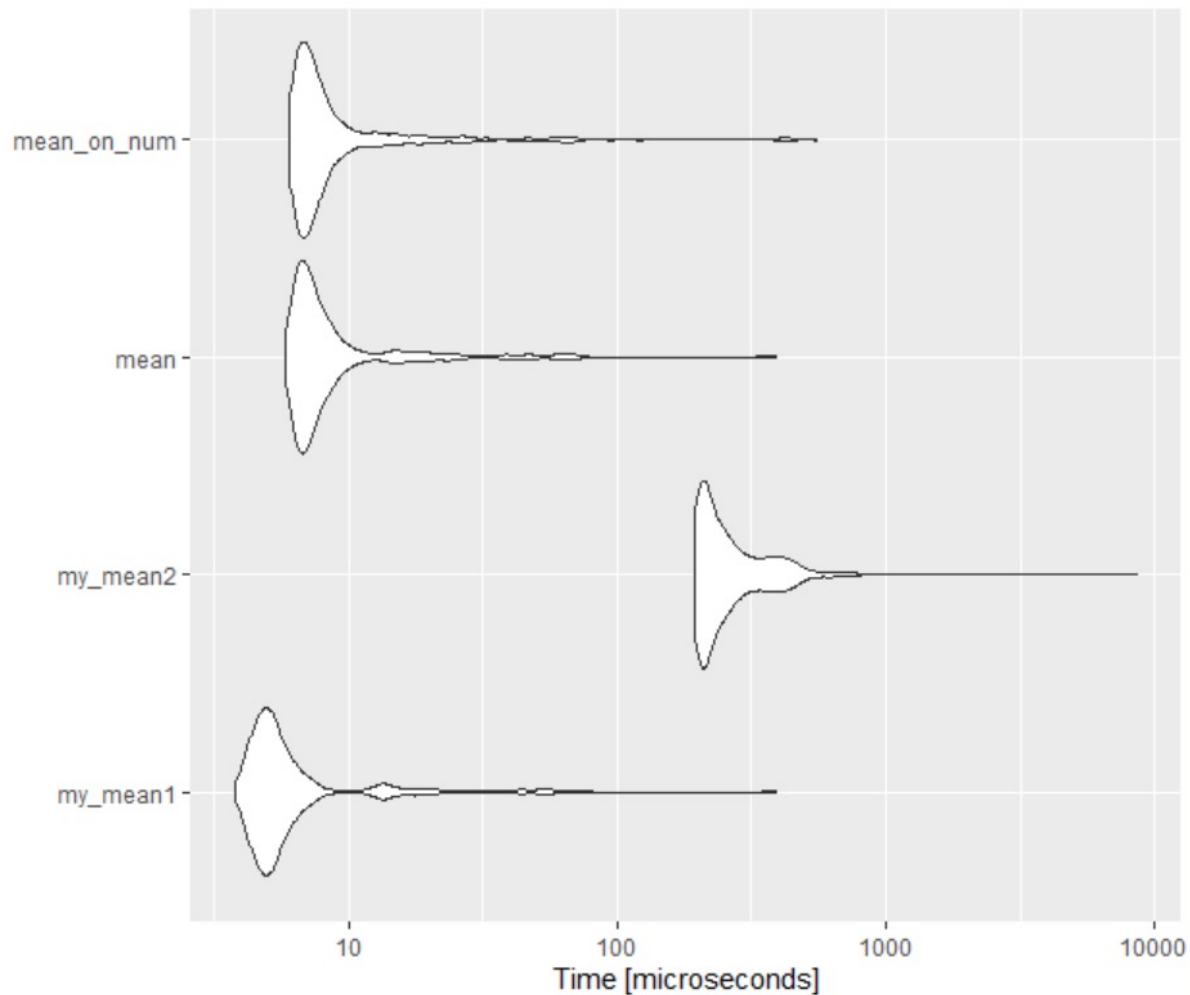
Lq – lower quintile in 25 % of executing time of execution was not higher than ...

Up – upper quartile only 25% of execution took longer than ...

Neval - time of execution

Cld - statistical differences across different codes. Multicomparable tests. Same letters – no statistical difference across codes. Different letters – statistical differences in terms of time execution.

Microbenchmark() – graphical analysis



Violin plot (require ggplot)

Horizontal xaxis – time

Yaxis – our functions

Frequency of our data

My_mean1 – most frequent time the bulb in violin plot

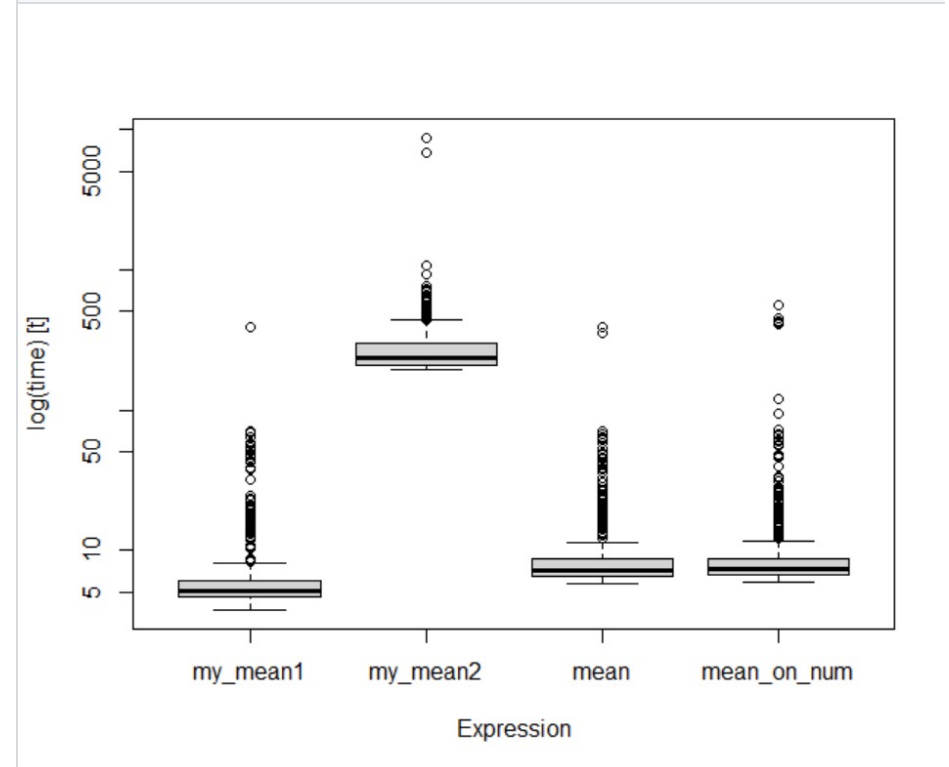
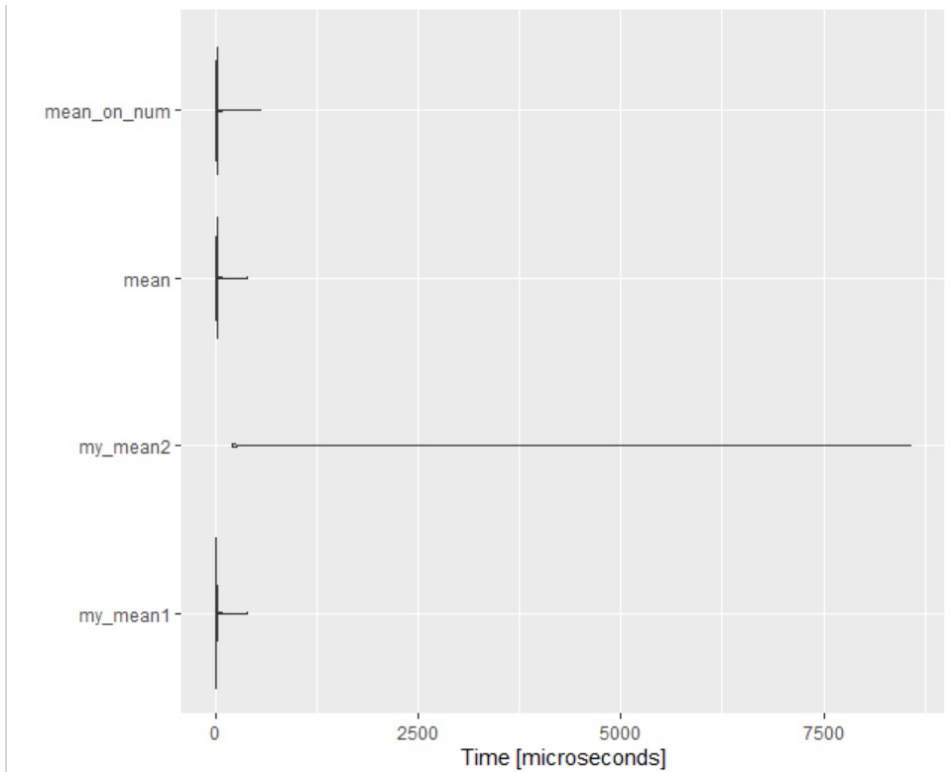
We see the tail with max time

Main part of distribution is the bulb of violin plot

The scale is transform logarimically

Violin plot using linear scale not visible distribution of violin plot

- Boxplot for microbenchmark similar as violin
- Suggest my_mean1 is the fastest



Byte compiler 42:00

Memory
address

- Compiling the code to byte – improve the time efficiency
- Different levels of compilations

R code

Byte code

High level
language
programming

Translated

Understood by
computer

Understood by
human

Compilation to byte code. Package compiler all functions are by default are compiled when they are used for the first time

Four different levels of compilation:

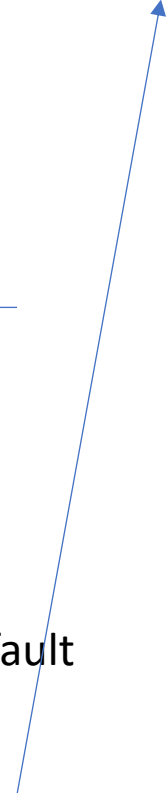
0 – no translation

1 – some translation

2

3 – by default in R all functions are precompiled

```
> median
function (x, na.rm = FALSE, ...)
  UseMethod("median")
<bytecode: 0x000001862e306f38>
<environment: namespace:stats>
```



Showing how time efficiency is improved due to pre compilation

- cmpfun() allows to pre-compile functions
- the cmpfile() function is used to precompile the code saved in an external file

```
> my_mean2
function(x) {
  result <- NA
  n <- length(x)
  for(i in 1:n)
    result <- sum(result, x[i], na.rm = T)
  result <- result/n
  return(result)
}
> |
```

Not compiled no byte code!!!!

Newly defined

Not used yet

Pre compilation of function in R

```
> my_mean2_cmp <- cmpfun(my_mean2)
> my_mean2_cmp
function(x) {
  result <- NA
  n <- length(x)
  for(i in 1:n)
    result <- sum(result, x[i], na.rm = T)
  result <- result/n
  return(result)
}
<bytecode: 0x000001865055e1d8>
>
```

Compare the time efficiency before and after compilation

```
my_mean2_cmp <- cmpfun(my_mean2)
```

```
# turn off compilation
```

```
enableJIT(0)
```

```
> benchmark("my_mean2" = {m1 <- my_mean2(myData$x[1:10000])},  
+          "my_mean2_cmp" = {m2 <- my_mean2_cmp(myData$x[1:10000])}  
+          )[, 1:6]  
      test replications elapsed relative user.self sys.self  
1    my_mean2           100    0.71     1.972     0.69      0  
2 my_mean2_cmp           100    0.36     1.000     0.36      0
```

```
# and compare the efficiency once again
```

```
benchmark("my_mean2" = {m1 <-  
my_mean2(myData$x[1:10000])},  
          "my_mean2_cmp" = {m2 <-  
my_mean2_cmp(myData$x[1:10000])}  
          )[, 1:6]
```

Function after compilation was two times faster than not compiled version of a function!!!!

Both compiled – time is the same

```
> enableJIT(3)
[1] 0
>
> # and compare the efficiency once again
>
> benchmark("my_mean2" = {m1 <- my_mean2(myData$x[1:10000])},
+           "my_mean2_cmp" = {m2 <- my_mean2_cmp(myData$x[1:10000])}
+           )[, 1:6]
      test replications elapsed relative user.self sys.self
1  my_mean2           100    0.34    1.000    0.33      0
2 my_mean2_cmp         100    0.36    1.059    0.36      0
> |
```

My_mean2 – 1 compilation 99 already compiled !!!!

External files with function definitions and run compile them

External files with function definitions and run compile them

Manual compilation before we run it – we can share with our colleague the compiled files

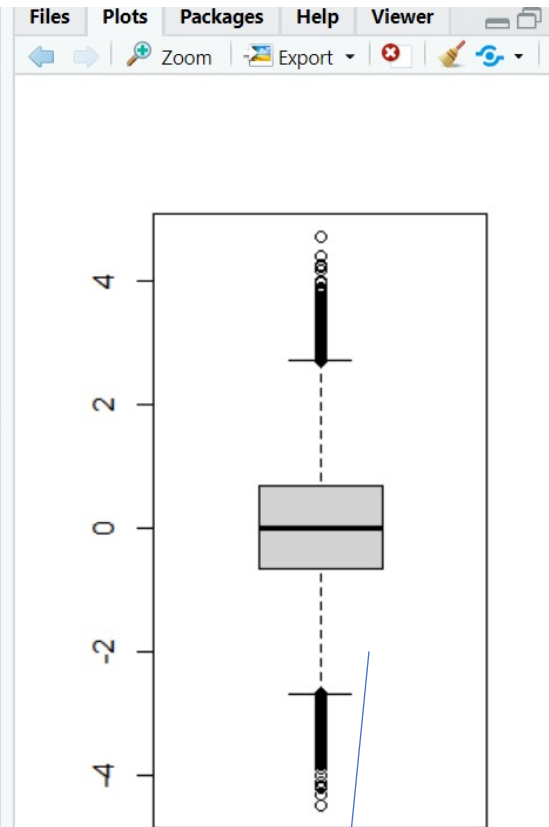
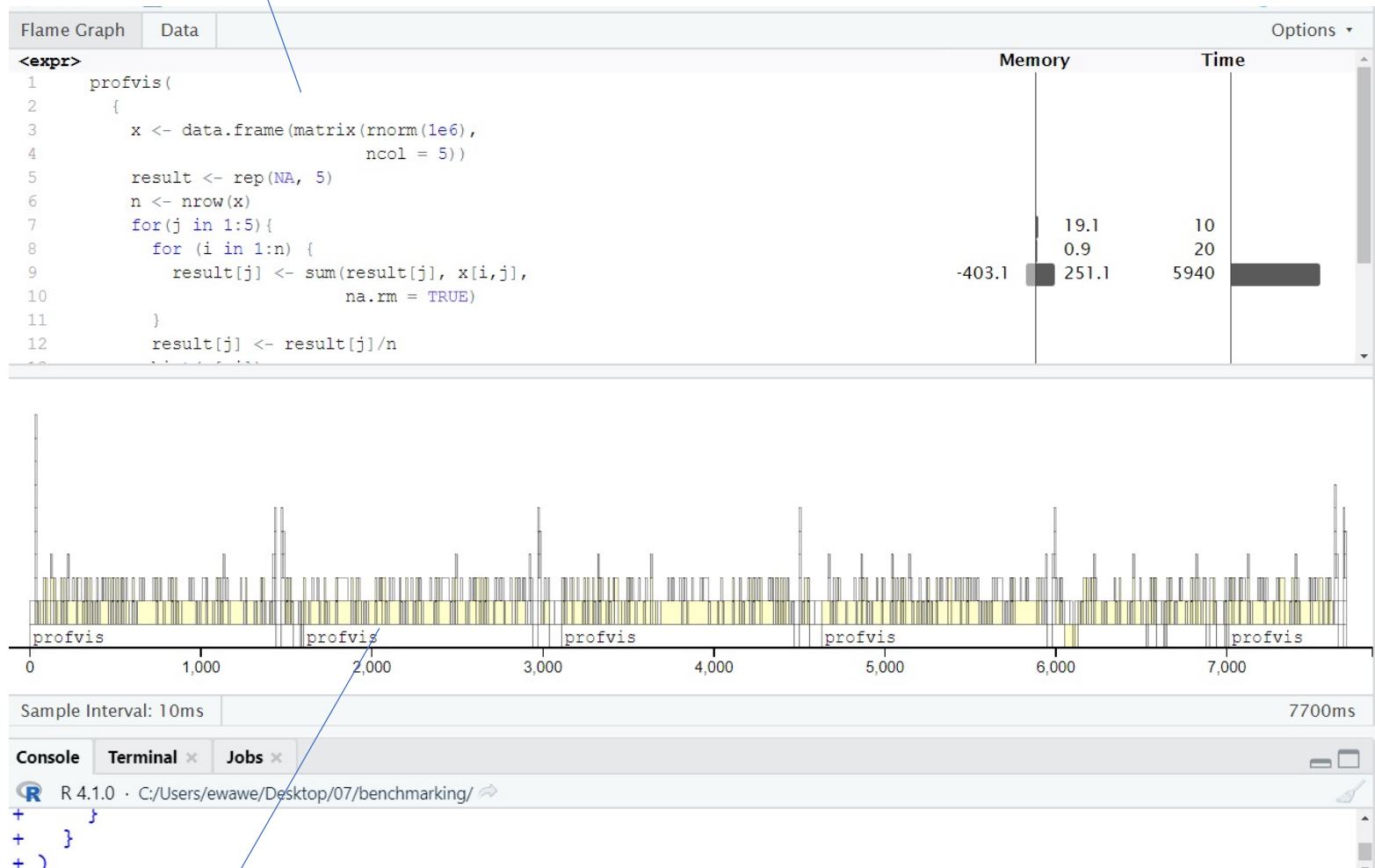
```
> cmpfile(infile = "my_mean2.R", # source file
+         outfile = "my_mean2_cmp.R") # destination file
saving to file "my_mean2_cmp.R" ... done
>
> # lets look into "my_mean2_cmp.R"
>
> # lets delete my_mean2() function from our workspace
>
> rm(my_mean2)
>
> # and read it from the file
>
> source("my_mean2.R")
>
> my_mean2
function(x) {
  result <- NA
  n <- length(x)
  for(i in 1:n)
    result <- sum(result, x[i], na.rm = TRUE)
  result <- result/n
  return(result)
}
```

```
> # it is a NON-compiled version
>
> rm(my_mean2)
>
> # lets load the compiled version with loadcmp()
>
> loadcmp("my_mean2_cmp.R")
>
> my_mean2
function(x) {
  result <- NA
  n <- length(x)
  for(i in 1:n)
    result <- sum(result, x[i], na.rm = TRUE)
  result <- result/n
  return(result)
}
<bytecode: 0x0000018646cf9770>
```

Code profiling

- Identify pieces of the code that slow down the code
- Profvis() – graphically represents the time and memory
- Argument – code that we want to profile

Upper panel show for each line the memory use
and time efficiency. Loop took the longest
Most time spend inside the loop.



Boxplot and
histogram