Statistics 360: Advanced R for Data Science

Lecture 6

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Debugging (Ch22) and Measuring performance (Ch 23)

- Reading: Text, Chapters 22 and 23
- Topics on debugging:
  - overview of debugging
  - tracing execution with `traceback()`
  - interactive debugging with `debug()` and `browser()`
  - non-interactive debugging: `dump.frames()` and printing
  - test cases to detect future bugs
- Topics on measuring performance:
  - profiling
  - microbenchmarking
  - final thoughts

Debugging

Overview

- Focus on the easy part of debugging: finding and fixing the source of unexpected errors.
  - Mistakes that give incorrect results but throw no errors are harder to find.
- Workflow tips for finding and fixing errors
  - Google it: If you don't understand the error message, try pasting it into a google search.
  - Make a small self-contained example (reproducible example, a.k.a. reprex).
  - Find it with tools like `traceback()`, `debug()` and `browser()`.
  - Fix it and make a test case to alert you if you accidentally re-introduce the bug.

Reproducible examples

- Reproducible means including any source code, data and library calls so that the code can run as it did when the error was triggered.
- Next reduce the code to a minimal example that triggers the problem.
  - For example, remove lines of code, compute on a smaller R object, use built-in data.
- The act of creating the reprex may show you the error.
- If not, you are in a position to ask for help from a class-mate, mailing list or stack overflow.
- I find it hard to construct reprexs without first finding the lines that throw the error ...

Tracing execution

- After an error, you can use `traceback()` to see the sequence of function calls ("call stack") that lead to the error.
  - The numbers appended to each entry are the line numbers of the function call in the (parent) calling function, but they usually just confuse me . . .

```
f <- function(x) { g(h(x)) }
g <- function(x) {
  x
}
h <- function(x) {
  if(!is.numeric(x)) stop("x must be numeric")
}
#f("cat") # uncomment to run
#traceback()
```

Interactive debugging

- Main tools are `browser()` and `debug()`.
- Stop and step through function execution.
  - Can print variables and execute R commands to investigate

```
h <- function(x) {
  browser()
  if(!is.numeric(x)) stop("x must be numeric")
}
#f("cat")
```

browser commands

- `n` executes the next step. Use `print(n)` to print a variable named `n`.
- `s` is like `n` but will step into a function call.
- `f` finishes execution of the current loop or function.
- `c` leaves interactive debugging and continues regular execution.
- Enter (Return) repeats the last browser command
- `Q` completely exits the function.

debug()

```r
h <- function(x) {
  if(!is.numeric(x)) stop("x must be numeric")
}
#debug(f)
#f("cat")
# undebug(f)
# debug(g)
# f("cat")
# undebug(g)
# debug(h)
# f("cat")
# undebug(h)
```

Non-interactive debugging

- You can insert `print()` or `cat()` statements to see values of variables in your code if you find the trace too confusing and browser too time-consuming.

Test cases

- After you find and fix a bug it is a good idea to devise a test of your code that will flag the problem if you ever accidentally re-introduce it.
- If you are writing an R package you should investigate the `testthat` package, which helps you compile and run "unit" tests on small pieces of your code.

```r
f <- function(x) { x + 3 }
# test
f(3) # should return 6
```

```
## [1] 6
```

Measuring performance

Measuring performance

- When you write code you develop an intuition about what parts will run slowly – don't trust this!
- As statisticians we know that the only thing you can trust is data.
- Profiling and benchmarking are ways to collect data on your code

```
library(profvis) #visualize profiling data
library(bench) # benchmarking tools
```

Profiling

- R uses a statistical profiler that records the call stack at small intervals.
  - Read the call stack from right to left

```
f <- function() {pause(0.1);g();h()} # pause() is from profvis
g <- function() {pause(0.1);h()}
h <- function() {pause(0.1)}
Rprof()
f()
```

```
## NULL
```

```
Rprof(NULL) # Now view Rprof.out
```

```
sample.interval=20000
"pause" "f"
"pause" "f"
"pause" "f"
"pause" "f"
"pause" "f"
"pause" "g" "f"
"pause" "g" "f"
"pause" "g" "f"
"pause" "g" "f"
"pause" "g" "f"
"pause" "h" "g" "f"
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"pause" "h" "g" "f"
"pause" "h" "f"
"pause" "h" "f"
"pause" "h" "f"
"pause" "h" "f"
"pause" "h" "f"
```

Summary of profile

```r
# summaryRprof() # uncomment and run
```

Visualize profile

- `profvis()` gives a nicer summary of the profiling.
- Two panels:
  - top shows the source code with graphs depicting memory use and execution time
  - bottom is a "flame graph" showing the call stack, read bottom to top

```
source("lec6profiling.R") # profiler will refer to this source f
# profvis({ f() }) # Or choose Profile from RStudio
```

Memory profiling

- The `profvis()` output also includes information about memory usage.
- Illustrate with an example from the week 2 exercises where we built a dataset of 500×1000 observations.
  - included in source file `lec6profiling.R`

```
# profvis({ bigd1() })
# profvis({ bigd2() })
# profvis({ bigd3() })
```

Notes on memory profiling

- The grey bars in the bar and flame graphs show memory being freed by the garbage collector (notice the `<GC>` when you hover over the grey bars in the flamegraph).
- Memory claiming and freeing in bigd1 $>$ bigd2 $>$ bigd3.

Microbenchmarking

- We have done benchmarking on bigd1/2/3 with `system.time()`.
- For small chunks of code that take less time, `system.time()` is less useful.
- Microbenchmarking measures performance of code chunks that run in very small time increments.
- To do this, the `bench` package uses a high precision timer.

bench

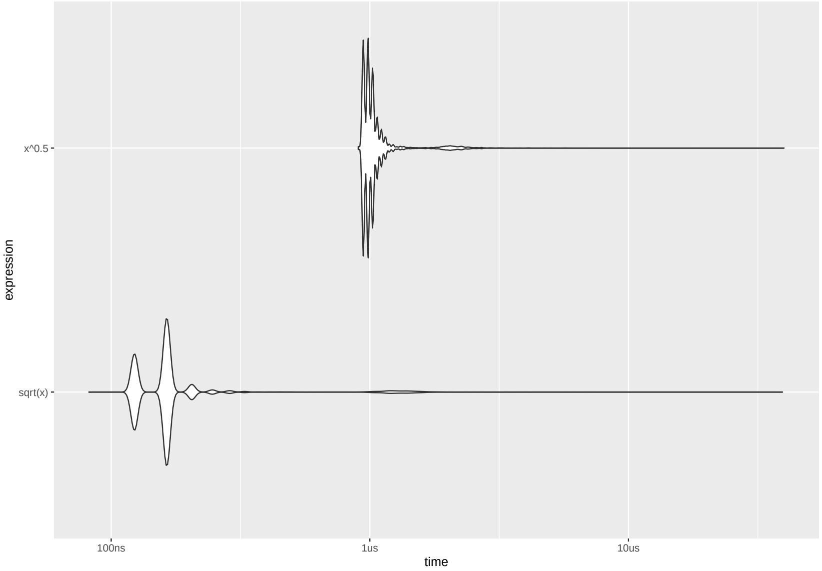
- Times the expression in multiple runs.
  - At least one run and at most the number of runs it can do in 1/2 sec.
- Output displayed as a summary table or graph.

```
library(bench)
x <- runif(100)
lb <- mark(
  sqrt(x),
  x ^ 0.5
)
lb
```

```
## # A tibble: 2 x 6
##   expression      min   median `itr/sec` mem_alloc `gc/sec`
##   <bch:expr> <bch:tm> <bch:tm>     <dbl> <bch:byt>    <dbl>
## 1 sqrt(x)        82ns    164ns  4411498.      848B        0
## 2 x^0.5         902ns    984ns   915017.      848B        0
```

```r
plot(lb,type="violin")
```

```
## Loading required namespace: tidyr
```



Interpretation

- Time units in the output table can be in microseconds, nanoseconds, ...
- Run-time summary statistics include min, mean, median, max, and itr/sec.
- `mem_alloc` and `gc/sec` related to memory usage
- There are other columns in the output not shown – see `?mark` for details.
- The bumps in the violin plot may indicate that your computer was doing something else during some of the runs
- Notice the highly skewed distribution – median is more useful than mean

Final thoughts

- Avoid the temptation to let performance considerations dominate your code development and lead you to profile and benchmark extensively.
- Remember that the most important performance improvement is code that gives the right answer.