Statistical Computing (36-350)
Lecture 8: Debugging

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Agenda

- Characterizing the error
- Localizing the error
- Program for debugging

**Reading for the Week:** Chapter 13 of Matloff
The machine *does something wrong*
Bugs

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Bugs are ubiquitous in programs

Debugging is an essential and unending part of programming

Debugging is largely about differential diagnosis figuring out what has gone wrong, by eliminating other possibilities

Stages of Debugging

1. Characterize the bug: figure out exactly what is going wrong
2. Localize the bug: find where the code introduces the mistake
3. Modify the code; check whether the bug has been eliminated; check that you haven't introduced new error
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Characterizing the Bug

1. Make the error reproducible
   - Can we always get the error when re-running the same code and values?
   - If we start the same code in a clean copy of R, does the same thing happen?

2. Bound the error
   - How much can we change the inputs and get the same error? A different error?
   - For what inputs (if any) does the bug go away?
   - How big is the error?

3. Get more information
   - Add extra output (e.g., number of optimization steps, did the loop converge, final value of optimized function)
   - Much of what's under localization below.
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Trying controlled inputs

Interactive debugging
traceback()

Traces back through all the function calls leading to the last error
Start your attention at the first of these functions which you wrote
Often the most useful bit is somewhere in the middle (there may be many low-level functions called)
Suppose I wrote my estimator like this:

```r
gamma.est <- function(data) {
  m <- mean(data)
  v <- var(data)
  s <- v/m
  a <- m/s
  return(list(a=a,s=s))
}
```

Now I write my jack-knife:

```r
gamma.jackknife <- function(data) {
  n <- length(data)
  jack.estimates <- c()
  for (omitted.point in 1:n) {
    jack.estimates <- rbind(jack.estimates, gamma.est(data[-omitted.point]))
  }
  var.of.ests <- apply(jack.estimates, 2, var)
  jack.var <- ((n-1)^2/n) * var.of.ests
  return(sqrt(jack.var))
}
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        jack.estimates <- rbind(jack.estimates, gamma.est(data[-omitted.point]))
    }
    var.of.ests <- apply(jack.estimates, 2, var)
    jack.var <- ((n-1)^2/n)*var.of.ests
    return(sqrt(jack.var))
}
```
What happens?

> gamma.jackknife(cats$Hwt[1:3])
Error: is.atomic(x) is not TRUE
> traceback()
5: stop(paste(ch, " is not ", if (length(r) > 1L) "all ", "TRUE", 
       sep = ":."), Call. = FALSE)
4: stopifnot(;;is.atomic(x))
3: FUN(newX[, i], ...)
2: apply(jack.estimates, 2, var)
1: gamma.jackknife.2(cats$Hwt[1:3])

Tells us that the error arose from trying to apply `var` to each column of `jack.estimates`
Adding commands to the code for intermediate messages

print forces values to the screen
stick it before the problematic part to see if values look funny

```r
print(paste("x is now",x))
y <- a.tricky.function(x)
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add more prints upstream or downstream as needed
Add `print(str(jack.estimates))` before the apply and run again:

```r
> gamma.jackknife(cats$Hwt[1:3])
List of 6
$ : num 32.4
$ : num 21.8
$ : num 648
$ : num 0.261
$ : num 0.379
$ : num 0.0111
- attr(*, "dim")= int [1:2] 3 2
- attr(*, "dimnames")=List of 2
  ..$ : NULL
  ..$ : chr [1:2] "a" "s"
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Re-write `gamma.est` to give a vector (as in the code provided), or wrap `unlist` around its output
warning: print warning messages along with the call that initiated the weirdness

```r
quadratic.solver <- function(a,b,c) {
  determinant <- b^2 - 4*a*c
  if (determinant < 0) {
    warning("Equation has complex roots")
    determinant <- as.complex(determinant)
  }
  return(c((-b+sqrt(determinant))/2*a, (-b-sqrt(determinant))/2*a))
}

> quadratic.solver(1,0,-1)
[1] 1 -1

> quadratic.solver(1,0,1)
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Warning message:
In quadratic.solver(1, 0, 1) : Equation has complex roots
stopifnot: halt when results aren’t as we expect, and say why
We’ve seen this before
N.B., once you have found the bug, it’s generally good to turn lots
of these off!
Test Cases and Dummy Functions

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To make sure the dummy is working, make its output as simple as you can
Example: Minimizing MSE

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  return((params[1]-6000)^2+(params[2]-0.13)^2)
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N.B., this dummy takes all the arguments but ignores some of them.
The browser, recover and debug functions modify how R executes other functions
Let you view and modify the environment of the target function, and step through it
You do not need to master them, though they can be very helpful
See chapter 13 of Matloff, and §§3.5–3.6 of Chambers
After diagnosis, treatment: once the error is characterized and localized, guess at what’s wrong with the code and how to fix it. Try the fix: does it work? Have you broken something else? Try small cases first!
Parenthesis mis-matches

[[...]] vs. [...]

== vs. =

Identity of floating-point numbers

Vectors vs. single values: code works for one value but not multiple ones, unexpected recycling

Element-wise comparison of structures (use identical, all.equal)

Silent type conversions
Common Issues: Logic

Confusing variable names
Confusing function names
Giving unnamed arguments in the wrong order
R expression does not match the math you mean (left something out, added something)
Common Issues: Scope and Global Variables

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Assuming that changing a variable inside the function will change it elsewhere
Confusing variables within a function and those from where the functional was called
You are going to have to debug
Debugging is frustrating and time-consuming
Writing now to make it easier to debug later is worth it, even if it takes a bit more time
A lot of the design ideas we’ve talked about already contribute to this
Comment your code

- Insist on the three comment lines for each function: purpose, inputs, outputs

- Comment the innards as well, especially anything which strikes you as tricky or clever

- If you borrowed an idea from somewhere, use the comment to remind yourself of where (and acknowledge the borrowing)

- Use meaningful names

  - No restrictions on name lengths, few on name content

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Designing for Debugging

- Use top-down design and write modular, functional programs
- Respect the interfaces
- Don’t write the same code multiple times
- Use tests
Top-Down Programming

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so get the lowest-level functions right, and then work back up the chain
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- Global variables considered *especially* harmful
- Special considerations for stochastic simulations, which we’ll come to later
Unified Code

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Either write parallel code for each instance, or a single function called multiple times
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- *and* there is no chance to introduce new errors by mistakes in copying or adjustment
Tests

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Much of what you did to characterize and localize the bug can be turned into tests
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Can also recover from not-really-errors (like optimizations that
don’t converge)
This system is very flexible, but rather complicated
see §3.7 of Chambers
Summary

- Debugging is largely about differential diagnosis
- When you find a bug, characterize it by making sure you can reproduce it, and figure out what inputs do and don’t give the error
- Once you know what the bug does, localize it by traceback and adding messaging from the code; by dummy input generators; and by interactive tracing
- Examine the localized error for syntax error and for logical errors; fix them, and see if that gets rid of the bug without introducing new ones
- Program for debugging: write with comments and meaningful names; write modular functions; avoid repeated code

Next time: scope