# Statistics 360: Advanced R for Data Science

## Lecture 4

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# Digging deeper into functions

- Reading: Text, sections 6.4-6.8
- Topics:
  - more on scoping (finding objects)
  - lazy evaluation and variable arguments with ...
  - exiting a function
  - prefix, infix, replacement and special function forms

# Scoping

# Lexical scoping in R

- We have already touched on the essence of scoping in R: When a computation needs an object we start by looking in the current environment, and then search successive enclosing environments.
- More formally R has four rules:
  - Name masking
  - Functions versus variables
  - A fresh start
  - Dynamic lookup

# Name masking

- A consequence of the search order for objects is that names defined *inside* a function mask names defined *outside*.

```
x <- y <- 200
z <- 30 # defined in global environment
f <- function() { # f's env enclosed by global
  x <- 100 # defined in f's environment
  y <- 20
  g <- function() { #g's env enclosed by f's
    x <- 10 # defined in g's environment
    c(x,y,z)
  }
  g()
}
f()
```

```
## [1] 10 20 30
```

# Functions *vs* names

- R does the "right thing" when you (stupidly) use the same name for a function and variable.

```
g09 <- function(x) x + 100
g10 <- function() {
  g09 <- 10
  g09(g09)
}
g10()
```

```
## [1] 110
```

# Each function call gets a new environment

- As we saw in lecture 3, function calls create an environment. On exit, this environment is (typically) unbound and will disappear.

```
x <- 100
f <- function(){
  print(environment())
  x <- x+1
  x
}
f()
```

```
## <environment: 0x111c26228>
```

```
## [1] 101
```

```
f()
```

```
## <environment: 0x111cb5840>
```

```
## [1] 101
```

# Dynamic lookup

- Be aware that functions only look for objects when run (dynamic lookup), not when created (static lookup).
- If a function gets an object from an enclosing environment, it will return different results whenever the object in the enclosing environment changes.
  - This may be what you intend, but it's also a common source of errors. What if I meant to define y in f() but forgot:

```
y <- 100
f <- function(x) {
  x + y
}
f(1)
```

```
## [1] 101
```

```
y <- 200
f(1)
```

```
## [1] 201
```

- consider adding `rm(list=ls())` to the start of your scripts

# Lazy evaluation and . . .

# Lazy evaluation

- Function arguments are only evaluated when needed.
  - The text describes how lazy evaluation is implemented (Section 6.5), but we will not discuss the details.

```
f<-function(xx,yy) {
  xx
}
f(1) # no value for yy, but OK since yy not used
```

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

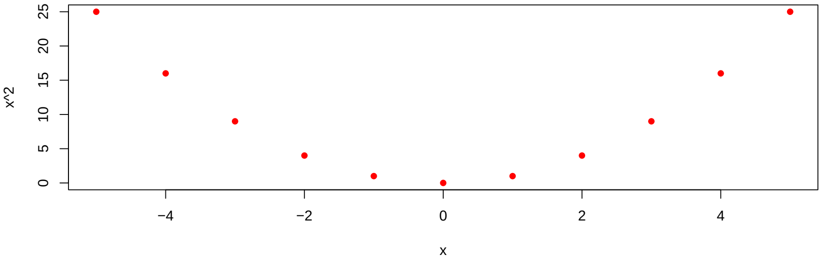
```
try(f(yy=1)) # xx is needed
```

```
## Error in f(yy = 1) : argument "xx" is missing, with no defaul
```

# Variable arguments with ...

- The special function argument `...` (dot-dot-dot) allows a function to take any number of arguments.
- A typical use is to pass these to another function, as in the following example.

```
myplot <- function(x,...) {
  plot(x,x^2,...) # pass any args not named x to plot
}
myplot((-5:5),col="red",pch=16)
```



# Exiting a function

# Exiting a function

- Functions can exit explicitly with `return()` or implicitly, where the last expression in the function is its return value
- When a function returns, explicitly or implicitly, the default is to print the return value.
  - You can suppress this with `invisible()`.

```
ff <- function(x) { x }
ff(1)
```

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

```
ff_invis <- function(x) { invisible(x) }
ff_invis(1) # but x <- ff_invis(1) same as x <- ff(1)
```

# Signalling conditions

- Functions can signal error, warning or message conditions with `stop()`, `warning()` and `message()`, respectively.
  - `stop()` stops execution, `warning()` and `message()` don't
- These signals can be "handled" by ignoring them
  - ignore errors with `try()`
  - ignore warnings with `suppressWarnings()`
  - ignore messages with `suppressMessages()`
- or implementing a custom handler that over-rides the default behaviour of a condition
  - see Chapter 8 of the text if you are interested in learning more about handling conditions
- We restrict attention to (i) signalling and (ii) cleaning up any changes to the R session before exiting.

# stop()

- If your function encounters an error, use stop() to stop and print an error message, also called "throwing" an error.

```
centre <- function(x,method) {
  switch(method,mean=mean(x),median=median(x),
         stop("method ",method," not implemented"))
}
try(centre(1:10,"mymean"))
```

```
## Error in centre(1:10, "mymean") : method mymean not implement
```

# warning()

- If you suspect an error but can proceed without stopping, throw a warning() instead.

```
centre <- function(x,method) {
  switch(method,mean=mean(x),median=median(x),
       {warning("\nmethod ",method,
                " not implemented, using mean\n");
         mean(x)})
}
centre(1:10,"mymean")
```

```
## Warning in centre(1:10, "mymean"):
## method mymean not implemented, using mean

## [1] 5.5
```

# message()

- If you don't think the condition warrants a warning, you can issue a message.

```
centre <- function(x,method) {
  switch(method,mean=mean(x),median=median(x),
         {message("\nmethod ",method,
                  " not implemented, using mean\n");
           mean(x)})
}
centre(1:10,"mymean")
```

```
##
## method mymean not implemented, using mean
## [1] 5.5
```

# Cleaning up with exit handlers

- An R session has a "global state" of options and parameters that control default behaviour.
  - type `options()` or `par()` to see some of these
- If your function temporarily modifies the global state, you can use an exit handler to re-set, even if your function stops.
  - Use `add=TRUE` to add more than one handler.

```
rplot <- function(y,x){
  opar <- par(mfrow=c(2,2))
  on.exit(par(opar),add=TRUE)
  plot(lm(y~x)) #could throw an error
}
y <- rnorm(100); x <- rnorm(10) # different length
try(rplot(y,x)) # Fails, but re-sets par mfrow
```

```
## Error in model.frame.default(formula = y ~ x, drop.unused.lev
##   variable lengths differ (found for 'x')
```

# Function forms

# Function forms

- We have been writing “prefix” functions, with a function name followed by arguments.
- Other forms are “infix”, “replacement” and “special”.
- We will cover each form very briefly; see the text, section 6.8 for more details.

# Infix functions

- An infix function has two arguments and is called by putting the name between arguments, as in `x+y`.
  - `x+y` calls + as `` `+`(x,y) ``
  - + and - are special infix functions that can be called with only one argument
  - You can define your own infix function by enclosing the function name in %.

```
`%-%` <- function(set1,set2){
  setdiff(set1,set2)
}
s1 <- 1:10; s2 <- 4:6
s1 %-% s2 # same as `%-%`(s1,s2)
```

```
## [1]  1  2  3  7  8  9 10
```

# Replacement functions

- Replacement functions are called to change values.
  - For example, change values of attributes of objects
- Must have arguments `x` and `value`, and must return the modified object.
- They are made to look like prefix functions, and may have prefix counterparts.

```
x <- c(a=1,b=2)
names(x)
```

```
## [1] "a" "b"
```

```
names(x) <- c("aa","bb")
x
```

```
## aa bb
##  1  2
```

```
x <- `names<-`(x,c("aaa","bbb"))
x
```

```
## aaa bbb
##   1   2
```

- You can write your own relacement functions if you end the function name with <-

```
`st360names<-` <- function(x,value){
  names(x) <- paste0(value,"360",names(x))
  x
}
st360names(x) <- c("a","b")
x
```

```
## a360aaa b360bbb
##       1       2
```

# Special functions

- Examples: subset `[` and extract `[[`, control flow `if`, `for`,etc.
- Key point: These are functions, and it is sometimes useful to know their names so that we can get help or use them like any other prefix function.

```
dd <- data.frame(x=1:2,y=3:4)
`[[`(dd,1) # compare to dd[[1]]
```

```
## [1] 1 2
```

```
dd <- `[[<-`(dd,1,value=5:6) #cf dd[[1]] <- 5:6
dd
```

```
##   x y
## 1 5 3
## 2 6 4
```

- It can be useful to know functions by name so that we can call them in `lapply`-like functions.

```
sapply(dd,`[[<-`,2,value=10)
```

```
##       x  y
## [1,]  5  3
## [2,] 10 10
```

# Functional Programming Basics

# Functional programming languages

- In a functional language functions are data structures.
  - Can assign them to variables, pass them as arguments to other functions and return them from other functions.
  - This is true of R functions, and is what we'll be focusing on.
- Many functional languages also require functions to be "pure".
  - Function output should only depend on the input, and the function should not have any side-effects.
  - We can see from our brief discussion of scoping that R functions can use global variables, and we know they have side-effects like generating plots.

# Functional style

- We will say that functional programming *style* means a top-down approach that breaks big problems into smaller pieces that we solve with small, easy (easier) to understand functions.
- This is the way we are approaching our implementation of MARS.
- Functional languages support this style with "higher-order" functions that take other functions as input .
  - The higher-order function is part of the "big problem", and its input is the "small function".

# Functionals

- You have already seen higher-order functions in Stat 260: The `map` family of functions from the `purrr` package, or `lapply()` from base R.
- The text calls these functionals and they are discussed in Chapter 9.
- You have already studied the `map` functions, so our discussion here will be brief, with an emphasis on parallelization:
    - Not only can we break a computation into pieces, but we can have the pieces computed on different cores of a computer or nodes of a compute cluster.

# Map-like functions such as `lapply()`

- Take a vector and function as input and return a list (or some simplification) whose elements are the function applied to each vector element.
  - We are mapping (in math sense) the vector elements $x$ to $f(x)$.
- Basically a for loop over the input vector, calling the input function at each iteration.

```
simple_map <- function(x, f, ...) { # text, Section 9.2
  out <- vector("list", length(x))
  for (i in seq_along(x)) {
    out[[i]] <- f(x[[i]], ...)
  }
  out
}
```

# Examples with lapply()

```
rfun <- function(seed,n) { set.seed(seed); return(rnorm(n))}
dat <- lapply(1:10,rfun,n=1e7) # specify non-vectorized arg by name
mfun <- function(x) { return(mean(quantile(x,probs=c(.25,.75)))) }
system.time( unlist(lapply(dat,mfun)) ) # Look at elapsed
```

```
##    user  system elapsed
##   1.709   0.255   2.007
```

# Parallel execution with `mclapply()`

- `mclapply()` is the multi-core version of `lapply()`; i.e., function calls are done on separate cores.

```
library(parallel) # comes with R
ncores <- detectCores() ; cat("number of cores=",ncores,"\n")
```

```
## number of cores= 8
```

```
system.time({ unlist(mclapply(dat,mfun,mc.cores=ncores)) })
```

```
##    user  system elapsed
##   1.640   0.835   1.060
```

# Another example

```r
dat2 <- lapply(1:10,rfun,n=1e5)
mfun2 <- function(x) { return(data.frame(sum=sum(x),n=length(x))) }
sumdat <- lapply(dat2,mfun2)
```

# Reduce-like functions

- Reduce functions successively combine vector elements.
  - Can use them to assemble output of a map-like function.
  - When implemented to parallelize over multiple computers, this is the MapReduce programming model you hear about for "big data".
- Reducers combine with a loop:

```
simple_reduce <- function(x, f) { # Text section 9.5
  out <- x[[1]]
  for (i in seq(2, length(x))) {
    out <- f(out, x[[i]])
  }
  out
}
```

# Example reduce

```r
allres <- simple_reduce(sumdat,rbind)
allres
```

```
##            sum      n
## 1  -224.40833 100000
## 2   307.85570 100000
## 3    36.96750 100000
## 4   -20.44743 100000
## 5  -726.27096 100000
## 6  -191.83899 100000
## 7   -50.00946 100000
## 8   270.86608 100000
## 9   -52.17403 100000
## 10 -595.83810 100000
```

```r
sum(allres$sum)/sum(allres$n) # mean
```

```
## [1] -0.001245298
```

# Further reading on parallel computing

- For parallel computing on a cluster, see the `doParallel` and `foreach` packages (canonical link to doParallel vignette currently broken):

http://users.iems.northwestern.edu/~nelsonb/Masterclass/getting startedParallel.pdf

# Other higher-order functions

- Other chapters discuss function factories (Chapter 10) and function operators (Chapter 11).
- These are used less and will not be discussed.

| In \ Out | Vector | Function |
|---|---|---|
| Vector | Regular function | Function factory |
| Function | Functional | Function operator |

Figure 1: Higher-order functions