

The very basics of programming

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One of the very nice features of R when one comes from other statistical software like SAS or Stata is that it is very easy to program. And that is a really good thing, because the manipulation, analysis, and visualization of data is considerably easier when one can write small functions. In addition, because R is open-source, you can inspect what every function does, so it is useful to get a sense of the most basic elements of programming to be able to take advantage of that feature.

Defining functions

Think about functions as a way of packing operations in one reusable expression. For instance, consider a trivial example in which we want to calculate a mean. Instead of doing `sum` over `length` in every situation, we could just pack those operations together and give them a name:

```
my_mean <- function(x) sum(x)/length(x)
my_mean(c(0, 1))
```

```
## [1] 0.5
```

To define a function, we use the keyword `function` followed by parenthesis and (optionally) the arguments that the function takes, and the expression that the function runs. We then assign this function to a name, in this case, `my_mean`.

See how typing `my_mean` allows you to see what you have just defined.

```
my_mean
## function(x) sum(x)/length(x)
## <environment: 0x00000000e4bba78>
```

The way we defined the function is perfectly valid but we could also be a bit more explicit by enclosing the statement in parenthesis and ensuring that it is returned.

```
my_mean <- function(x) {
  return(sum(x)/length(x))
}
```

Now that we have the fundamentals of how to define a function, let's take a look at control flow operations.

Loops

`for` allows us to iterate and repeat an operation over a sequence. As you can imagine, we need to be explicit about two things: the sequence and the variable that will be taking values over that sequence.

```
for (i in 1:3) print(i)
```

```
## [1] 1
## [1] 2
## [1] 3
```

Let's see a less trivial example in which we want to calculate the sum of a vector:

```
myvector <- c(1, 2, 3, 4)
out <- 0
for (i in 1:length(myvector)) {
```

```

    out <- myvector[i] + out
  }
  out

```

```
## [1] 10
```

Here `out` will hold the result of progressively adding the values of `myvector`. Notice how `i` takes, in each iteration, a different value in the sequence between 1 and the length of `myvector` that we then use to retrieve the value in each position.

Depending on the context, it will probably make sense to wrap this operations in a function. At the end of the day, the only thing that will change in different calculations of a sum is the vector it operates over, so we can *parametrize* over that vector:

```

my_sum <- function(x) {
  out <- 0
  for (i in 1:length(x)) {
    out <- x[i] + out
  }
  return(out)
}
my_sum(c(1, 2, 3, 4))

```

```
## [1] 10
```

Another way to build loops is with the statement `while`. It will evaluate an expression until a condition is not met:

```

i <- 0
while (i < 3) {
  print(i)
  i <- i + 1
}

```

```
## [1] 0
## [1] 1
## [1] 2
```

The thing to notice is that how in each iteration of the loop, the value of `i` changes: when it takes the value 3, the condition `i < 3` evaluates to `FALSE`, and the loop stops –and therefore, 3 is not printed to the screen.

There are some cases in which the use of `which` is natural, like when we want to run algorithms until something converges. Take for instance the calculation of Newton-Raphson:

```

tol <- 0.01
x_last <- 10; diff <- 1
while (abs(diff) > tol) {
  x <- x_last - (x_last^2)/(2*x_last)
  diff <- (x - x_last)
  x_last <- x
  print(x)
}

```

```
## [1] 5
## [1] 2.5
## [1] 1.25
## [1] 0.625
## [1] 0.3125
## [1] 0.15625
```

```
## [1] 0.078125
## [1] 0.0390625
## [1] 0.01953125
## [1] 0.009765625
```

However, `while` may end up producing infinite loops if one is not careful.

Conditionals

As you can imagine, conditionals execute an action depending on the value (TRUE or FALSE) of another statement. In R, they use the follow syntax:

```
if (x > 0) {
  print("It's positive")
} else if (x == 0) {
  print("It's neither positive nor negative")
} else {
  print("It's negative")
}
```

which we may wrap up in a function

```
my_sign <- function(x) {
  if (x > 0) {
    out <- "It's positive!"
  } else if (x == 0) {
    out <- "It's neither positive nor negative!"
  } else {
    out <- "It's negative!"
  }
  return(out)
}
```

and use it to illustrate what happens when you are not careful:^[1]

```
my_sign("A cow")
```

```
## [1] "It's positive!"
```

How to deal with the previous issue? By issuing an error:

```
my_sign <- function(x) {
  if (!is.numeric(x)) {
    stop("Input is not a number")
  }

  if (x > 0) {
    out <- "It's positive!"
  } else if (x == 0) {
    out <- "It's neither positive nor negative!"
  } else {
    out <- "It's negative!"
  }
  return(out)
}
```

Two things to notice here. First, that `!` is the negation operator (`TRUE == !FALSE`). Second, that `stop` interrupts the evaluation and produces an error, so the function never reaches the next conditional.

The if-else structure is the building block of a rejection sampling algorithm, so let's use to make samples out of a $Beta(3,6)$.

```
R <- 10000
samples <- matrix(NA, nrow=R, ncol=2)

for(i in 1:R) {
  samples[i, 1] <- runif(1, 0, 1)
  U <- runif(1, 0, 1)
  if(dunif(samples[i, 1], 0, 1)*3*U <= dbeta(samples[i, 1], 3, 6)) {
    samples[i, 2] <- 1
  }
  else if(dunif(samples[i, 1], 0, 1)*3*U > dbeta(samples[i, 1], 3, 6)) {
    samples[i, 2] <- 0
  }
}

samples <- data.frame(samples)
names(samples) <- c("candidate", "accept")
samples <- samples[samples$accept == 1,]

library(ggplot2)
p <- ggplot(samples, aes(x=candidate))
p + geom_density() +
  stat_function(fun=dbeta, args=list(3, 6), colour="red", linetype=2)
```

