

# Functions

## Packages for this section

```
library(tidyverse)
library(broom)
```

# Don't repeat yourself

► See this:

```
a <- 50  
b <- 11  
d <- 3  
as <- sqrt(a - 1)  
as
```

```
[1] 7
```

```
bs <- sqrt(b - 1)  
bs
```

```
[1] 3.162278
```

```
ds <- sqrt(d - 1)  
ds
```

```
[1] 1.414214
```

# What's the problem?

- ▶ Same calculation done three different times, by copying, pasting and editing.
- ▶ Dangerous: what if you forget to change something after you pasted?
- ▶ Programming principle: “don't repeat yourself”.
- ▶ Hadley Wickham: don't copy-paste more than twice.
- ▶ Instead: *write a function*.

# Anatomy of function

- ▶ Header line with function name and input value(s).
- ▶ Body with calculation of values to output/return.
- ▶ Return value: the output from function. In our case:

```
sqrt_minus_1 <- function(x) {  
  ans <- sqrt(x - 1)  
  return(ans)  
}
```

or more simply (“the R way”, better style)

```
sqrt_minus_1 <- function(x) {  
  sqrt(x - 1)  
}
```

If last line of function calculates value without saving it, that value is returned.

## About the input; testing

- ▶ The input to a function can be called anything. Here we called it x. This is the name used inside the function.
- ▶ The function is a “machine” for calculating square-root-minus-1. It doesn't do anything until you call it:

```
sqrt_minus_1(50)
```

```
[1] 7
```

```
sqrt_minus_1(11)
```

```
[1] 3.162278
```

```
sqrt_minus_1(3)
```

```
[1] 1.414214
```

- ▶ It works!

## Vectorization 1/2

- ▶ We conceived our function to work on numbers:

```
sqrt_minus_1(3.25)
```

```
[1] 1.5
```

- ▶ but it actually works on vectors too, as a free bonus of R:

```
sqrt_minus_1(c(50, 11, 3))
```

```
[1] 7.000000 3.162278 1.414214
```

- ▶ or... (over)

## Vectorization 2/2

▶ or even data frames:

```
d <- tibble(x = 1:2, y = 3:4)
sqrt_minus_1(d)
```

	x	y
1	0	1.414214
2	1	1.732051



## More than one input

- ▶ Allow the value to be subtracted, before taking square root, to be input to function as well, thus:

```
sqrt_minus_value <- function(x, d) {  
  sqrt(x - d)  
}
```

- ▶ Call the function with the x and d inputs in the right order:

```
sqrt_minus_value(51, 2)
```

```
[1] 7
```

- ▶ or give the inputs names, in which case they can be in *any order*:

```
sqrt_minus_value(d = 2, x = 51)
```

```
[1] 7
```

## Defaults 1/2

- ▶ Many R functions have values that you can change if you want to, but usually you don't want to, for example:

```
x <- c(3, 4, 5, NA, 6, 7)
mean(x)
```

```
[1] NA
```

```
mean(x, na.rm = TRUE)
```

```
[1] 5
```

- ▶ By default, the mean of data with a missing value is missing, but if you specify `na.rm=TRUE`, the missing values are removed before the mean is calculated.
- ▶ That is, `na.rm` has a default value of `FALSE`: that's what it will be unless you change it.

## Defaults 2/2

- ▶ In our function, set a default value for `d` like this:

```
sqrt_minus_value <- function(x, d = 1) {  
  sqrt(x - d)  
}
```

- ▶ If you specify a value for `d`, it will be used. If you don't, 1 will be used instead:

```
sqrt_minus_value(51, 2)
```

```
[1] 7
```

```
sqrt_minus_value(51)
```

```
[1] 7.071068
```

# Catching errors before they happen

- ▶ What happened here?

```
sqrt_minus_value(6, 8)
```

Warning in sqrt(x - d): NaNs produced

```
[1] NaN
```

- ▶ Message not helpful. Actually, function tried to take square root of negative number.
- ▶ In fact, not even error, just warning.
- ▶ Check that the square root will be OK first. Here's how:

```
sqrt_minus_value <- function(x, d = 1) {  
  stopifnot(x - d >= 0)  
  sqrt(x - d)  
}
```

# What happens with stopifnot

- ▶ This should be good, and is:

```
sqrt_minus_value(8, 6)
```

```
[1] 1.414214
```

- ▶ This should fail, and see how it does:

```
sqrt_minus_value(6, 8)
```

```
Error in sqrt_minus_value(6, 8): x - d >= 0 is not TRUE
```

- ▶ Where the function fails, we get informative error, but if everything good, the stopifnot does nothing.
- ▶ stopifnot contains one or more logical conditions, and all of them have to be true for function to work. So put in everything that you want to be true.

## Using R's built-ins

- ▶ When you write a function, you can use anything built-in to R, or even any functions that you defined before.
- ▶ For example, if you will be calculating a lot of regression-line slopes, you don't have to do this from scratch: you can use R's regression calculations, like this:

```
my_df <- tibble(x = 1:4, y = c(10, 11, 10, 14))  
# my_df  
my_df.1 <- lm(y ~ x, data = my_df)  
# summary(my_df.1)  
tidy(my_df.1)
```

```
# A tibble: 2 x 5
```

	term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
1	(Intercept)	8.5	1.88	4.53	0.0455
2	x	1.1	0.686	1.60	0.250

## Pulling out just the slope

Use pluck:

```
tidy(my_df.1) %>% pluck("estimate", 2)
```

```
[1] 1.1
```

## Making this into a function

- ▶ First step: make sure you have it working without a function (we do)
- ▶ Inputs: two, an x and a y.
- ▶ Output: just the slope, a number. Thus:

```
slope <- function(xx, yy) {  
  y.1 <- lm(yy ~ xx)  
  tidy(y.1) %>% pluck("estimate", 2)  
}
```

- ▶ Check using our data from before: correct:

```
with(my_df, slope(x, y))
```

```
[1] 1.1
```



## Passing things on

- ▶ `lm` has a lot of options, with defaults, that we might want to change. Instead of intercepting all the possibilities and passing them on, we can do this:

```
slope <- function(xx, yy, ...) {  
  y.1 <- lm(yy ~ xx, ...)  
  tidy(y.1) %>% pluck("estimate", 2)  
}
```

- ▶ The `...` in the header line means “accept any other input”, and the `...` in the `lm` line means “pass anything other than `x` and `y` straight on to `lm`”.

## Using ...

- ▶ One of the things `lm` will accept is a vector called `subset` containing the list of observations to include in the regression.
- ▶ So we should be able to do this:

```
with(my_df, slope(x, y, subset = 3:4))
```

```
[1] 4
```

- ▶ Just uses the last two observations in `x` and `y`:

```
my_df %>% slice(3:4)
```

```
# A tibble: 2 x 2
```

	x	y
	<int>	<dbl>
1	3	10
2	4	14

- ▶ so the slope should be  $(14 - 10)/(4 - 3) = 4$  and is.

## Running a function for each of several inputs

- ▶ Suppose we have a data frame containing several different x's to use in regressions, along with the y we had before:

```
(d <- tibble(x1 = 1:4, x2 = c(8, 7, 6, 5), x3 = c(2, 4, 6,
```

```
# A tibble: 4 x 3
```

	x1	x2	x3
	<int>	<dbl>	<dbl>
1	1	8	2
2	2	7	4
3	3	6	6
4	4	5	9

- ▶ Want to use these as different x's for a regression with y from my\_df as the response, and collect together the three different slopes.
- ▶ Python-like way: a for loop.
- ▶ R-like way: map\_dbl: less coding, but more thinking.

## The loop way

- ▶ “Pull out” column `i` of data frame `d` as `d %>% pull(i)`.
- ▶ Create empty vector `slopes` to store the slopes.
- ▶ Looping variable `i` goes from 1 to 3 (3 columns, thus 3 slopes):

```
slopes <- numeric(3)
for (i in 1:3) {
  d %>% pull(i) -> xx
  slopes[i] <- slope(xx, my_df$y)
}
slopes
```

```
[1] 1.1000000 -1.1000000 0.5140187
```

- ▶ Check this by doing the three `lms`, one at a time.

## The map\_dbl way

- ▶ In words: for each of these (columns of d), run function (slope) with inputs “it” and y), and collect together the answers.
- ▶ Since slope returns a decimal number (a dbl), appropriate function-running function is map\_dbl:

```
map_dbl(d, \(d) slope(d, my_df$y))
```

x1	x2	x3
1.1000000	-1.1000000	0.5140187

- ▶ Same as loop, with a lot less coding.

# Square roots

► “Find the square roots of each of the numbers 1 through 10”:

```
x <- 1:10  
map_dbl(x, \(x) sqrt(x))
```

```
[1] 1.000000 1.414214 1.732051 2.000000 2.236068 2.449490  
[9] 3.000000 3.162278
```

## Summarizing all columns of a data frame, two ways

► use my d from above:

```
map_dbl(d, \(d) mean(d))
```

```
  x1    x2    x3  
2.50 6.50 5.25
```

```
d %>% summarize(across(everything(), \(x) mean(x)))
```

```
# A tibble: 1 x 3  
  x1    x2    x3  
<dbl> <dbl> <dbl>  
1  2.5    6.5  5.25
```

The mean of each column, with the columns labelled.

## What if summary returns more than one thing?

- ▶ For example, finding quartiles:

```
quartiles <- function(x) {  
  quantile(x, c(0.25, 0.75))  
}  
quartiles(1:5)
```

```
25% 75%  
 2   4
```

- ▶ When function returns more than one thing, `map` (or `map_df`) instead of `map_dbl`.



## map results

► Try:

```
map(d, \(d) quartiles(d))
```

\$x1

25% 75%

1.75 3.25

\$x2

25% 75%

5.75 7.25

\$x3

25% 75%

3.50 6.75

► A list.

Or

- ▶ Better: pretend output from `quartiles` is one-column data frame:

```
map_df(d, \(d) quartiles(d))
```

```
# A tibble: 3 x 2
  `25%` `75%`
  <dbl> <dbl>
1  1.75  3.25
2  5.75  7.25
3  3.5   6.75
```

Or even

```
d %>% map_df(\(d) quartiles(d))
```

```
# A tibble: 3 x 2
```

```
  `25%` `75%`
```

```
  <dbl> <dbl>
```

```
1  1.75  3.25
```

```
2  5.75  7.25
```

```
3  3.5   6.75
```

## Comments

- ▶ This works because the implicit first thing in `map` is (the columns of) the data frame that came out of the previous step.
- ▶ These are 1st and 3rd quartiles of each column of `d`, according to R's default definition (see help for `quantile`).

## Map in data frames with mutate

- ▶ map can also be used within data frames to calculate new columns. Let's do the square roots of 1 through 10 again:

```
d <- tibble(x = 1:10)
d %>% mutate(root = map_dbl(x, \(x) sqrt(x)))
```

```
# A tibble: 10 x 2
```

	x	root
	<int>	<dbl>
1	1	1
2	2	1.41
3	3	1.73
4	4	2
5	5	2.24
6	6	2.45
7	7	2.65
8	8	2.83
9	9	3
10	10	3.16

## Write a function first and then map it

- ▶ If the “for each” part is simple, go ahead and use `map_-whatever`.
- ▶ If not, write a function to do the complicated thing first.
- ▶ Example: “half or triple plus one”: if the input is an even number, halve it; if it is an odd number, multiply it by three and add one.
- ▶ This is hard to do as a one-liner: first we have to figure out whether the input is odd or even, and then we have to do the right thing with it.

## Odd or even?

- ▶ Odd or even? Work out the remainder when dividing by 2:

```
6 %% 2
```

```
[1] 0
```

```
5 %% 2
```

```
[1] 1
```

- ▶ 5 has remainder 1 so it is odd.

## Write the function

- First test for integerness, then test for odd or even, and then do the appropriate calculation:

```
hotpo <- function(x) {  
  stopifnot(round(x) == x) # passes if input an integer  
  remainder <- x %% 2  
  if (remainder == 1) {  
    ans <- 3 * x + 1  
  }  
  else {  
    ans <- x %/% 2 # integer division  
  }  
  ans  
}
```



## Test it

```
hotpo(3)
```

```
[1] 10
```

```
hotpo(12)
```

```
[1] 6
```

```
hotpo(4.5)
```

```
Error in hotpo(4.5): round(x) == x is not TRUE
```

## One through ten

- Use a data frame of numbers 1 through 10 again:

```
tibble(x = 1:10) %>% mutate(y = map_int(x, \(x) hotpo(x)))
```

```
# A tibble: 10 x 2
```

	x	y
	<int>	<int>
1	1	4
2	2	1
3	3	10
4	4	2
5	5	16
6	6	3
7	7	22
8	8	4
9	9	28
10	10	5

## Until I get to 1 (if I ever do)

- ▶ If I start from a number, find hotpo of it, then find hotpo of that, and keep going, what happens?
- ▶ If I get to 4, 2, 1, 4, 2, 1 I'll repeat for ever, so let's stop when we get to 1:

```
hotpo_seq <- function(x) {  
  ans <- x  
  while (x != 1) {  
    x <- hotpo(x)  
    ans <- c(ans, x)  
  }  
  ans  
}
```

- ▶ Strategy: keep looping “while x is not 1”.
- ▶ Each new x: add to the end of ans. When I hit 1, I break out of the while and return the whole ans.

## Trying it 1/2

► Start at 6:

```
hotpo_seq(6)
```

```
[1]  6  3 10  5 16  8  4  2  1
```



## Which starting points have the longest sequences?

- ▶ The `length` of the vector returned from `hotpo_seq` says how long it took to get to 1.
- ▶ Out of the starting points 1 to 100, which one has the longest sequence?

## Top 10 longest sequences

```
tibble(start = 1:100) %>%  
  mutate(seq_length = map_int(  
    start, \(start) length(hotpo_seq(start)))) %>%  
  slice_max(seq_length, n = 10)
```

```
# A tibble: 10 x 2
```

	start	seq_length
	<int>	<int>
1	97	119
2	73	116
3	54	113
4	55	113
5	27	112
6	82	111
7	83	111
8	41	110
9	62	108
10	63	108

## What happens if we save the entire sequence?

```
tibble(start = 1:7) %>%  
  mutate(sequence = map(start, \(start) hotpo_seq(start)))
```

```
# A tibble: 7 x 2  
  start sequence  
  <int> <list>  
1     1 <int [1]>  
2     2 <dbl [2]>  
3     3 <dbl [8]>  
4     4 <dbl [3]>  
5     5 <dbl [6]>  
6     6 <dbl [9]>  
7     7 <dbl [17]>
```

- Each entry in sequence is itself a vector. sequence is a “list-column”.



## Using the whole sequence to find its length and its max

```
tibble(start = 1:7) %>%  
  mutate(sequence = map(start, \(start) hotpo_seq(start)))  
  mutate(  
    seq_length = map_int(sequence, \(sequence) length(sequence))  
    seq_max = map_int(sequence, \(sequence) max(sequence))  
  )
```

# A tibble: 7 x 4

	start	sequence	seq_length	seq_max
	<int>	<list>	<int>	<int>
1	1	<int [1]>	1	1
2	2	<dbl [2]>	2	2
3	3	<dbl [8]>	8	16
4	4	<dbl [3]>	3	4
5	5	<dbl [6]>	6	16
6	6	<dbl [9]>	9	16
7	7	<dbl [17]>	17	52

## Does it work with rowwise?

```
tibble(start=1:7) %>%  
  rowwise() %>%  
  mutate(sequence = list(hotpo_seq(start))) %>%  
  mutate(seq_length = length(sequence)) %>%  
  mutate(seq_max = max(sequence))
```

# A tibble: 7 x 4

# Rowwise:

	start	sequence	seq_length	seq_max
	<int>	<list>	<int>	<dbl>
1	1	<int [1]>	1	1
2	2	<dbl [2]>	2	2
3	3	<dbl [8]>	8	16
4	4	<dbl [3]>	3	4
5	5	<dbl [6]>	6	16
6	6	<dbl [9]>	9	16
7	7	<dbl [17]>	17	52

It does.

## Final thoughts on this

- ▶ Called the **Collatz conjecture**.
- ▶ Nobody knows whether the sequence always gets to 1.
- ▶ Nobody has found an  $n$  for which it doesn't.
- ▶ A tree.