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DSFBA: Control Flow and Functions

Data Science for Business Analytics

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Today

- Control flow:
  - **Choices**:
    - E.g. `if()`, `ifelse()`, `switch()`.
    - Allows to run different code depending on the input.
  - **Loops**:
    - E.g. `for`, `while`, `repeat`.
    - Allows to repeatedly run code, typically with changing options.
  - You might want to have a look at chapter 8 for condition system (messages, warnings, and errors)...
- Reducing code duplication:
  - Three main benefits:
    - Easier to see the intent of your code.
    - Easier to respond to changes in requirements.
    - Likely to have fewer bugs.
  - **Functions**: identify repeated patterns of code and extract them out into independent pieces.
  - **Iteration**: helps you when you need to do the same thing to multiple inputs.

Outline

if() statements

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- The basic idea for if statements:
  - If condition is TRUE, true_action is evaluated.
  - If condition is FALSE, the optional false_action is evaluated.

```
if (condition) true_action
if (condition) true_action else false_action
```

- Typically, actions are compound statements contained within {.

```
grade <- function(x) {
  if (x > 90) {
    "A"
  } else if (x > 80) {
    "B"
  } else if (x > 50) {
    "C"
  } else {
    "F"
  }
}
```

`if()` statements cont'd

- `if` returns a value so that you can assign the results:
  - Only do that when it fits on one line; otherwise hard to read.

```r
x1 <- if (TRUE) 1 else 2
x2 <- if (FALSE) 1 else 2

c(x1, x2)
#> [1] 1 2
```

- When using `if` without `else`:
  - Returns `NULL` if the condition is `FALSE`.
  - Useful with functions like `c()`/`paste()` dropping `NULL` inputs.

```r
greet <- function(name, birthday = FALSE) {
  paste0("Hi ", name, if (birthday) " and HAPPY BIRTHDAY")
}
greet("Maria", FALSE)
#> [1] "Hi Maria"
greet("Jaime", TRUE)
#> [1] "Hi Jaime and HAPPY BIRTHDAY"
```

Invalid inputs

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- The condition should evaluate to a single TRUE or FALSE:

```
if ("x") 1
#> Error in if ("x") 1: argument is not interpretable as logical
if (logical()) 1
#> Error in if (logical()) 1: argument is of length zero
if (NA) 1
#> Error in if (NA) 1: missing value where TRUE/FALSE needed
```

- The exception (frequent source of bugs, avoid):
  - A logical vector of length greater than 1 generates a warning.

```
if (c(TRUE, FALSE)) 1
#> Warning in if (c(TRUE, FALSE)) 1: the condition has length > 1 and
#> only the first element will be used
#> [1] 1
```

Vectorised `if()` statements

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- `if` only works with a single `TRUE` or `FALSE`.
- What if you have a vector of logical values?
- Answer: `ifelse()`
  - Vectorized function with `test`, `yes`, and `no` vectors (recycled).
  - Missing values propagated into the output.
  - Advice: use only when `yes` and `no` vectors are of the same type.

```
x <- 1:9
ifelse(x %% 5 == 0, "XXX", as.character(x))
#> [1] "1"   "2"   "3"   "4"   "XXX" "6"   "7"   "8"   "9"
ifelse(x %% 2 == 0, "even", "odd")
#> [1] "odd"  "even" "odd"  "even" "odd"  "even" "odd"  "even" "odd"
```

- For any number of condition-vector pairs:

```
dplyr::case_when(
  x %% 35 == 0 ~ "fizz buzz",
  x %% 5 == 0 ~ "fizz",
  x %% 7 == 0 ~ "buzz",
  TRUE ~ as.character(x)
  )
#> [1] "1"    "2"    "3"    "4"    "fizz" "6"    "buzz" "8"    "9"
```

switch() statements

- Lets you replace code like:

```
x_option <- function(x) {
  if (x == "a") {
    "option 1"
  } else if (x == "b") {
    "option 2"
  } else {
    stop("Invalid `x` value")
  }
}
```

- With:

```
x_option <- function(x) {
  switch(x,
    a = "option 1",
    b = "option 2",
    stop("Invalid `x` value")
  )
}
```

Outline

For loops

- Let's compute the median of each column:

```r
df <- tibble(a = rnorm(10),
             b = rnorm(10),
             c = rnorm(10),
             d = rnorm(10))

c(median(df$a), median(df$b), median(df$c), median(df$d))
#> [1]  0.204 -0.355  0.090 -0.258
```

- What's "wrong" here?

For loops

- Let's compute the median of each column:

```
df <- tibble(a = rnorm(10),
             b = rnorm(10),
             c = rnorm(10),
             d = rnorm(10))

c(median(df$a), median(df$b), median(df$c), median(df$d))
#> [1]  0.204 -0.355  0.090 -0.258
```

- What's "wrong" here?

- A better solution:

```
output <- vector("double", ncol(df))  # 1. output
for (i in seq_along(df)) {            # 2. sequence
  output[[i]] <- median(df[[i]])      # 3. body
}
output
#> [1]  0.204 -0.355  0.090 -0.258
```

For loops cont'd

- `for` loops are used to iterate over items in a vector.

```
for (item in vector) perform_action
```

- For each item in `vector`, `perform_action` is called once; updating the value of `item` each time.

```
for (i in 1:3) {
  print(i)
}
#> [1] 1
#> [1] 2
#> [1] 3
```

- When iterating over indices, use short names like `i`, `j`, or `k`.
- Important: `for` assigns the `item` to the current environment.

```
i <- 100
for (i in 1:3) {}
i
#> [1] 3
```

Early termination

- Two ways to terminate a `for` loop early:
  - `next` exits the current iteration.
  - `break` exits the entire `for` loop.

```
for (i in 1:10) {
  if (i < 3)
    next

  print(i)

  if (i >= 5)
    break
}
#> [1] 3
#> [1] 4
#> [1] 5
```

Common pitfalls

- Common pitfalls to watch out for when using `for`:
  - Preallocation.
  - Iteration over e.g. `1:length(x)`.
- Preallocation:
  - If you're generating data, preallocate the output.
  - Otherwise the loop will be very slow.
  - `vector()` function is helpful.

```r
means <- c(1, 50, 20)
out <- vector("list", length(means))
for (i in 1:length(means)) {
  out[[i]] <- rnorm(10, means[[i]])
}
```

Common pitfalls cont’d

- Next, beware of iterating over `1:length(x)`, which will fail in unhelpful ways if `x` has length 0.

```r
means <- c()
out <- vector("list", length(means))
for (i in 1:length(means)) {
  out[[i]] <- rnorm(10, means[[i]])
}
#> Error in rnorm(10, means[[i]]): invalid arguments

# The reason? `:` works with both increasing and decreasing sequences.
1:length(means)
#> [1] 1 0
```

- Use `seq_along(x)` instead.

```r
seq_along(means)
#> integer(0)

out <- vector("list", length(means))
for (i in seq_along(means)) {
  out[[i]] <- rnorm(10, means[[i]])
}
```

Related tools

- `for` loops:
  - Useful when known in advance the set of values to iterate over.
  - Otherwise:
    - `while(condition) action`: performs `action` while `condition` is `TRUE`.
    - `repeat(action)`: repeats `action` forever (i.e. until it encounters `break`).
    - Possible to write any `for` using `while`, and any `while` using `repeat`, but not the converse.
    - Good practice to use the least-flexible (i.e., simplest) solution to a problem.
- Generally speaking you shouldn't need to use `for` loops for **data analysis tasks**, we'll see better solutions.

Outline

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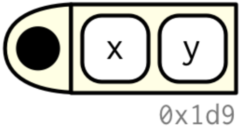
Functions

- Two **important ideas**:
  - Functions can be broken down into three components: arguments, body, and environment.
  - Functions are objects, just as vectors are objects.
- In the following:
  - **The basics:**
    - How to create functions.
    - The three main components of a function.
    - How can a function exit.
    - Anonymous functions.
    - Lazy evaluation.
    - The special ... argument.
  - **Lexical scoping:** how R finds the value associated with a given name.
    - Name masking.
    - Functions versus variables.
    - A fresh start.
    - Dynamic lookup.

Function components

- A function has three parts:
  - The `formals()`, the arguments controlling how you call the function.
  - The `body()`, the code inside the function.
  - The `environment()`, the data structure determining how the function finds the values associated with the names.

```
f02 <- function(x, y) {
  # A comment
  x + y
}
formals(f02)
#> $x
#>
#>
#> $y
body(f02)
#> {
#>     x + y
#> }
environment(f02)
#> <environment: R_GlobalEnv>
```



Primitive functions

- One exception to the three components rule.
- Call C code directly.

```
sum
#> function (..., na.rm = FALSE)  .Primitive("sum")
`[`
#> .Primitive("[")
```

- Type is either `builtin` or `special`.

```
typeof(sum)
#> [1] "builtin"
typeof(`[`)
#> [1] "special"
```

- `formals()`, `body()`, and `environment()` are all `NULL`.

```
formals(sum)
#> NULL
body(sum)
#> NULL
environment(sum)
#> NULL
```

Exiting a function

- Most functions exit in one of two ways:
  - They either return a value, indicating success.
  - Or they throw an error, indicating failure.
- In the next few slides:
  - Return values.
    - Implicit versus explicit.
    - Visible versus invisible.
  - Errors.

Implicit versus explicit returns

- Implicit, where the last evaluated expression is the return value.

```r
j01 <- function(x) {
  if (x < 10) {
    0
  } else {
    10
  }
}
j01(5)
#> [1] 0
j01(15)
#> [1] 10
```

- Explicit, by calling `return()`.

```r
j02 <- function(x) {
  if (x < 10) {
    return(0)
  } else {
    return(10)
  }
}
```

Errors

- If a function cannot complete its assigned task, it should throw an error with `stop()`:
  - Immediately terminates the execution of the function.
  - Indicates that something has gone wrong, and forces the user to deal with the problem.

```r
j05 <- function() {
  stop("I'm an error")
  return(10)
}
j05()
#> Error in j05(): I'm an error
```

- Some languages rely on special return values to indicate problems, but in R you should always throw an error.

Anonymous function

- Unlike in many other languages, no special syntax:
  - Create a function object (with `function`).
  - Bind it to a name with `<-`.

```
f01 <- function(x) {
  sin(x)
}
```

- . . . but the binding step is not compulsory!
- A function without a name is called an **anonymous function**:

```
integrate(function(x) sin(x), 0, pi)
#> 2 with absolute error < 2.2e-14
sapply(1:10, function(x) x + 1)
#>  [1]  2  3  4  5  6  7  8  9 10 11
```

Lazy evaluation

- In R, function arguments are **lazily evaluated**:
  - Only evaluated if accessed.
  - What will this code return?

```
h01 <- function(x) {
  10
}
h01(stop("This is an error!"))
```

- Allows to include expensive computations in function arguments that are only evaluated if needed.

. . . (dot-dot-dot)

- The special argument ... (pronounced dot-dot-dot).
  - Makes a function take any number of additional arguments.
  - In other programming languages:
    - This is often called *varargs* (short for variable arguments).
    - A function that uses it is said to be variadic.
- Can pass those additional arguments on to another function.

```r
i01 <- function(y, z) {
  list(y = y, z = z)
}

i02 <- function(x, ...) {
  i01(...)
}

str(i02(x = 1, y = 2, z = 3))
#> List of 2
#>  $ y: num 2
#>  $ z: num 3
```

Outline

Lexical scoping

- **Scoping:** the act of finding the value associated with a name.
- What does the following code return?

```
x <- 10
g01 <- function() {
  x <- 20
  x
}

g01()
```

- R uses **lexical scoping**[1]:
  - Looks up the values of names based on how a function is defined, not how it is called.
  - Follows four primary rules:
    - Name masking
    - Functions versus variables
    - A fresh start
    - Dynamic lookup

[1]but possible to override the default rules.

Name masking

- Names defined inside a function mask names defined outside.

```
x <- 10
y <- 20
g02 <- function() {
  x <- 1
  y <- 2
  c(x, y)
}
g02()
#> [1] 1 2
```

- If a name isn't defined inside a function, R looks one level up.

```
x <- 2
g03 <- function() {
  y <- 1
  c(x, y)
}
g03()
#> [1] 2 1
y
#> [1] 20
```

Name masking cont'd

- Same applies if a function is defined inside another function:
  - First, R looks inside the current function.
  - Then, where that function was defined (and so on, all the way up to the global environment).
  - Finally, in other loaded packages.
- What does the following code return?

```r
x <- 1
g04 <- function() {
  y <- 2
  i <- function() {
    z <- 3
    c(x, y, z)
  }
  i()
}
g04()
```

Functions versus variables

- Functions are ordinary objects, the same rules apply to them.

```
g07 <- function(x) x + 1
g08 <- function() {
  g07 <- function(x) x + 100
  g07(10)
}
g08()
#> [1] 110
```

- When a function and a non-function share the same name, the rules get a little more complicated.
  - For function calls, R ignores non-functions when scoping.

```
g09 <- function(x) x + 100
g10 <- function() {
  g09 <- 10
  g09(g09)
}
g10()
#> [1] 110
```

- But using the same name for different things is best avoided!

A fresh start

- What happens to values between invocations of a function?
- What will happen the first time you run this function?
- What will happen the second time?

```r
g11 <- function() {
  if (!exists("a")) {
    a <- 1
  } else {
    a <- a + 1
  }
  a
}

g11()
g11()
```

Dynamic lookup

- The output of a function can depend on objects outside its environment, because:
  - Lexical scoping determines where, not when, to look for values.
  - R looks for values when the function is run, not when the function is created.

```
g12 <- function() x + 1
x <- 15
g12()
#> [1] 16

x <- 20
g12()
#> [1] 21
```

- Can be quite annoying.
  - With spelling mistakes, no error when creating a function.
  - Depending on the global environment, maybe not even an error when running the function.

Outline

For loops vs. functionals

- To compute the mean of every column:

```
output <- vector("double", length(df))
for (i in seq_along(df)) {
  output[[i]] <- mean(df[[i]])
}

output
#> [1]  0.3589 -0.3625  0.0694  0.1539
```

- As a function:

```
col_mean <- function(df) {
  output <- vector("double", length(df))
  for (i in seq_along(df)) {
    output[i] <- mean(df[[i]])
  }
  output
}

col_mean(df)
#> [1]  0.3589 -0.3625  0.0694  0.1539
```

How about other quantities?

```
col_median <- function(df) {
  output <- vector("double", length(df))
  for (i in seq_along(df)) {
    output[i] <- median(df[[i]])
  }
  output
}

col_sd <- function(df) {
  output <- vector("double", length(df))
  for (i in seq_along(df)) {
    output[i] <- sd(df[[i]])
  }
  output
}

col_median(df)
#> [1]  0.204 -0.355  0.090 -0.258
col_sd(df)
#> [1] 1.205 0.679 0.697 0.772
```

- What's “wrong” here?

A simple “functional”

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```r
col_summary <- function(df, fun) {
  out <- vector("double", length(df))
  for (i in seq_along(df)) {
    out[i] <- fun(df[[i]])
  }
  out
}

col_summary(df, median)
#> [1]  0.204 -0.355  0.090 -0.258
col_summary(df, mean)
#> [1]  0.3589 -0.3625  0.0694  0.1539
```

The two programming paradigms

- **Imperative:**
  - The programmer instructs the machine how to change its state.
  - Examples:
    - **Procedural:** groups instructions into procedures.
    - **Object-oriented:** groups instructions together with the part of the state they operate on.
- **Declarative:**
  - The programmer declares properties of the desired result, but not how to compute it.
  - Examples:
    - **Functional:** the output results of a series of function applications.
    - **Mathematical:** the output is the solution of an optimization problem.

What about R?

- A bit of everything:
  - Powerful but complex.
- Imperative:
  - Procedural: functions loaded with `source()`.
  - Object-oriented: the `S3` class system (and others).
- Declarative:
  - Mathematical: optimization with `optim` and specialized packages.
  - Functional: **the hearth** of R.

Functional programming languages

- Functional programming:
  - Uses **functions that return functions** as output.
  - Passes functions as arguments to others function.
  - Much more in the Advanced-R book chapter on FP
- What makes a programming language functional?
  - Many definitions but two common threads:
    - **First-class** functions.
    - **Pure** functions.
- **Functional style**:
  - Hard to describe exactly, but essentially:
    - Decompose a problem into small pieces, then solve each piece with a (combination of) function(s).
    - Each function is simple and straightforward to understand.
    - Complexity is handled by composing functions.

First-class functions

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- Functions behave like any other data structure.
- In R, means that you can:
    - Assign them to variables.
    - Store them in lists.
    - Pass them as arguments to other functions.
    - Create them inside functions.
    - And even return them as the result of a function.

```
f1 <- function(x) x
l1 <- list(
  mean,
  sd,
  median
)
y <- rnorm(1e1)
sapply(l1, function(f) f(y))
#> [1] -0.1050  0.7437 -0.0493
```

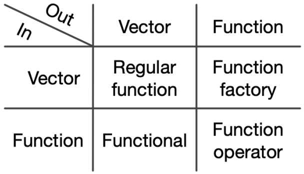
Pure functions

- Two main properties:
  - The output only depends on the inputs:
    - Call it again with the same inputs, get the same outputs.
    - Excludes functions like `runif()` or `read.csv()` (why?).
  - No side-effects:
    - E.g., no changing the value of a global variable, writing to disk, or displaying to the screen.
    - Excludes functions like `print()`, `write.csv()` and `<-`.
- Two remarks:
  - Much easier to reason about, but some downsides:
    - How to do data analysis without generate random numbers or read files from disk?
  - Strictly speaking:
    - R isn't a functional *language* (why?).
    - While you don't *have* to write pure functions, you often *should*.

Functional style

- Three techniques:
  - **Functionals**:
    - Replace many loops.
    - E.g., `lapply()`, `sapply()`.
    - The most important, used all the time in data analysis.
  - **Function factories**:
    - Functions that create functions.
    - Partition work between different parts of your code.
  - **Function operators**:
    - Functions that take/return functions as inputs/output.
    - Typically modify the operation of a function.

- Called **higher-order functions**



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

Outline

Functionals

To become significantly more reliable, code must become more transparent. In particular, nested conditions and loops must be viewed with great suspicion. Complicated control flows confuse programmers. Messy code often hides bugs.
— Bjarne Stroustrup

- **Functional**:
  - Takes/returns a function/vector as an input/output.
  - `lapply()`, `apply()`, `tapply()`, purrr's `map()`, `integrate()` or `optim()`.

```
randomise <- function(f) f(runif(1e3))
randomise(mean)
#> [1] 0.497
randomise(mean)
#> [1] 0.487
randomise(sum)
#> [1] 497
```

Outline

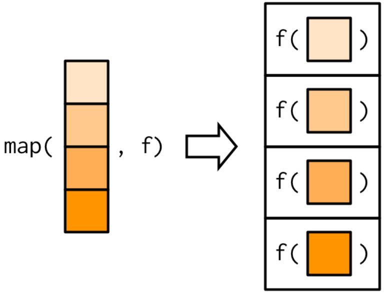
- `purrr::map()`:
  - The basic map functions
    - Take a vector as input.
    - Apply a function to each piece.
    - Return a new vector that's the same length (and has the same names) as the input.
  - The return type is determined by the suffix.
    - `map()` makes a list.
    - `map_lgl()` makes a logical vector.
    - `map_int()` makes an integer vector.
    - `map_dbl()` makes a double vector.
    - `map_chr()` makes a character vector.
- `purrr::reduce()`.
- Predicates and the functionals using them.
- Mathematical functionals.
- Focus on the purrr package:

```
library(purrr)
```

Warm-up: `purrr::map()`

- The most fundamental functional:
  - Takes a vector and a function.
  - Calls the function once for each element of the vector
  - Returns the results in a list.
- `map(1:3, f)` is equivalent to `list(f(1), f(2), f(3))`.
- The R base equivalent: `lapply()`.

```r
triple <- function(x) x * 3
map(1:3, triple)
#> [[1]]
#> [1] 3
#>
#> [[2]]
#> [1] 6
#>
#> [[3]]
#> [1] 9
```



How does that work?

- Simple implementation:
  - Allocate a list the same length as the input.
  - Fill in the list with a for loop.

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

- A few differences for the real implementation:
  - Written in C for performance.
  - Preserves names
  - Supports a few shortcuts.

Producing atomic vectors

- `map()` returns a list
- 4 more specific variants:
  - `map_dbl()`, `map_chr()`, `map_int()` and `map_lgl()`.
- `map_dbl()` always returns a double vector.

```
map_dbl(mtcars, mean)
#>     mpg     cyl    disp      hp    drat      wt    qsec      vs
#>  20.091   6.188 230.722 146.688   3.597   3.217  17.849   0.438
#>      am    gear    carb
#>   0.406   3.688   2.812
```

- `map_chr()` always returns a character vector

```
map_chr(mtcars, typeof)
#>      mpg      cyl     disp       hp     drat       wt     qsec
#> "double" "double" "double" "double" "double" "double" "double"
#>       vs       am     gear     carb
#> "double" "double" "double" "double"
```

Producing atomic vectors con'd

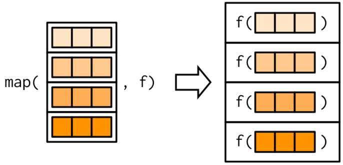
- `map_int()` always returns an integer vector.

```
map_int(mtcars, function(x) length(unique(x)))
#>  mpg  cyl disp   hp drat   wt qsec   vs   am gear carb
#>   25    3   27   22   22   29   30    2    2    3    6
```

- `map_lgl()` always returns a logical vector.

```
map_lgl(mtcars, is.double)
#>  mpg  cyl disp   hp drat   wt qsec   vs   am gear carb
#> TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
```

- Remarks:
  - Suffixes refer to the output.
  - But `map_*()` can take any type of vector as input.
- Examples rely on two facts:
  - `mtcars` is a data frame.
  - data frames are lists containing vectors of the same length.



Producing atomic vectors con'd

- Each call to the function must return a single value.

```
map_dbl(1:2, function(x) c(x, x))
#> Error: Result 1 must be a single double, not an integer vector of length 2
```

- And obviously return the correct type.

```
map_dbl(1:2, as.character)
#> Error: Can't coerce element 1 from a character to a double
```

- In either case, use `map()` to see the problematic output!
- In base R:
  - `sapply()`.
    - Tries to simplify the result,.
    - Can return a list, a vector, or a matrix.
    - Difficult to program with, avoid in non-interactive settings.
  - `vapply()`.
    - `FUN.VALUE` to describe the output shape.
    - Verbosity: `vapply(x, mean, na.rm = TRUE, FUN.VALUE = double(1))` for `map_dbl(x, mean, na.rm = TRUE)`.

Anonymous functions and shortcuts

- map can use anonymous functions.

```
map_dbl(mtcars, function(x) length(unique(x)))
#>  mpg  cyl disp   hp drat   wt qsec   vs   am gear carb
#>   25    3   27   22   22   29   30    2    2    3    6
```

- Less verbose shortcut.

```
map_dbl(mtcars, ~ length(unique(.x)))
#>  mpg  cyl disp   hp drat   wt qsec   vs   am gear carb
#>   25    3   27   22   22   29   30    2    2    3    6
```

- Useful for generating random data.

```
x <- map(1:3, ~ runif(2))
str(x)
#> List of 3
#>  $ : num [1:2] 0.22 0.089
#>  $ : num [1:2] 0.131 0.879
#>  $ : num [1:2] 0.652 0.0281
```

- Rule of thumb: a function spans lines/uses {}, give it a name.

Passing arguments with . . .

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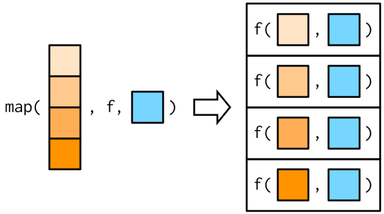
- To pass along additional arguments, use an anonymous function.

```
x <- list(1:5, c(1:10, NA))
map_dbl(x, ~ mean(.x, na.rm = TRUE))
#> [1] 3.0 5.5
```

- Or the simpler form.

```
map_dbl(x, mean, na.rm = TRUE)
#> [1] 3.0 5.5
```



- A subtle difference.

```
plus <- function(x, y) x + y
x <- c(0, 0, 0, 0)

map_dbl(x, plus, runif(1))
#> [1] 0.131 0.131 0.131 0.131

map_dbl(x, ~ plus(.x, runif(1)))
#> [1] 0.158 0.473 0.751 0.840
```

Map variants

- 23 primary variants of `map()`:
  - `map()`, `map_dbl()`, `map_chr()`, `map_int()`, `map_lgl()`
  - 18 (!!) more to learn.
  - Five new ideas:
    - Output same type as input with `modify()`
    - Iterate over two inputs with `map2()`.
    - Iterate with an index using `imap()`
    - Return nothing with `walk()`.
    - Iterate over any number of inputs with `pmap()`.

	List	Atomic	Same type	Nothing
One argument	`map()`	`map_lgl()`, ...	`modify()`	`walk()`
Two arguments	`map2()`	`map2_lgl()`, ...	`modify2()`	`walk2()`
One argument + index	`imap()`	`imap_lgl()`, ...	`imodify()`	`iwalk()`
N arguments	`pmap()`	`pmap_lgl()`, ...	—	`pwalk()`

Two inputs: `map2()` and friends

- How do we find the vector of weighted means?

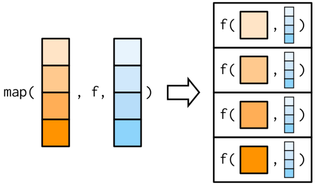
```
xs <- map(1:8, ~ runif(10))
xs[[1]][[1]] <- NA
ws <- map(1:8, ~ rpois(10, 5) + 1)
```

- Use `map_dbl()` to compute the unweighted means.

```
map_dbl(xs, mean)
#> [1]    NA 0.428 0.524 0.568 0.583 0.571 0.530 0.465
```

- Passing `ws` as an additional argument doesn't work.

```
map_dbl(xs, weighted.mean, w = ws)
#> Error in weighted.mean.default(.x[[i]], ...): 'x' and 'w' must have the same
```



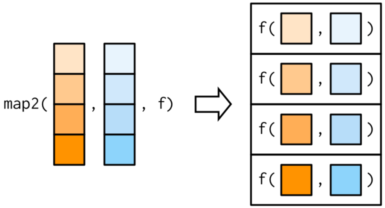
map2() and friends cont'd

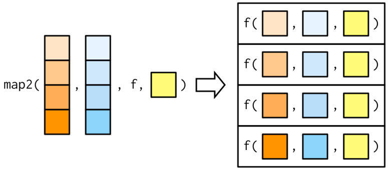
- Both arguments are varied in each call.

```
map2_dbl(xs, ws, weighted.mean)
#> [1]    NA 0.433 0.515 0.565 0.571 0.668 0.539 0.433
```

- Additional arguments still go afterwards.

```
map2_dbl(xs, ws, weighted.mean, na.rm = TRUE)
#> [1] 0.378 0.433 0.515 0.565 0.571 0.668 0.539 0.433
```



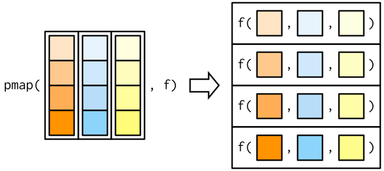


Any number of inputs: pmap()

- map() and map2()... map3(), map4(), map5()?
- Instead, there is pmap():
  - Supply it a single list, which contains any number of arguments.
  - In most cases, a list of equal-length vectors (e.g., a data frame).

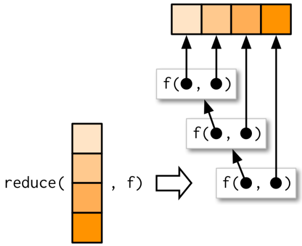
```r
params <- tibble::tribble(
  ~ n, ~ min, ~ max,
   1L,     0,     1,
   2L,    10,   100,
   3L,   100,  1000
)

pmap(params, runif)
#> [[1]]
#> [1] 0.0704
#>
#> [[2]]
#> [1] 73.5 16.7
#>
#> [[3]]
#> [1] 393 423 449
```



Reduce family

- The next most important (family of) functionals.
  - Much smaller (two main variants).
  - Powers the map-reduce framework.
- `purrr::reduce()`:
  - Takes a vector of length *n*.
  - Produces a vector of length 1 by calling a function with a pair of values at a time.
  - `reduce(1:4, f)` is equivalent to `f(f(f(1, 2), 3), 4)`.



Reduce family cont’d

- Useful to generalize a function that works with two inputs to work with any number of inputs.
- Problem: find the values that occur in every element.

```
l <- map(1:4, ~ sample(1:10, 15, replace = TRUE))
str(l)
#> List of 4
#>  $ : int [1:15] 3 7 10 2 7 3 4 5 8 2 ...
#>  $ : int [1:15] 6 8 3 4 3 10 9 8 1 2 ...
#>  $ : int [1:15] 6 8 8 3 3 2 9 2 10 9 ...
#>  $ : int [1:15] 6 10 1 8 6 10 6 8 3 2 ...
```

- Two solutions:

```
out <- l[[1]]
out <- intersect(out, l[[2]])
out <- intersect(out, l[[3]])
out <- intersect(out, l[[4]])
out
#> [1]  3 10  2  8  6
```

```
reduce(l, intersect)
#> [1]  3 10  2  8  6
```

Accumulate

```
accumulate(l, intersect)
#> [[1]]
#>  [1]  3  7 10  2  7  3  4  5  8  2  7  6  8  3  4
#> 
#> [[2]]
#> [1]  3  7 10  2  4  8  6
#> 
#> [[3]]
#> [1]  3 10  2  4  8  6
#> 
#> [[4]]
#> [1]  3 10  2  8  6

x <- c(4, 3, 10)
reduce(x, `+`)
#> [1] 17
reduce(x, `+`) == sum(x)
#> [1] TRUE
accumulate(x, `+`)
#> [1]  4  7 17
accumulate(x, `+`) == cumsum(x)
#> [1] TRUE TRUE TRUE
```

Predicate functionals

- A **predicate**:
  - Function that returns a single `TRUE` or `FALSE`.
  - E.g., `is.character()`, `is.null()`, or `all()`.
  - **Matches** a vector if it returns `TRUE`.
- A **predicate functional**:
  - `f(x, p)` applies a predicate `p` to each element of a vector `x`.
  - `some()`/`every()`: `TRUE` if *any*/*all* element matches.
  - `detect()`/`detect_index()`: *value*/*location* of the first match.
  - `keep()`/`discard()`: *keeps*/*drops* all matching elements.

```
df <- tibble(x = 1:3, y = c("a", "b", "c"))
```

```
detect(df, is.character)
#> [1] "a" "b" "c"
```

```
detect_index(df, is.character)
#> [1] 2
```

```
keep(df, is.character)
#> # A tibble: 3 x 1
#>   y
#>   <chr>
#> 1 a
#> 2 b
#> 3 c
```

```
discard(df, is.character)
#> # A tibble: 3 x 1
#>       x
#>   <int>
#> 1     1
#> 2     2
#> 3     3
```

Mathematical functionals

```
integrate(sin, 0, pi)
#> 2 with absolute error < 2.2e-14
str(uniroot(sin, pi * c(1 / 2, 3 / 2)))
#> List of 5
#>  $ root      : num 3.14
#>  $ f.root    : num 1.22e-16
#>  $ iter      : int 2
#>  $ init.it   : int NA
#>  $ estim.prec: num 6.1e-05
str(optimise(sin, c(0, 2 * pi)))
#> List of 2
#>  $ minimum  : num 4.71
#>  $ objective: num -1
str(optimise(sin, c(0, pi), maximum = TRUE))
#> List of 2
#>  $ maximum  : num 1.57
#>  $ objective: num 1
```

Outline

Function operators

- Functions that takes one (or more) functions as input and returns a function as output.

```r
chatty <- function(f) {
  function(x, ...) {
    cat("Processing ", x, "\n", sep = "")
    f(x, ...)
  }
}

f <- function(x) x ^ 2
map_dbl(c(3, 2, 1), chatty(f))
#> Processing 3
#> Processing 2
#> Processing 1
#> [1] 9 4 1
```

- For Python users: decorators is just another name!

Dealing with failure using `safely()`

- The modified function always returns a list with two elements:
  1. `result` is the original result.
  2. `error` is an error object.

```
safe_log <- safely(log)
str(safe_log(10))
#> List of 2
#>  $ result: num 2.3
#>  $ error : NULL
str(safe_log("a"))
#> List of 2
#>  $ result: NULL
#>  $ error :List of 2
#>   ..$ message: chr "non-numeric argument to mathematical function"
#>   ..$ call   : language .Primitive("log")(x, base)
#>   ..- attr(*, "class")= chr [1:3] "simpleError" "error" "condition"
```

safely() and map()

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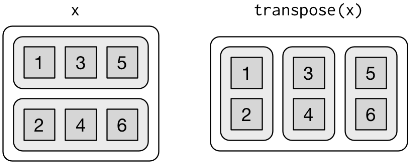
```r
x <- list(1, 10, "a")
y <- map(x, safely(log))
str(y)
#> List of 3
#>  $ :List of 2
#>   ..$ result: num 0
#>   ..$ error : NULL
#>  $ :List of 2
#>   ..$ result: num 2.3
#>   ..$ error : NULL
#>  $ :List of 2
#>   ..$ result: NULL
#>   ..$ error :List of 2
#>   .. ..$ message: chr "non-numeric argument to mathematical function"
#>   .. ..$ call   : language .Primitive("log")(x, base)
#>   .. ..- attr(*, "class")= chr [1:3] "simpleError" "error" "condit"..
```

transpose()

```
y <- transpose(y)
str(y)
#> List of 2
#>  $ result:List of 3
#>   ..$ : num 0
#>   ..$ : num 2.3
#>   ..$ : NULL
#>  $ error :List of 3
#>   ..$ : NULL
#>   ..$ : NULL
#>   ..$ :List of 2
#>   .. ..$ message: chr "non-numeric argument to mathematical function"
#>   .. ..$ call   : language .Primitive("log")(x, base)
#>   .. ..- attr(*, "class")= chr [1:3] "simpleError" "error" "condit"..
```



Typical use

```
is_ok <- map_lgl(y$error, is_null)
x[!is_ok]
#> [[1]]
#> [1] "a"
flatten_dbl(y$result[is_ok])
#> [1] 0.0 2.3
```

Two other useful adverbs

- `possibly()`: "simpler" than `safely()`, because you give it a default value to return when there is an error.

```
map_dbl(x, possibly(log, NA_real_))
#> [1] 0.0 2.3  NA
```

- `quietly()`: instead of capturing errors, it captures printed output, messages, and warnings.

```
map(list(1, -1), quietly(log)) %>% str()
#> List of 2
#>  $ :List of 4
#>   ..$ result  : num 0
#>   ..$ output  : chr ""
#>   ..$ warnings: chr(0)
#>   ..$ messages: chr(0)
#>  $ :List of 4
#>   ..$ result  : num NaN
#>   ..$ output  : chr ""
#>   ..$ warnings: chr "NaNs produced"
#>   ..$ messages: chr(0)
```

Caching computations with `memoise()`

- Provided by the `memoise` package.
- **Memoises** a function
  - The function remembers previous inputs/returns cached results.
  - Classic CS tradeoff of memory versus speed:
    - A memoised function is faster, but uses more memory.

```r
slow_fct <- function(x) {
  Sys.sleep(1)
  x * 10 * runif(1)
}

system.time(print(slow_fct(1)))
#> [1] 9.57
#>    user  system elapsed
#>   0.001   0.000   1.002
system.time(print(slow_fct(1)))
#> [1] 2.39
#>    user  system elapsed
#>   0.004   0.000   1.004
```

```r
library(memoise)
fast_fct <- memoise(slow_fct)



system.time(print(fast_fct(1)))
#> [1] 4.07
#>    user  system elapsed
#>   0.001   0.000   1.003
system.time(print(fast_fct(1)))
#> [1] 4.07
#>    user  system elapsed
#>   0.020   0.004   0.024
```

Fibonacci series

- Defined recursively:
  - $f(0) = 0$, $f(1) = 1$,
  - And then $f(n) = f(n-1) + f(n-2)$.

```
fib <- function(n) {
  if (n < 2) return(1)
  fib(n - 2) + fib(n - 1)
}

system.time(fib(23))
#>    user  system elapsed
#>   0.043   0.000   0.042
system.time(fib(24))
#>    user  system elapsed
#>   0.062   0.000   0.061
```

```
fib2 <- memoise(function(n) {
  if (n < 2) return(1)
  fib2(n - 2) + fib2(n - 1)
})

system.time(fib2(23))
#>    user  system elapsed
#>   0.007   0.000   0.008
system.time(fib2(24))
#>    user  system elapsed
#>   0.001   0.000   0.001
```

- An example of **dynamic programming**:
  - Complex problem broken down into overlapping subproblems.
  - Remembering the results of a subproblem considerably improves performance.