

Functional programming

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Motivation

Copy and paste is a rich source of errors

```
# Fix missing values
df$a[df$a == -99] <- NA
df$b[df$b == -99] <- NA
df$c[df$c == -99] <- NA
df$d[df$d == -99] <- NA
df$e[df$e == -99] <- NA
df$f[df$f == -99] <- NA
df$g[df$g == -98] <- NA
df$h[df$h == -99] <- NA
df$i[df$i == -99] <- NA
df$i[df$j == -99] <- NA
df$k[df$k == -99] <- NA
```

Copy and paste is a rich source of errors

```
# Fix missing values
df$a[df$a == -99] <- NA
df$b[df$b == -99] <- NA
df$c[df$c == -99] <- NA
df$d[df$d == -99] <- NA
df$e[df$e == -99] <- NA
df$f[df$f == -99] <- NA
df$g[df$g == -98] <- NA
df$h[df$h == -99] <- NA
df$i[df$i == -99] <- NA
df$i[df$j == -99] <- NA
df$k[df$k == -99] <- NA
```

Functions can remove some sources of duplication

```
fix_missing <- function(x) {  
  x[x == -99] <- NA  
  x  
}  
  
df$a <- fix_missing(df$a)  
df$b <- fix_missing(df$b)  
df$c <- fix_missing(df$c)  
df$d <- fix_missing(df$d)  
df$e <- fix_missing(df$e)  
df$f <- fix_missing(df$f)  
df$g <- fix_missing(df$g)  
df$h <- fix_missing(df$h)  
df$h <- fix_missing(df$i)
```

Functions can remove some sources of duplication

```
fix_missing <- function(x) {  
  x[x == -99] <- NA  
  x  
}  
  
df$a <- fix_missing(df$a)  
df$b <- fix_missing(df$b)  
df$c <- fix_missing(df$c)  
df$d <- fix_missing(df$d)  
df$e <- fix_missing(df$e)  
df$f <- fix_missing(df$f)  
df$g <- fix_missing(df$g)  
df$h <- fix_missing(df$h)  
dfh <- fix_missing(df$i)
```

For loops can remove others

```
fix_missing <- function(x) {  
  x[x == -99] <- NA  
  x  
}
```

```
for (i in seq_along(df)) {  
  df[[i]] <- fix_missing(df[[i]])  
}
```

Why for loops are bad

A detour with cupcakes

Why for loops
are ~~bad~~
suboptimal

A detour with cupcakes

Vanilla cupcakes

The hummingbird
bakery cookbook

1 cup flour
a scant $\frac{3}{4}$ cup sugar
1 $\frac{1}{2}$ t baking powder
3 T unsalted butter
 $\frac{1}{2}$ cup whole milk
1 egg
 $\frac{1}{4}$ t pure vanilla extract

Preheat oven to 350°F.

Put the flour, sugar, baking powder, salt, and butter in a freestanding electric mixer with a paddle attachment and beat on slow speed until you get a sandy consistency and everything is combined.

Whisk the milk, egg, and vanilla together in a pitcher, then slowly pour about half into the flour mixture, beat to combine, and turn the mixer up to high speed to get rid of any lumps.

Turn the mixer down to a slower speed and slowly pour in the remaining milk mixture. Continue mixing for a couple of more minutes until the batter is smooth but do not overmix.

Spoon the batter into paper cases until $\frac{2}{3}$ full and bake in the preheated oven for 20-25 minutes, or until the cake bounces back when touched.

Chocolate cupcakes

The hummingbird
bakery cookbook

$\frac{3}{4}$ cup + 2T flour
2 $\frac{1}{2}$ T cocoa powder
a scant $\frac{3}{4}$ cup sugar
1 $\frac{1}{2}$ t baking powder
3 T unsalted butter
 $\frac{1}{2}$ cup whole milk
1 egg
 $\frac{1}{4}$ t pure vanilla extract

Preheat oven to 350°F.

Put the flour, cocoa, sugar, baking powder, salt, and butter in a freestanding electric mixer with a paddle attachment and beat on slow speed until you get a sandy consistency and everything is combined.

Whisk the milk, egg, and vanilla together in a pitcher, then slowly pour about half into the flour mixture, beat to combine, and turn the mixer up to high speed to get rid of any lumps.

Turn the mixer down to a slower speed and slowly pour in the remaining milk mixture. Continue mixing for a couple of more minutes until the batter is smooth but do not overmix.

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1 $\frac{1}{2}$ t baking powder

3 T unsalted butter

$\frac{1}{2}$ cup whole milk

1 egg

$\frac{1}{4}$ t pure vanilla extract

Preheat oven to 350°F.

Put the flour, **cocoa**, sugar, baking powder, salt, and butter in a freestanding electric mixer with a paddle attachment and beat on slow speed until you get a sandy consistency and everything is combined.

Whisk the milk, egg, and vanilla together in a pitcher, then slowly pour about half into the flour mixture, beat to combine, and turn the mixer up to high speed to get rid of any lumps.

Turn the mixer down to a slower speed and slowly pour in the remaining milk mixture. Continue mixing for a couple of more minutes until the batter is smooth but do not overmix.

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Vanilla cupcakes

The hummingbird
bakery cookbook

120g flour

140g sugar

1.5 t baking powder

40g unsalted butter

120ml milk

1 egg

0.25 t pure vanilla extract

Preheat oven to 170°C.

Put the flour, sugar, baking powder, salt, and butter in a freestanding electric mixer with a paddle attachment and beat on slow speed until you get a sandy consistency and everything is combined.

Whisk the milk, egg, and vanilla together in a pitcher, then slowly pour about half into the flour mixture, beat to combine, and turn the mixer up to high speed to get rid of any lumps.

Turn the mixer down to a slower speed and slowly pour in the remaining milk mixture. Continue mixing for a couple of more minutes until the batter is smooth but do not overmix.

Spoon the batter into paper cases until $\frac{2}{3}$ full and bake in the preheated oven for 20-25 minutes, or until the cake bounces back when touched.

Vanilla cupcakes

The hummingbird
bakery cookbook

120g flour
140g sugar
1.5 t baking powder
40g butter
120ml milk
1 egg
0.25 t vanilla

Beat flour, sugar, baking powder, salt, and butter until sandy.

Whisk milk, egg, and vanilla. Mix half into flour mixture until smooth (use high speed). Beat in remaining half. Mix until smooth.

Bake 20-25 min at 170°C.

Vanilla cupcakes

The hummingbird
bakery cookbook

120g flour

140g sugar

1.5 t baking powder

40g butter

120ml milk

1 egg

0.25 t vanilla

Beat **dry ingredients** + butter until sandy.

Whisk together **wet ingredients**. Mix half into dry until smooth (use high speed). Beat in remaining half. Mix until smooth.

Bake 20-25 min at 170°C.

Cupcakes

Beat dry ingredients + butter until sandy.

Whisk together wet ingredients. Mix half into dry until smooth (use high speed). Beat in remaining half. Mix until smooth.

Bake 20-25 min at 170°C.

Vanilla

120g flour

140g sugar

1.5t baking powder

40g butter

120ml milk

1 egg

0.25 t vanilla

Chocolate

100g flour

20g cocoa

140g sugar

1.5t baking powder

40g butter

120ml milk

1 egg

0.25 t vanilla

What do these for loops do?

```
out1 <- vector("double", ncol(mtcars))  
for(i in seq_along(mtcars)) {  
  out1[[i]] <- mean(mtcars[[i]], na.rm = TRUE)  
}
```

```
out2 <- vector("double", ncol(mtcars))  
for(i in seq_along(mtcars)) {  
  out2[[i]] <- median(mtcars[[i]], na.rm = TRUE)  
}
```

For loops emphasise the objects

```
out1 <- vector("double", ncol(mtcars))  
for(i in seq_along(mtcars)) {  
  out1[[i]] <- mean(mtcars[[i]], na.rm = TRUE)  
}
```

```
out2 <- vector("double", ncol(mtcars))  
for(i in seq_along(mtcars)) {  
  out2[[i]] <- median(mtcars[[i]], na.rm = TRUE)  
}
```

Not the actions

```
out1 <- vector("double", ncol(mtcars))  
for(i in seq_along(mtcars)) {  
  out1[[i]] <- mean(mtcars[[i]], na.rm = TRUE)  
}
```

```
out2 <- vector("double", ncol(mtcars))  
for(i in seq_along(mtcars)) {  
  out2[[i]] <- median(mtcars[[i]], na.rm = TRUE)  
}
```

Functional programming emphasises the actions

```
library(purrr)
```

```
means <- map_dbl(mtcars, mean)
```

```
medians <- map_dbl(mtcars, median)
```

And back...

For loops can remove others

```
fix_missing <- function(x) {  
  x[x == -99] <- NA  
  x  
}
```

```
for (i in seq_along(df)) {  
  df[[i]] <- fix_missing(df[[i]])  
}
```

FP tools allow you to focus on what happens

```
fix_missing <- function(x) {  
  x[x == -99] <- NA  
  x  
}
```

```
df <- modify(df, fix_missing)
```


And provide useful tools for **generalisation**

```
fix_missing <- function(x) {  
  x[x == -99] <- NA  
  x  
}
```

```
df <- modify_if(df, is.numeric, fix_missing)
```

Principle:

Solve a single problem

Principle:

Scale up with map & friends

Warmups

What is NA_real_? NA_integer_?

NA_character_?

Why don't you normally need to care?

```
# One NA for each basic atomic vector
```

```
typeof(NA)
```

```
typeof(NA_real_)
```

```
typeof(NA_integer_)
```

```
typeof(NA_character_)
```

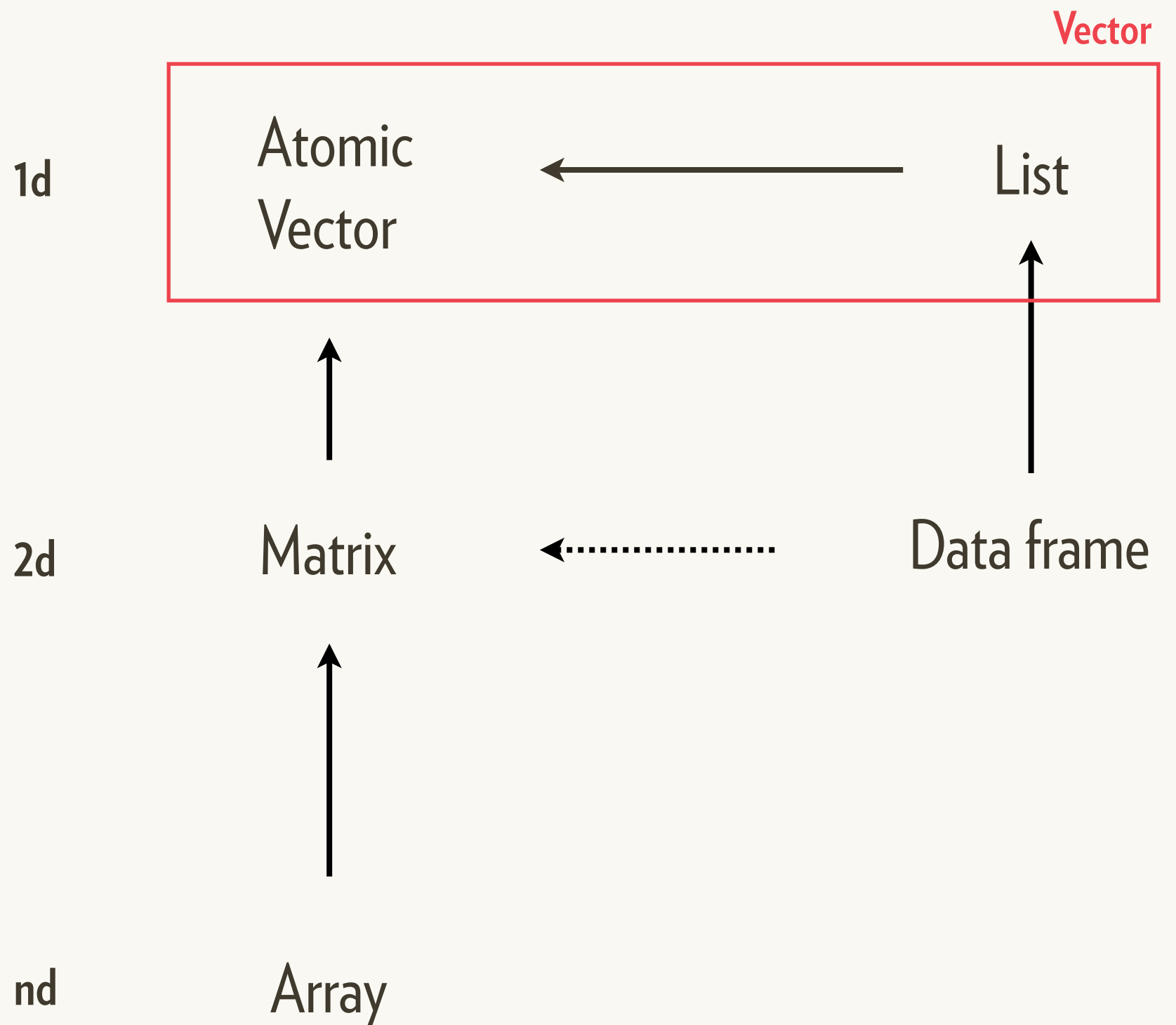
```
c(NA, "x")
```

Your turn

How is a list different from an atomic vector?

How is a data frame different from a matrix?

How do you examine the structure of an object?



str()

view()

(If you have RStudio 1.1)

Your turn

What's the difference between [and [[?

Single

Multiple

Vectors

`x[[1]]`

`x[1:4]`

Lists

`x[[1]]`

`x$name`

`x[1]`



What does this code do?

```
trans <- list(  
  disp = function(x) x * 0.0163871,  
  am = function(x) {  
    factor(x, labels = c("auto", "manual"))  
  }  
)  
for(var in names(trans)) {  
  mtcars[[var]] <- trans[[var]](mtcars[[var]])  
}
```

Change project to:

[colsum]

This package automatically loads purrr

```
devtools::load_all(".")
```

```
Loading colsum
```

```
Loading required package: purrr
```

```
Attaching package: 'purrr'
```

```
# Because earlier I ran
```

```
use_package("purrr", "depends")
```

Pros

Cons

Easily call purrr
functions

Affects global
search path

Not acceptable on
CRAN

Map family

minis



map(minis, antennate)



antennate(minis[[1]])

antennate(minis[[2]])

antennate(minis[[3]])

antennate(minis[[4]])

antennate(minis[[5]])



Your turn

Look at the help for `map()`.

What other functions are documented there? How do they differ from `map()`?

Each variant always produces the same type

| Function | Output |
|------------------------|---------------------|
| <code>map_lgl()</code> | Logical vector |
| <code>map_int()</code> | Integer vector |
| <code>map_dbl()</code> | Double vector |
| <code>map_chr()</code> | Character vector |
| <code>map()</code> | List |
| <code>map_dfc()</code> | Data frame (by col) |
| <code>map_dfr()</code> | Data frame (by row) |

Your turn

Compute the mean of every column in mtcars.

Generate 10 random normals for the following means:

-10, 0, 10, 100

Compute the number of unique values in each column of iris

When working with purrr

For each task, identify:

1. The output type (i.e. which map function do you need?)
2. The object that gets transformed
3. The function that transforms it

Solutions:

```
map_dbl(mtcars, mean)
```

```
mu <- c(-10, 0, 10, 100)
```

```
map(mu, rnorm, n = 10)
```

```
nunique <- function(x) length(unique(x))
```

```
map_int(iris, nunique)
```

```
# Or use an anonymous function
```

```
map_int(iris, function(x) length(unique(x)))
```

```
# Or use the formula helper
```

```
map_int(iris, ~ length(unique(.x)))
```

Which to prefer?

```
iris %>%  
  map_int(~ length(unique(.x)))
```

```
iris %>%  
  map_int(iris, . %>% unique() %>% length())
```

```
iris %>%  
  map(unique) %>%  
  map_int(length)
```

Two common mistakes

```
iris %>% map(length(unique))
```

```
iris %>% map(length(unique(.)))
```

```
# Why do they work?
```

```
length(unique)
```

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

```
length(unique(iris))
```

```
#> [1] 5
```

```
iris %>% map(1)
```

```
iris %>% map(5)
```

minis



map(minis, 3)



`map(minis, ~ .x[[3]])`



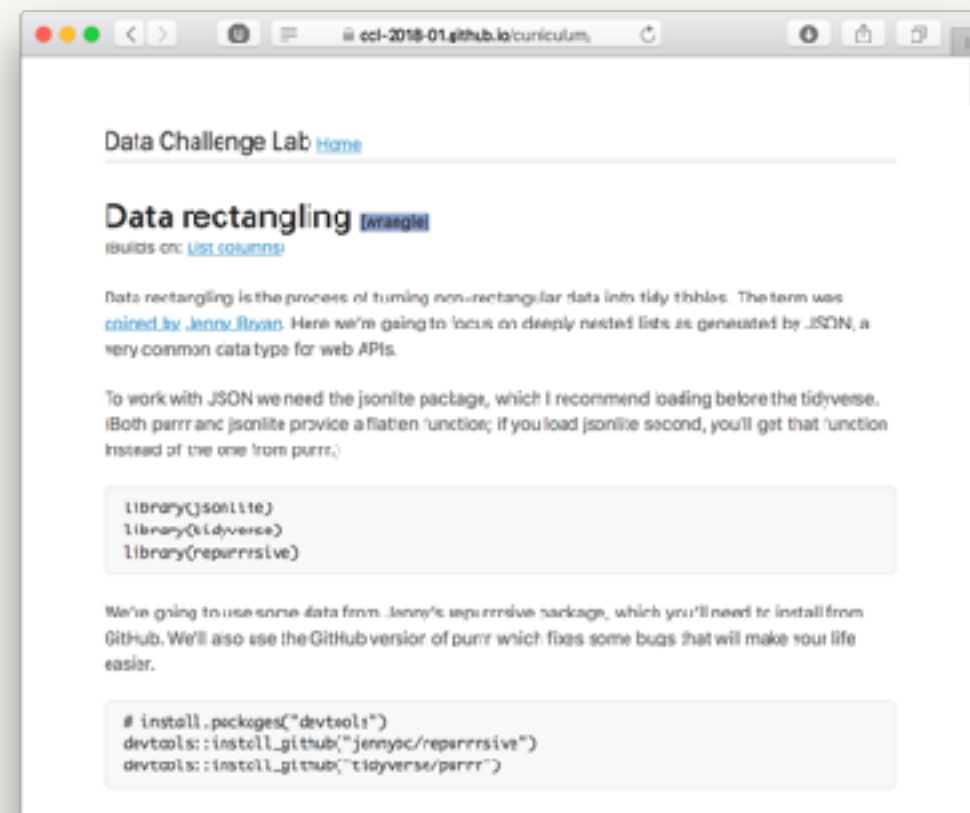

```
map(minis, "pants")
```




```
map(minis, ~ .x$pants)
```



<https://speakerdeck.com/jennybc/data-rectangling>



<https://dcl-2018-01.github.io/curriculum/rectangling.html>

purrr vs dplyr

purrr

vectors

lists

dplyr

data frames

But data frames are lists

purrr

vectors

lists

dplyr

data frames

For column-wise operations you can use either purrr or dplyr

Type stability

Why is sapply challenging to program with?

```
df <- data.frame(  
  a = 1L,  
  b = 1.5,  
  y = Sys.time(),  
  z = ordered(1)  
)
```

Guess the type of output

```
df[1:4] %>% sapply(class) %>% str()  
df[1:2] %>% sapply(class) %>% str()  
df[3:4] %>% sapply(class) %>% str()
```

Principle:

Minimise context needed to
predict output type

The extreme is a type-stable function which
always returns the same type regardless of the input

The purrr alternative

```
df <- data.frame(  
  a = 1L,  
  b = 1.5,  
  y = Sys.time(),  
  z = ordered(1)  
)
```

Guess the type of output

```
df[1:4] %>% map_chr(class) %>% str()  
df[1:2] %>% map_chr(class) %>% str()  
df[3:4] %>% map_chr(class) %>% str()
```

A more realistic example

```
col_means <- function(df) {  
  numeric <- sapply(df, is.numeric)  
  numeric_cols <- df[, numeric]  
  
  as.data.frame(lapply(numeric_cols, mean))  
}
```


What's wrong with col_means?

```
col_means(mtcars)
col_means(mtcars[, 0])
col_means(mtcars[0, ])
col_means(mtcars[, "mpg", drop = F])
```

```
df <- data.frame(
  x = 1:26,
  y = letters
)
col_means(df)
```

apply and [are not type stable

```
col_means <-  
  numeric <- apply(df, is.logical)  
  numeric_cols <- df[, numeric]  
  as.data.frame(numeric_cols, mean))  
}
```

list or logical vector

vector or data frame

One possible solution

```
col_means <- function(df) {  
  numeric <- map_lgl(df, is.numeric)  
  numeric_cols <- df[, numeric, drop = FALSE]  
  
  as.data.frame(map(numeric_cols, mean))  
}
```

One possible solution

always returns logical vector

```
col_means <- function(df) {  
  numeric <- map_lgl(df, is.numeric)  
  numeric_cols <- df[, numeric, drop = FALSE]  
  
  as.data.frame(map(numeric_cols, function(x) {  
    sum(x) / length(x)  
  }))  
}
```

always returns data frame

Can simplify further with other helpers

```
col_means <- function(df) {  
  numeric_cols <- keep(df, is.numeric)  
  map_dfc(numeric_cols, mean)  
}
```

Is keep() type stable? It
returns the output the
same type as its input

Which is particularly elegant with the pipe

```
col_means <- function(df) {  
  df %>%  
    keep(is.numeric) %>%  
    map_dfc(mean)  
}
```

Type stability and stringr

Instead of suffixes

`str_replace()`

`str_replace_all()`

could use an argument

`str_replace(n = 1)`

`str_replace(n = Inf)`

which generalises better

`str_replace(n = 2)`

`str_replace(n = -1)`

But that would violate type stability

```
strings <- c("x y", "x y x")
str_locate(strings, "x", n = 1)
#>      start end
#> [1,]      1  1
#> [2,]      1  1

str_locate(strings, "x", n = Inf)
#> [[1]]
#>      start end
#> [1,]      1  1
#>
#> [[2]]
#>      start end
#> [1,]      1  1
#> [2,]      5  5
```


What type does this code return?

```
str_locate(strings, "x", n = x)
```

Handling errors

What happens when there is an error?

```
input <- list(1:10, sqrt(4), 5, "n")  
map(input, log)
```

Principle:

Turn side-effects into data

What does safely() do?

```
# safely() modifies a function so it never fails  
input <- list(1:10, sqrt(4), 5, "n")  
map(input, safely(log))
```

```
# What does it return when the function succeeds?
```

```
# What does it return when the function fails?
```

A more useful example

```
urls <- c(
  "https://google.com",
  "https://en.wikipedia.org",
  "asdfasdasdkfjlda"
)
```

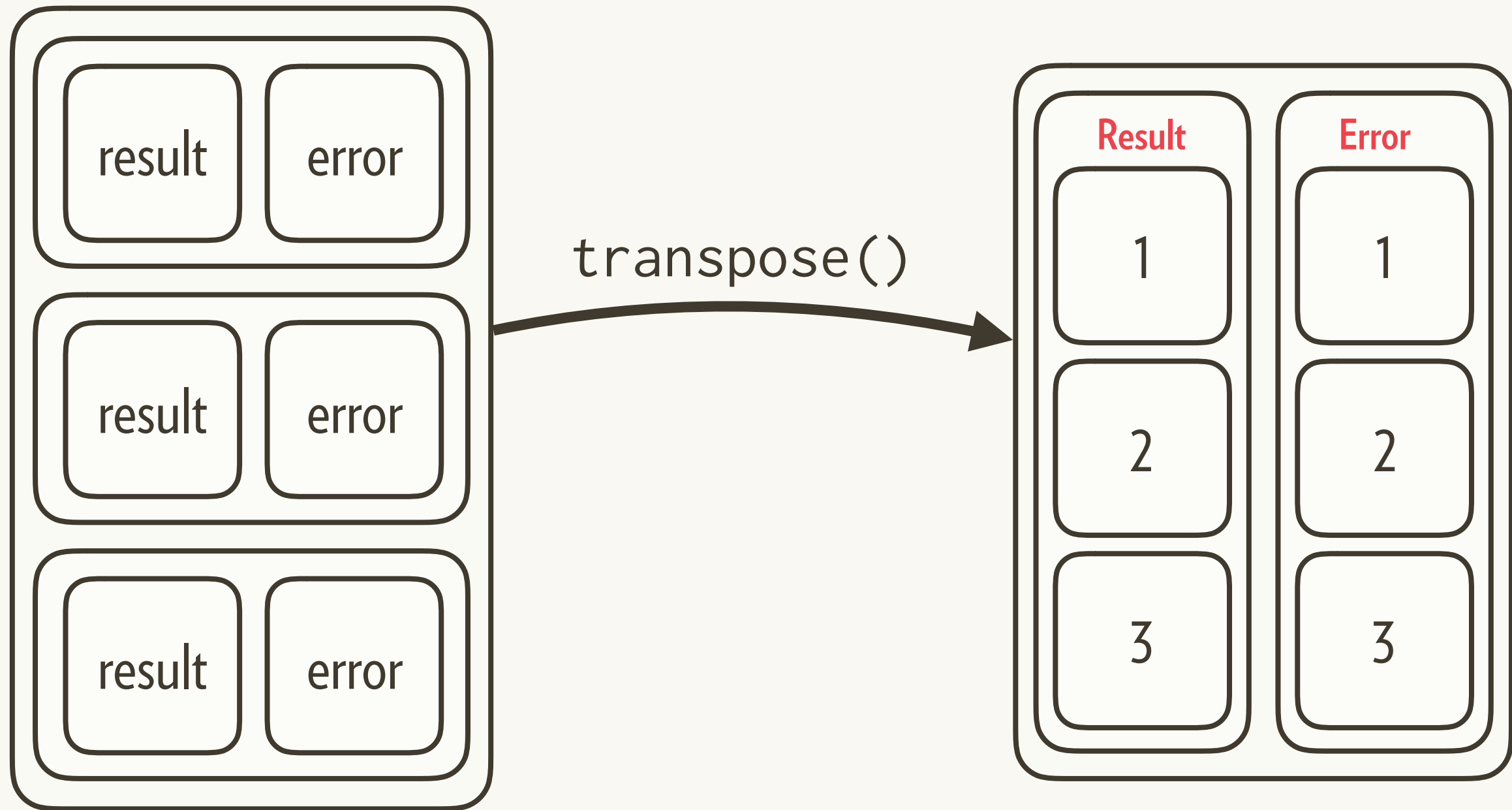
```
# Fails
```

```
contents <- map(urls, readLines, warn = FALSE)
```

```
# Always succeeds
```

```
contents <- urls %>%
  map(safely(readLines), warn = FALSE)
str(contents)
```

But `map()` + `safely()` gives awkward output



Your turn

Apply `transpose()` to the previous result then:

1. List failed urls
2. Extract successfully retrieved text

Common pattern with safely()

```
contents <- urls %>%  
  map(safely(readLines)) %>%  
  transpose()
```

```
ok <- map_lgl(contents$error, is.null)  
# This is suboptimal:  
ok <- !map_lgl(contents$result, is.null)
```

```
urls[!ok]  
contents$result[ok]
```

Parallel maps

(Not parallel programming, sorry!)



hair

minis




```
enhair(minis[[1]], hair[[1]])
```

```
enhair(minis[[2]], hair[[2]])
```

```
enhair(minis[[3]], hair[[3]])
```

```
enhair(minis[[4]], hair[[4]])
```

```
enhair(minis[[5]], hair[[5]])
```



map2(minis, hair, enhair)





weapons

minis



map2(minis, weapons, arm)



stringr application

```
# How do we go from locations to words?  
# Easy if we have a single location  
pos <- str_locate(sentences, "\\b\\w{5,}\\b")  
str_sub(sentences, pos)  
  
# NB: str_sub can take one 2 col matrix  
# or two vectors
```


What if we have multiple locations?

```
pos <- sentences %>%  
  str_locate_all("\\b\\w{5,}\\b")
```

```
pos[[1]]
```

```
# How do we generalise?
```

```
str_sub(sentences[[1]], pos[[1]])
```

```
str_sub(sentences[[2]], pos[[2]])
```

```
str_sub(sentences[[3]], pos[[3]])
```

| | |
|-----------|--------------|
| 1 | map() |
| 2 | map2() |
| 1 + index | imap() |
| 3+ | pmap() |
| fun | invoke_map() |

Isolate side effects

Principle:

It's easier to understand a function when it has either a **side effect** or a **return value**

Your turn

Any action other than returning a value is a **side-effect**.
What are some common side-effects in base R?

Some important side-effects

`plot()`

`write.csv()`

`print()`

`message()` / `warning()` / `stop()`

`library(dplyr)`

`x <- 1`

`setClass()` etc

`options()`

`par()`

`setwd()`

A few functions legitimately need to do both

```
# One exception are random number generators
```

```
.Random.seed[2]
```

```
#> [1] 624
```

```
runif(5)
```

```
#> [1] 0.0808 0.8343 0.6008 0.1572 0.0074
```

```
.Random.seed[2]
```

```
#> [1] 5
```

summary() is a interesting mix

```
x <- runif(100)
```

```
summary(x)
```

```
# But actually two parts
```

```
y <- summary(x)
```

```
str(y)
```

```
print(y)
```

```
# This is a very useful technique
```

```
# We'll come back to this in OO programming
```


Same idea in ggplot2

```
library(ggplot2)
p <- ggplot(mpg, aes(mpg, wt)) +
  geom_point()
str(p)
print(p)
```

```
# This works because of implicit printing:
# results of most R expressions are
# automatically printed. Makes it
# possible to return value and have one
# side effect when used interactively
```

Principle:

Compose value functions
with `map()`; compose effect
functions with `walk()`

`walk()` returns its output **invisibly**

```
species <- split(iris, iris$Species)
file_name <- paste0(names(species), ".csv")

walk2(species, file_name, readr::write_csv)
```

Your turn

Create a `col_write(df, path)` function that writes out each column into a separate file named `colname.txt`, which one value on each line.

The package includes a unit test that you can use to check your work.

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