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
```

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df$b[df$b == -99] <- NA
df$c[df$c == -99] <- NA
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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)
df$h <- fix_missing(df$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

1 cup flour
a scant ¾ cup sugar
1 ½ t baking powder
3 T unsalted butter
½ cup whole milk
1 egg
¼ 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 2/3 full and bake in the preheated oven for 20-25 minutes, or until the cake bounces back when touched.

Chocolate cupcakes

¾ cup + 2T flour
2 ½ T cocoa powder
a scant ¾ cup sugar
1 ½ t baking powder
3 T unsalted butter
½ cup whole milk
1 egg
¼ 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.

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The hummingbird bakery cookbook

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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 2/3 full and bake in the preheated oven for 20-25 minutes, or until the cake bounces back when touched.

1. Convert units

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.

2. Rely on domain knowledge

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.

3. Use variables

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	Chocolate
120g flour	100g flour
	20g cocoa
140g sugar	140g sugar
1.5t baking powder	1.5t baking powder
40g butter	40g butter
120ml milk	120ml milk
1 egg	1 egg
0.25 t vanilla	0.25 t vanilla

4. Extract out common code

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

```r
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

Your turn

What is `NA_real_`? `NA_integer_`? `NA_character_`?

Why don't you normally need to care?

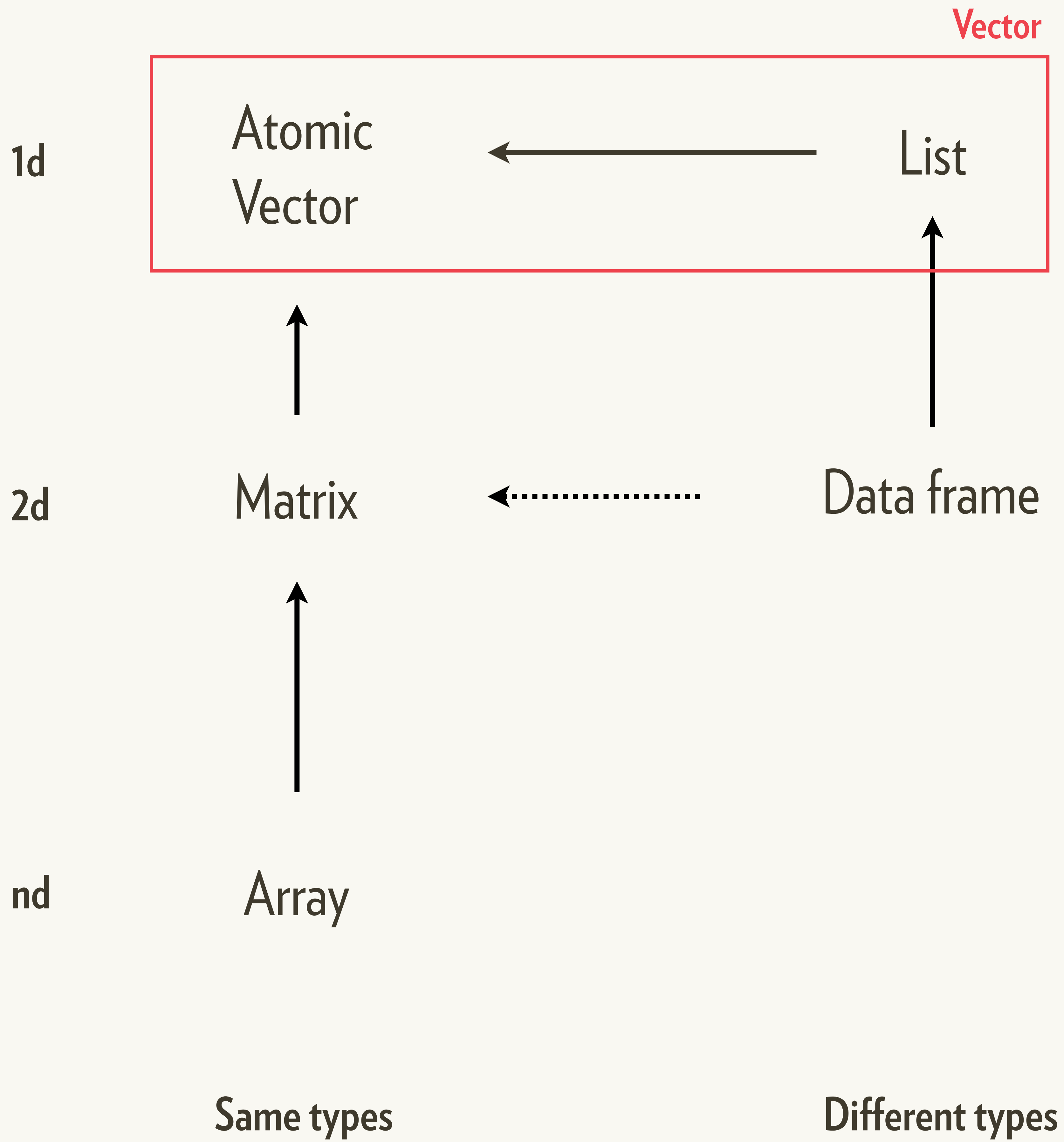
```r
# One NA for each basic atomic vector
typeof(NA)
typeof(NA_real_)
typeof(NA_integer_)
typeof(NA_character_)

c(NA, "x")
```

Your turn

How is a list different from an atomic vector?

How is a data frame different from a list?

How do you examine the structure of an object?



http://adv-r.had.co.nz/Data-structures.html `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]`

http://r4ds.had.co.nz/lists.html

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]])
}
```

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

Map strategy

For each task, identify:

1. Solve for single .x
2. Generalise solution with appropriate map() function
3. Simplify (if possible)

Each variant always produces the same type

Function	Output
`map_lgl()`	Logical vector
`map_int()`	Integer vector
`map_dbl()`	Double vector
`map_chr()`	Character vector
`map()`	List
`map_dfc()`	Data frame (by col)
`map_dfr()`	Data frame (by row)

Find first element of compound string

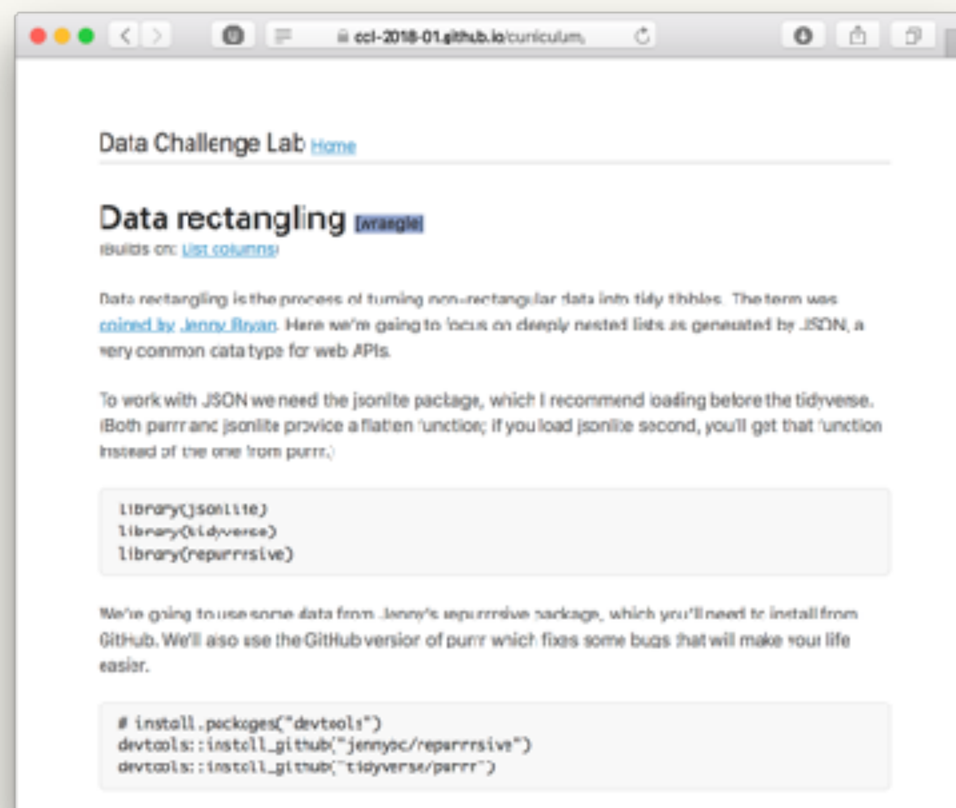
```
x1 <- c("a|b", "a|b|c", "d|e", "b|c|d")
                    "|", fixed = TRUE)

                    the problem for one element?
.x <- x2[[1]]
.x

# Turn into a recipe with ~ and pass to map
map(x2, ~ .x[[1]])
map_chr(x2, ~ .x[[1]])

# Simplify (optionally)
map_chr(x2, 1)
```

Specially named pronoun that map understands

Simplify extraction

```
map(z, ~ .x[[1]])
map(z, 1)

map(z, ~ .x[["string"]])
map(z, "string")

map(z, ~ .x[["string"]][[1]] %||% NA)
map(z, list("string", 1), .default = NA))
```

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



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

Simplify function calls

```
map(z, ~ f(.x))
map(z, f)

map(z, ~ f(.x, a = 1, b = 2))
map(z, f, a = 1, b = 2)

map(z, ~ f(1, .x))
map(z, f, first_arg = 1)
```

Your turn

Back at 3:30pm

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

Compute the mean of every column in mtcars

```
# Solve for one
.x <- mtcars[[1]]
mean(.x)

# Generalise
map_dbl(mtcars, ~ mean(.x))

# Simplify (optional)
map_dbl(mtcars, mean)
```

Generate 10 random normals

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

# Solve for one
.x <- mu[[1]]
rnorm(10, mean = .x)

# Generalise
map(mu, ~ rnorm(10, mean = .x))

# Simplify (optional)
map(mu, rnorm, n = 10)
```

Compute the number of unique values in each column

```
# Solve for one
.x <- iris[[1]]
length(unique(.x))

# Generalise
map_int(iris, ~ length(unique(.x)))

# Simplify ?
nunique <- length(unique(.x))
map_int(iris, ~ nunique(.x))
map_int(iris, nunique)
```

purrr vs dplyr

purrr

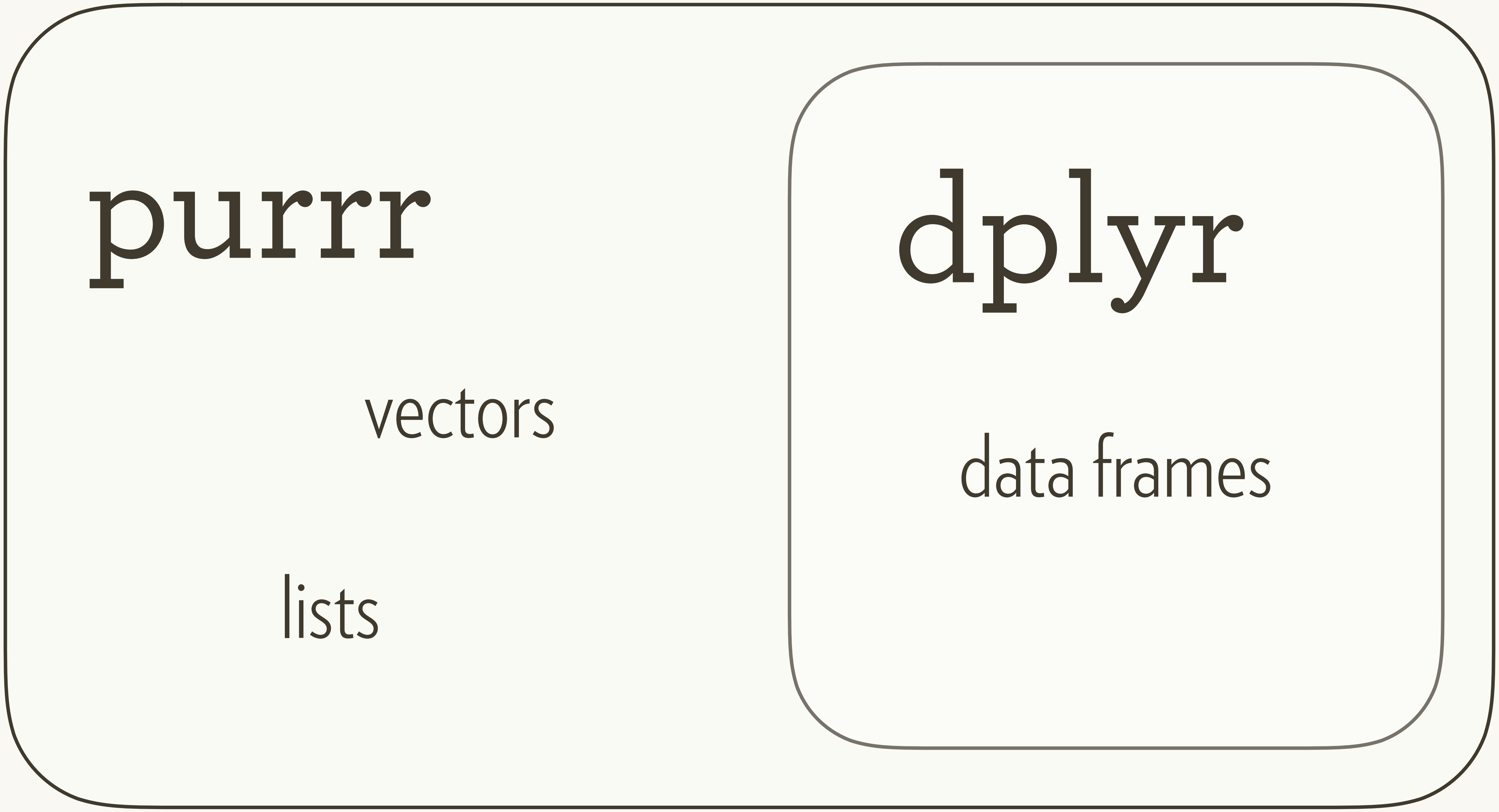
vectors

lists

dplyr

data frames

But data frames are lists



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

Why not base R?

Compare to purrr, base R fucnction:

- Have inconsistent names (lapply() vs. Map())
- Have inconsistent argument order (lapply() vs. mapply())
- Require functions (no 1, or extract helpers)
- Either type-unstable (sapply()) or verbose (vapply())
- Lack side-effect form (no walk())
- Lack paired maps (no map2())
- Lack data frame output (no _dfc(), _dfr())

	Scalar	Anything	Nothing
1	map_lgl(), map_int(), map_dbl(), map_chr()	map()	walk()
2	map2_lgl(), map2_int(), map2_dbl(), map2_chr()	map2()	walk2()
n	pmap_lgl(), pmap_int(), pmap_dbl(), pmap_chr()	pmap()	pwalk()

	Scalar	Anything	Nothing
1	`sapply()` / `vapply()`	`lapply()`	
2			
n	`mapply()`	`Map()`	

Paired map

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 <- str_locate_all(
  sentences, "\\b\\w{5,}\\b"
)

# Solve for one instance: now have two inputs!
.x <- sentences[[1]]
.y <- pos[[1]]
str_sub(.x, .y)
```

Generalise & simplify

```
# Generalise
map2(sentences, pos, ~ str_sub(.x, .y))

# Simplify
map2(sentences, pos, str_sub)
```

walk2() is often useful when writing files

```
diamonds <- ggplot2::diamonds
by_color <- split(diamonds, diamonds$color)
paths <- paste0(names(by_color), ".csv")

# Solve for one
.x <- by_color[[1]]
.y <- paths[[1]]
write.csv(.x, .y)

# Solve for all
walk2(by_color, paths, ~ write.csv(.x, .y))

# Simplify
walk2(by_color, paths, write.csv)
```

Principle:

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

Change project to:

[colsum]

Your turn

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

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

```
col_write <- function(df, path = tempdir()) {
  filenames <- paste0(path, "/", names(df),
".txt")

  walk2(df, filenames, ~
writeLines(as.character(.x), .y))
}
```

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

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

`map()` `sapply()` `data.frame()`

Returns list, or dies trying

Output type depends on input type, length & function

Factor vs character depends on global setting

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)
```

Principle:
Think about invariants

What should always be true?

What are the invariants?

```
# What should always be true about the output?
# * should be a data frame
expect_s3_class(out, "data.frame")

# * one row
expect_equal(nrow(out), 1)

# * one col for each numeric column in the input
expect_equal(ncol(out), sum(map_lgl(in, is.numeric))
```

sapply and [are not type stable

list or logical vector

```
col_means <- 
  numeric <- sapply(df, is.logical)
  numeric_cols <- df[, numeric]

  as.data.frame(l              _cols, mean))
}
```

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

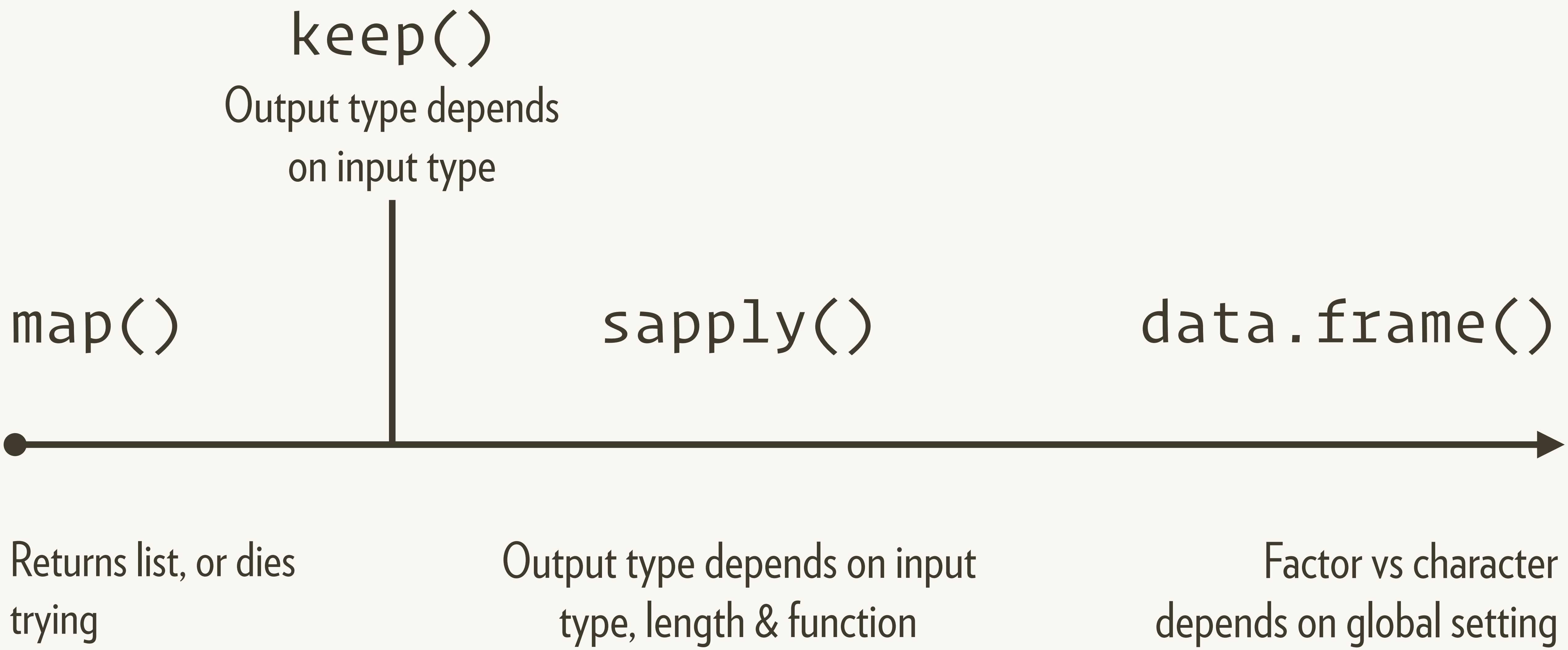
```
col_means <- function(df) {
  numeric <- map_lgl(df, is.numeric)
  numeric_cols <- df[, numeric, drop = FALSE]

  as.data.frame(map(numeric_cols
}
```

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


keep()
Output type depends
on input type
map()
sapply()
data.frame()
Returns list, or dies
trying
Output type depends on input
type, length & function
Factor vs character
depends on global setting

Which is particularly elegant with the pipe

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

Failed invariant

```
col_means(data.frame())
#> data frame with 0 columns and 0 rows

# Should be
#> data frame with 0 columns and 1 rows

# Is fixing this important? 🤷‍♂️
```

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

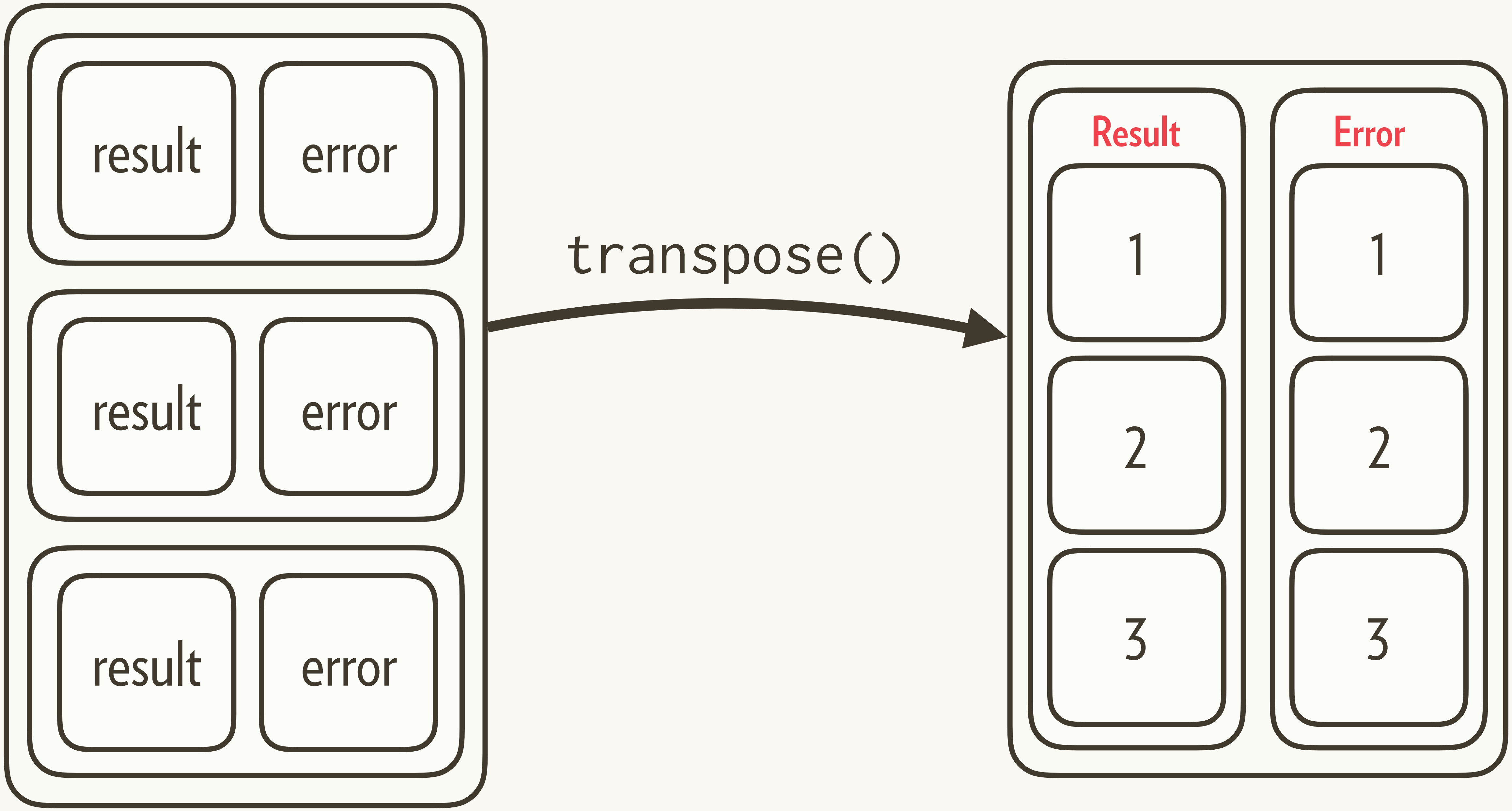
What does safely() do?

```
# 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:

0. Make logical vector that is TRUE if download succeeded.

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]
```

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
```

```r
mod <- lm(mpg ~ wt, data = mtcars)
summary(mod)
# Can't get p-value!

ggplot(mpg, aes(mpg, wt)) +
  geom_smooth() +
  geom_point()
# Can't get model fit!
# Frustrating!
```

Principle:
Effect-functions should invisibly return their input

Because it allows you to string them together in a pipe

What should a effect-function return?

Nothing makes sense

So might as well invisibly return the first argument

Because that lets you use it in pipe

```
flights %>%
  group_by(dest) %>%
  print() %>%
  summarise(
    n = n(),
    delay = mean(dep_delay, na.rm = TRUE)
  ) %>%
  print() %>%
  filter(n > 25) %>%
  print() %>%
  arrange(desc(delay))
```