Functional programming and iteration with purrr

2020-08-22

purrr: A functional programming toolkit for R

Complete and consistent set of tools for working with functions and vectors

Problems we want to solve:

1. **Making code clear**
2. **Making code safe**
3. **Working with lists and data frames**

Lists, vectors, and data.frames (or tibbles)

```
c(char = "hello", num = 1)
```

```
##    char     num 
## "hello"     "1" 
```

lists can contain any object

```r
list(char = "hello", num = 1, fun = mean)
```

```
## $char
## [1] "hello"
##
## $num
## [1] 1
##
## $fun
## function (x, ...)
## UseMethod("mean")
## <bytecode: 0x7fb922834d08>
## <environment: namespace:base>
```

Your Turn 1

```r
measurements <- list(
  blood_glucose = rnorm(10, mean = 140, sd = 10),
  age = rnorm(5, mean = 40, sd = 5),
  heartrate = rnorm(20, mean = 80, sd = 15)
)
```

There are two ways to subset lists: dollar signs and brackets. Try to subset `blood_glucose` **from** `measurements` **using these approaches. Are they different? What about** `measurements[["blood_glucose"]]`**?**

Your Turn 1

```
measurements["blood_glucose"]
```

```
## $blood_glucose
##  [1] 127.9293 142.7743 150.8444 116.5430 144.2912 145.0606 134.2526 134.5337 134.3555 131.0996
```

```
measurements$blood_glucose
```

```
##  [1] 127.9293 142.7743 150.8444 116.5430 144.2912 145.0606 134.2526 134.5337 134.3555 131.0996
```

```
measurements[["blood_glucose"]]
```

```
##  [1] 127.9293 142.7743 150.8444 116.5430 144.2912 145.0606 134.2526 134.5337 134.3555 131.0996
```

data frames are lists

```
x <- list(char = "hello", num = 1)
as.data.frame(x)
```

```
##    char num
## 1 hello   1
```

data frames are lists

```
library(gapminder)
head(gapminder$pop)
```

```
## [1]  8425333  9240934 10267083 11537966 13079460 14880372
```

data frames are lists

```r
gapminder[1:6, "pop"]
```

data frames are lists

```
gapminder[1:6, "pop"]
```

```
## # A tibble: 6 x 1
##         pop
##       <int>
## 1  8425333
## 2  9240934
## 3 10267083
## 4 11537966
## 5 13079460
## 6 14880372
```

data frames are lists

```r
head(gapminder[["pop"]])
```

```
## [1]  8425333  9240934 10267083 11537966 13079460 14880372
```

vectorized functions don't work on lists

```
sum(rnorm(10))
```

vectorized functions don't work on lists

```
sum(rnorm(10))
```

```
## [1] -3.831574
```

vectorized functions don't work on lists

```r
sum(rnorm(10))
```

```
## [1] -3.831574
```

```r
sum(list(x = rnorm(10), y = rnorm(10), z = rnorm(10)))
```

vectorized functions don't work on lists

```r
sum(rnorm(10))
```

```
## [1] -3.831574
```

```r
sum(list(x = rnorm(10), y = rnorm(10), z = rnorm(10)))
```

```
## Error in sum(list(x = rnorm(10), y = rnorm(10), z = rnorm(10))): inval
```

map(.x, .f)

.x: a vector, list, or data frame

.f: a function

Returns a list

Using map()

```
library(purrr)
x_list <- list(x = rnorm(10), y = rnorm(10), z = rnorm(10))

map(x_list, mean)
```

Using map()

```r
library(purrr)
x_list <- list(x = rnorm(10), y = rnorm(10), z = rnorm(10))

map(x_list, mean)
```

Using map()

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library(purrr)
x_list <- list(x = rnorm(10), y = rnorm(10), z = rnorm(10))

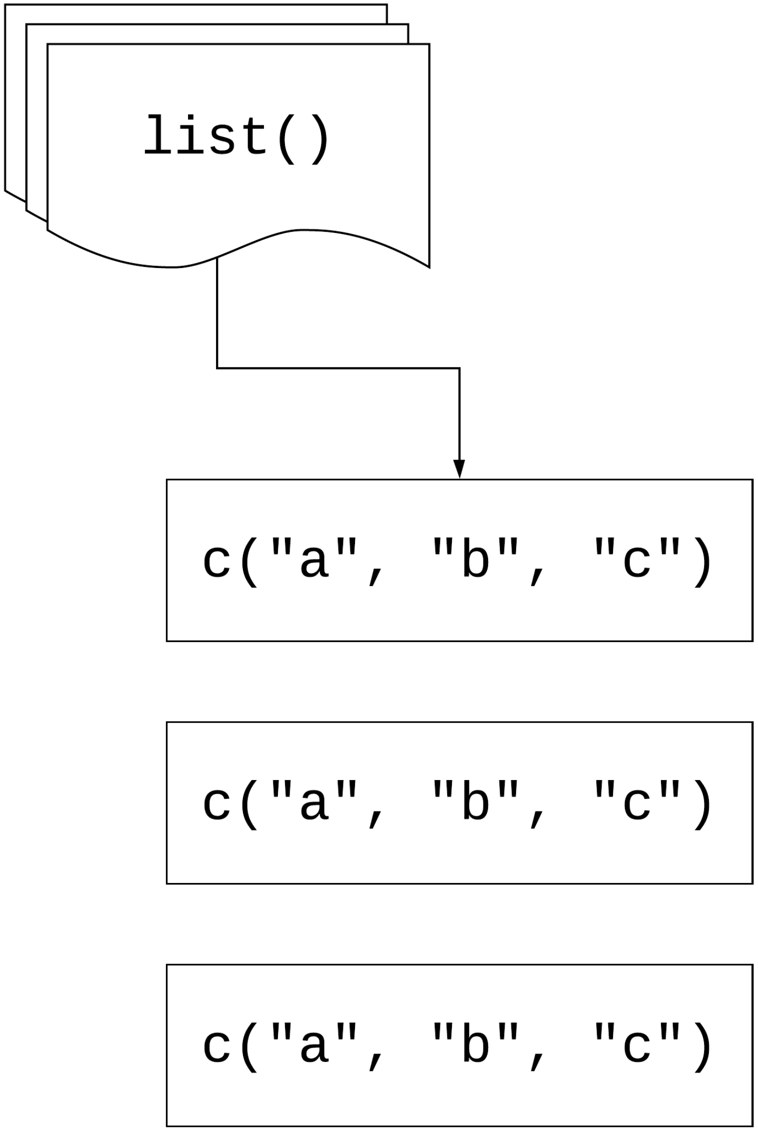
map(x_list, mean)
```

Using map()

```r
library(purrr)
x_list <- list(x = rnorm(10), y = rnorm(10), z = rnorm(10))

map(x_list, mean)
```

```
## $x
## [1] -0.6097971
##
## $y
## [1] -0.2788647
##
## $z
## [1] 0.6165922
```

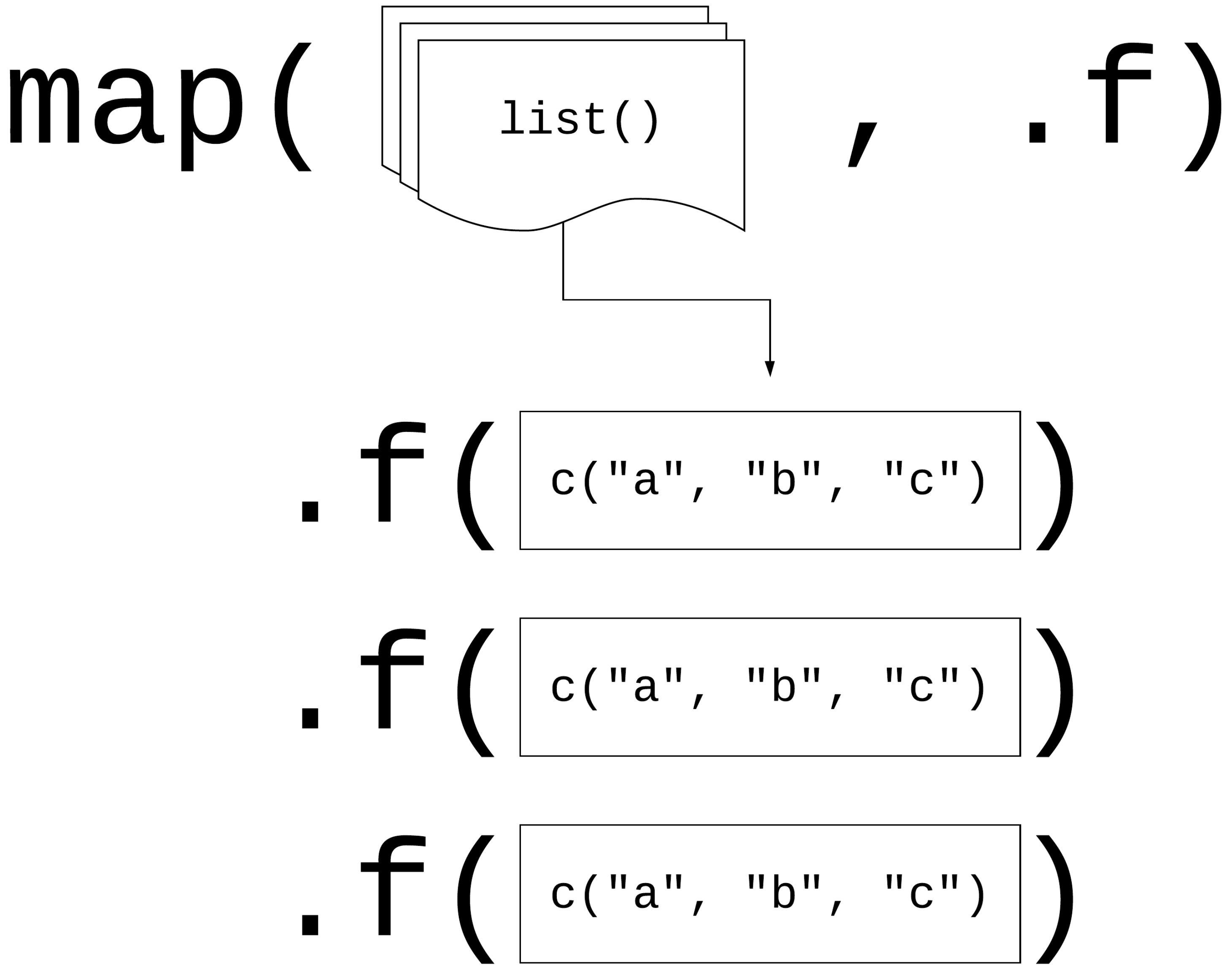


list()

c("a", "b", "c")

c("a", "b", "c")

c("a", "b", "c")



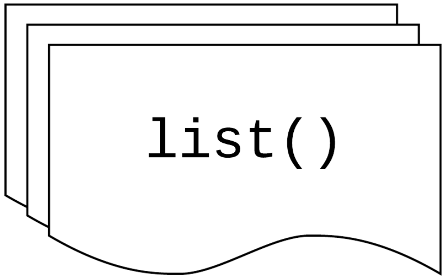
map(list() , .f)

.f(c("a", "b", "c"))

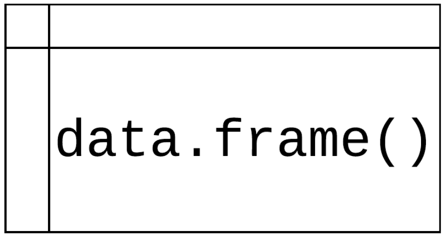
.f(c("a", "b", "c"))

.f(c("a", "b", "c"))

```
map( c("a", "b", "c") , .f)
```



```
map( list() , .f)
```



```
map( data.frame() , .f)
```

Your Turn 2

Read the code in the first chunk and predict what will happen

Run the code in the first chunk. What does it return?

```
list(
  sum_blood_glucose = sum(measurements$blood_glucose),
  sum_age = sum(measurements$age),
  sum_heartrate = sum(measurements$heartrate)
)
```

Now, use `map()` to create the same output.

Your Turn 2

```
map(measurements, sum)
```

```
## $blood_glucose
## [1] 1361.684
##
## $age
## [1] 193.8606
##
## $heartrate
## [1] 1509.304
```

using map() with data frames

```
library(dplyr)
gapminder %>%
  select(where(is.numeric)) %>%
  map(sd)
```

using map() with data frames

```
library(dplyr)
gapminder %>%
  select(where(is.numeric)) %>%
  map(sd)
```

using map() with data frames

```r
library(dplyr)
gapminder %>%
  select(where(is.numeric)) %>%
  map(sd)
```

using `map()` with data frames

```r
library(dplyr)
gapminder %>%
  select(where(is.numeric)) %>%
  map(sd)
```

```
## $year
## [1] 17.26533
##
## $lifeExp
## [1] 12.91711
##
## $pop
## [1] 106157897
##
## $gdpPercap
## [1] 9857.455
```

Your Turn 3

Pass diabetes to `map()` **and map using** `class()`**. What are these results telling you?**

Your Turn 3

```r
head(
  map(diabetes, class),
  3
)
```

```
## $id
## [1] "numeric"
##
## $chol
## [1] "numeric"
##
## $stab.glu
## [1] "numeric"
```

Review: writing functions

```r
x <- x^2
x <- scale(x)
x <- max(x)
```

Review: writing functions

```
x <- x^2
x <- scale(x)
x <- max(x)

y <- x^2
y <- scale(y)
y <- max(y)

z <- z^2
z <- scale(x)
z <- max(z)
```

Review: writing functions

```r
x <- x^2
x <- scale(x)
x <- max(x)

y <- x^2
y <- scale(y)
y <- max(y)

z <- z^2
z <- scale(x)
z <- max(z)
```

Review: writing functions

```
x <- x^3
x <- scale(x)
x <- max(x)

y <- x^2
y <- scale(y)
y <- max(y)

z <- z^2
z <- scale(x)
z <- max(z)
```

Review: writing functions

```r
.f <- function(x) {
  x <- x^3
  x <- scale(x)

  max(x)
}

.f(x)
.f(y)
.f(z)
```

If you copy and paste your code three times, it's time to write a function

Your Turn 4

Write a function that returns the mean and standard deviation of a numeric vector.

Give the function a name

Find the mean and SD of `x`

Map your function to `measurements`

Your Turn 4

```r
mean_sd <- function(x) {
  x_mean <- mean(x)
  x_sd <- sd(x)
  tibble(mean = x_mean, sd = x_sd)
}

map(measurements, mean_sd)
```

Your Turn 4

```
## $blood_glucose
## # A tibble: 1 x 2
##    mean    sd
##   <dbl> <dbl>
## 1  136.  9.96
##
## $age
## # A tibble: 1 x 2
##    mean    sd
##   <dbl> <dbl>
## 1  38.8  3.91
##
## $heartrate
## # A tibble: 1 x 2
##    mean    sd
##   <dbl> <dbl>
## 1  75.5  13.8
```

Three ways to pass functions to map()

1. **pass directly to** map()
2. **use an anonymous function**
3. **use ~**

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

```
map(
  .x,
  function(.x) {
    mean(.x,
    na.rm = TRUE)
  }
)
```

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

```
map(gapminder, ~length(unique(.x)))
```

```r
map(gapminder, ~length(unique(.x)))
```

```
## $country
## [1] 142
##
## $continent
## [1] 5
##
## $year
## [1] 12
##
## $lifeExp
## [1] 1626
##
## $pop
## [1] 1704
##
## $gdpPercap
## [1] 1704
```

Returning types

map	returns
map()	list
map_chr()	character vector
map_dbl()	double vector (numeric)
map_int()	integer vector
map_lgl()	logical vector
map_dfc()	data frame (by column)
map_dfr()	data frame (by row)

Returning types

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

Returning types

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

```
##   country continent      year   lifeExp       pop gdpPercap 
##       142         5        12      1626      1704      1704
```

Your Turn 5

Do the same as #3 above but return a vector instead of a list.

Your Turn 5

```
map_chr(diabetes, class)
```

```
##          id        chol    stab.glu         hdl       ratio       glyhb    location         age
##   "numeric"   "numeric"   "numeric"   "numeric"   "numeric"   "numeric" "character"   "numeric" "cha
##       bp.2d       waist         hip    time.ppn
##   "numeric"   "numeric"   "numeric"   "numeric"
```

Your Turn 6

Check diabetes **for any missing data.**

Using the ~.f(.x) shorthand, check each column for any missing values using is.na() **and** any()

Return a logical vector. Are any columns missing data? What happens if you don't include any()**? Why?**

Try counting the number of missing, returning an integer vector

Your Turn 6

```
map_lgl(diabetes, ~any(is.na(.x)))
```

```
##       id     chol stab.glu      hdl    ratio    glyhb location      age   gender   height   weight
##    FALSE     TRUE    FALSE     TRUE     TRUE     TRUE    FALSE    FALSE    FALSE     TRUE     TRUE
```

Your Turn 6

```
map_int(diabetes, ~sum(is.na(.x)))
```

```
##       id     chol stab.glu      hdl    ratio    glyhb location      age   gender   height   weight
##        0        1        0        1        1       13        0        0        0        5        1
```

Your Turn 7

Turn diabetes **into a list split by** location **using the** split() **function. Check its length.**

Fill in the model_lm **function to model** chol **(the outcome) with** ratio **and pass the** .data **argument to** lm()

map model_lm **to** diabetes_list **so that it returns a data frame (by row).**

Your Turn 7

```r
diabetes_list <- split(diabetes, diabetes$location)
length(diabetes_list)
model_lm <- function(.data) {
  mdl <- lm(chol ~ ratio, data = .data)
  # get model statistics
  broom::glance(mdl)
}

map(diabetes_list, model_lm)
```

Your Turn 7

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

```
## $Buckingham
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>
## 1     0.252         0.248  38.8      66.4 4.11e-14     1
## # … with 6 more variables: logLik <dbl>, AIC <dbl>,
## #   BIC <dbl>, deviance <dbl>, df.residual <int>,
## #   nobs <int>
##
## $Louisa
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>
## 1     0.204         0.201  39.4      51.7 1.26e-11     1
## # … with 6 more variables: logLik <dbl>, AIC <dbl>,
## #   BIC <dbl>, deviance <dbl>, df.residual <int>,
## #   nobs <int>
```

map2(.x, .y, .f)

.x, .y: a vector, list, or data frame

.f: a function

Returns a list

map2(

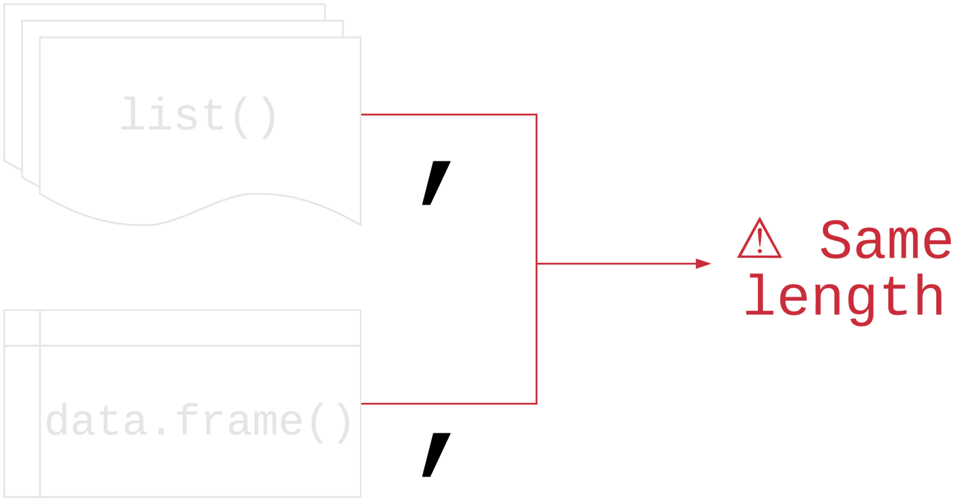
list() ,

data.frame() ,

.f

)

```
map2(
```



list()

,

data.frame()

,

⚠ Same length

```
    .f
)
```

```
map2(
```

list()

,

data.frame()

,

```
    ~.f(.x, .y)
)
```

map2()

```r
means <- c(-3, 4, 2, 2.3)
sds <- c(.3, 4, 2, 1)

map2_dbl(means, sds, rnorm, n = 1)
```

map2()

```r
means <- c(-3, 4, 2, 2.3)
sds <- c(.3, 4, 2, 1)

map2_dbl(means, sds, rnorm, n = 1)
```

map2()

```r
means <- c(-3, 4, 2, 2.3)
sds <- c(.3, 4, 2, 1)

map2_dbl(means, sds, rnorm, n = 1)
```

```
## [1] -2.997932  2.178125  1.266952  2.948287
```

Your Turn 8

Split the gapminder dataset into a list by country

Create a list of models using map()**. For the first argument, pass** gapminder_countries**. For the second, use the** ~.f() **notation to write a model with** lm()**. Use** lifeExp **on the left hand side of the formula and** year **on the second. Pass** .x **to the** data **argument.**

Use map2() **to take the models list and the data set list and map them to** predict()**. Since we're not adding new arguments, you don't need to use** ~.f()**.**

Your Turn 8

```r
gapminder_countries <- split(gapminder, gapminder$country)
models <- map(gapminder_countries, ~ lm(lifeExp ~ year, data = .x))
preds <- map2(models, gapminder_countries, predict)
head(preds, 3)
```

Your Turn 8

```r
gapminder_countries <- split(gapminder, gapminder$country)
models <- map(gapminder_countries, ~ lm(lifeExp ~ year, data = .x))
preds <- map2(models, gapminder_countries, predict)
head(preds, 3)
```

Your Turn 8

```r
gapminder_countries <- split(gapminder, gapminder$country)
models <- map(gapminder_countries, ~ lm(lifeExp ~ year, data = .x))
preds <- map2(models, gapminder_countries, predict)
head(preds, 3)
```

Your Turn 8

```
## $Afghanistan
##        1        2        3        4        5        6
## 29.90729 31.28394 32.66058 34.03722 35.41387 36.79051
##
## $Albania
##        1        2        3        4        5        6
## 59.22913 60.90254 62.57596 64.24938 65.92279 67.59621
##
## $Algeria
##        1        2        3        4        5        6
## 43.37497 46.22137 49.06777 51.91417 54.76057 57.60697
```

input 1	input 2	returns
map()	map2()	list
map_chr()	map2_chr()	character vector
map_dbl()	map2_dbl()	double vector (numeric)
map_int()	map2_int()	integer vector
map_lgl()	map2_lgl()	logical vector
map_dfc()	map2_dfc()	data frame (by column)
map_dfr()	map2_dfr()	data frame (by row)

Other mapping functions

pmap() and friends: take n lists or data frame with argument names

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imap() and friends: includes counter i

Other mapping functions

pmap() and friends: take n lists or data frame with argument names

walk() and friends: for side effects like plotting; returns input invisibly

imap() and friends: includes counter i

map_if(), map_at(): Apply only to certain elements

input 1	input 2	input n	returns
map()	map2()	pmap()	list
map_chr()	map2_chr()	pmap_chr()	character vector
map_dbl()	map2_dbl()	pmap_dbl()	double vector (numeric)
map_int()	map2_int()	pmap_int()	integer vector
map_lgl()	map2_lgl()	pmap_lgl()	logical vector
map_dfc()	map2_dfc()	pmap_dfc()	data frame (by column)
map_dfr()	map2_dfr()	pmap_dfr()	data frame (by row)
walk()	walk2()	pwalk()	input (side effects!)

Your turn 9

Create a new directory using the fs package. Call it "figures".

Write a function to plot a line plot of a given variable in gapminder over time, faceted by continent. Then, save the plot (how do you save a ggplot?). For the file name, paste together the folder, name of the variable, and extension so it follows the pattern "folder/variable_name.png"

Create a character vector that has the three variables we'll plot: "lifeExp", "pop", and "gdpPercap".

Use walk() **to save a plot for each of the variables**

Your turn 9

```
fs::dir_create("figures")

ggsave_gapminder <- function(variable) {
  # we're using `aes_string()` so we don't need the curly-curly syn
  p <- ggplot(
    gapminder,
    aes_string(x = "year", y = variable, color = "country")
  ) +
    geom_line() +
    scale_color_manual(values = country_colors) +
    facet_wrap(vars(continent.)) +
    theme(legend.position = "none")

  ggsave(
    filename = paste0("figures/", variable, ".png"),
    plot = p,
    dpi = 320
  )
}
```

Your turn 9

```
vars <- c("lifeExp", "pop", "gdpPercap")
walk(vars, ggsave_gapminder)
```

Base R

base R	purrr
lapply()	map()
vapply()	map_*()
sapply()	?
x[] <- lapply()	map_dfc()
mapply()	map2(), pmap()

Benefits of purrr

1. Consistent
2. Type-safe
3. ~f(.x)

Loops vs functional programming

```
x <- rnorm(10)
y <- map(x, mean)
```

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

Loops vs functional programming

```r
x <- rnorm(10)
y <- map(x, mean)
```

```r
x <- rnorm(10)
y <- vector("list", length(x))
for (i in seq_along(x)) {
  y[[i]] <- mean(x[[i]])
}
```

Loops vs functional programming

```
x <- rnorm(10)
y <- map(x, mean)
```

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

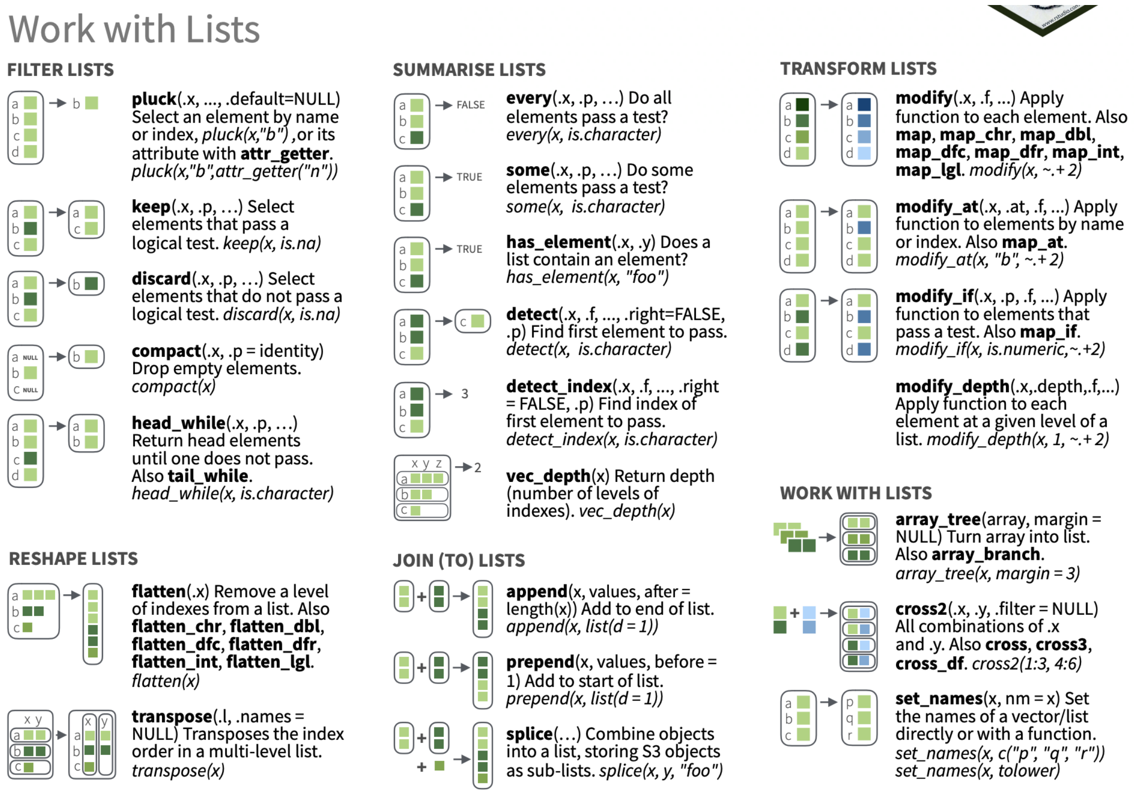
Loops vs functional programming

```
x <- rnorm(10)
y <- map(x, mean)
```

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

> Of course someone has to write loops. It doesn’t have to be you.
>
> —Jenny Bryan

Working with lists and nested data



FALSE
TRUE
TRUE
3
2
NULL
www.rstudio.com

Work with Lists

FILTER LISTS

pluck(.x, ..., .default=NULL) Select an element by name or index, *pluck(x,"b")* ,or its attribute with **attr_getter**. *pluck(x,"b",attr_getter("n"))*

keep(.x, .p, …) Select elements that pass a logical test. *keep(x, is.na)*

discard(.x, .p, …) Select elements that do not pass a logical test. *discard(x, is.na)*

compact(.x, .p = identity) Drop empty elements. *compact(x)*

head_while(.x, .p, …) Return head elements until one does not pass. Also **tail_while**. *head_while(x, is.character)*

RESHAPE LISTS

flatten(.x) Remove a level of indexes from a list. Also **flatten_chr**, **flatten_dbl**, **flatten_dfc**, **flatten_dfr**, **flatten_int**, **flatten_lgl**. *flatten(x)*

transpose(.l, .names = NULL) Transposes the index order in a multi-level list. *transpose(x)*

SUMMARISE LISTS

every(.x, .p, …) Do all elements pass a test? *every(x, is.character)*

some(.x, .p, …) Do some elements pass a test? *some(x, is.character)*

has_element(.x, .y) Does a list contain an element? *has_element(x, "foo")*

detect(.x, .f, ..., .right=FALSE, .p) Find first element to pass. *detect(x, is.character)*

detect_index(.x, .f, ..., .right = FALSE, .p) Find index of first element to pass. *detect_index(x, is.character)*

vec_depth(x) Return depth (number of levels of indexes). *vec_depth(x)*

JOIN (TO) LISTS

append(x, values, after = length(x)) Add to end of list. *append(x, list(d = 1))*

prepend(x, values, before = 1) Add to start of list. *prepend(x, list(d = 1))*

splice(…) Combine objects into a list, storing S3 objects as sub-lists. *splice(x, y, "foo")*

TRANSFORM LISTS

modify(.x, .f, ...) Apply function to each element. Also **map**, **map_chr**, **map_dbl**, **map_dfc**, **map_dfr**, **map_int**, **map_lgl**. *modify(x, ~.+ 2)*

modify_at(.x, .at, .f, ...) Apply function to elements by name or index. Also **map_at**. *modify_at(x, "b", ~.+ 2)*

modify_if(.x, .p, .f, ...) Apply function to elements that pass a test. Also **map_if**. *modify_if(x, is.numeric,~.+2)*

modify_depth(.x,.depth,.f,...) Apply function to each element at a given level of a list. *modify_depth(x, 1, ~.+ 2)*

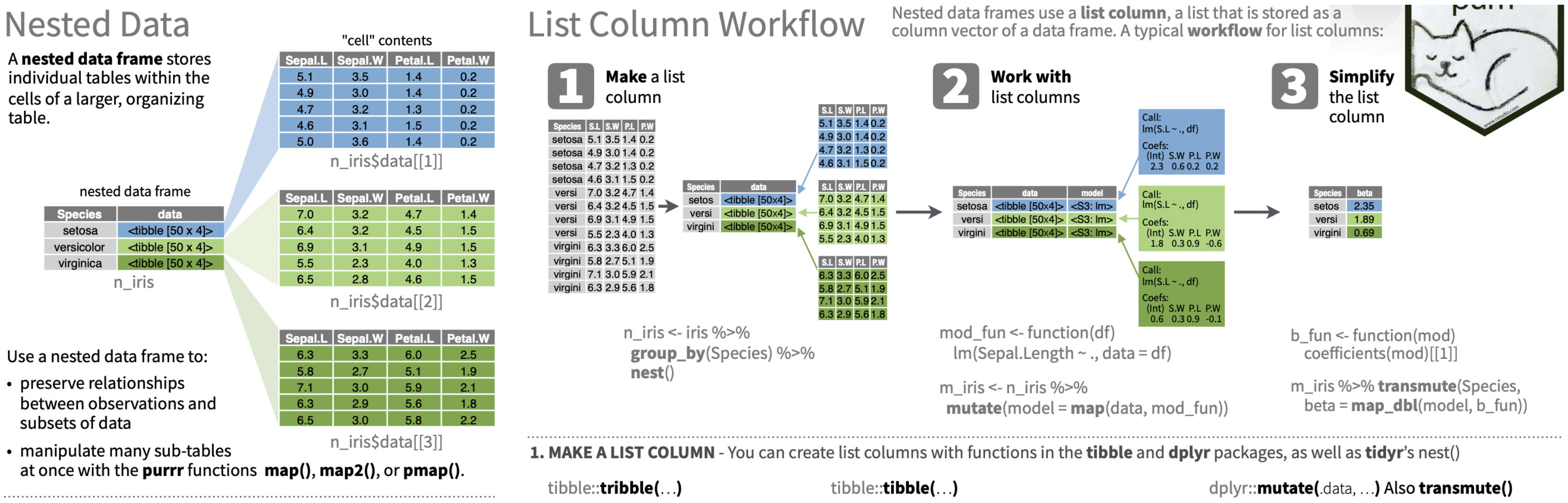
WORK WITH LISTS

array_tree(array, margin = NULL) Turn array into list. Also **array_branch**. *array_tree(x, margin = 3)*

cross2(.x, .y, .filter = NULL) All combinations of .x and .y. Also **cross**, **cross3**, **cross_df**. *cross2(1:3, 4:6)*

set_names(x, nm = x) Set the names of a vector/list directly or with a function. *set_names(x, c("p", "q", "r"))* *set_names(x, tolower)*

Working with lists and nested data



Nested Data

A **nested data frame** stores individual tables within the cells of a larger, organizing table.

nested data frame

Species	data
setosa	<tibble [50 x 4]>
versicolor	<tibble [50 x 4]>
virginica	<tibble [50 x 4]>

n_iris

"cell" contents

Sepal.L	Sepal.W	Petal.L	Petal.W
5.1	3.5	1.4	0.2
4.9	3.0	1.4	0.2
4.7	3.2	1.3	0.2
4.6	3.1	1.5	0.2
5.0	3.6	1.4	0.2

n_iris$data[[1]]

Sepal.L	Sepal.W	Petal.L	Petal.W
7.0	3.2	4.7	1.4
6.4	3.2	4.5	1.5
6.9	3.1	4.9	1.5
5.5	2.3	4.0	1.3
6.5	2.8	4.6	1.5

n_iris$data[[2]]

Sepal.L	Sepal.W	Petal.L	Petal.W
6.3	3.3	6.0	2.5
5.8	2.7	5.1	1.9
7.1	3.0	5.9	2.1
6.3	2.9	5.6	1.8
6.5	3.0	5.8	2.2

n_iris$data[[3]]

Use a nested data frame to:

- preserve relationships between observations and subsets of data
- manipulate many sub-tables at once with the **purrr** functions **map()**, **map2()**, or **pmap()**.

List Column Workflow

Nested data frames use a **list column**, a list that is stored as a column vector of a data frame. A typical **workflow** for list columns:

1 **Make** a list column

Species	S.L	S.W	P.L	P.W
setosa	5.1	3.5	1.4	0.2
setosa	4.9	3.0	1.4	0.2
setosa	4.7	3.2	1.3	0.2
setosa	4.6	3.1	1.5	0.2
versi	7.0	3.2	4.7	1.4
versi	6.4	3.2	4.5	1.5
versi	6.9	3.1	4.9	1.5
versi	5.5	2.3	4.0	1.3
virgini	6.3	3.3	6.0	2.5
virgini	5.8	2.7	5.1	1.9
virgini	7.1	3.0	5.9	2.1
virgini	6.3	2.9	5.6	1.8

Species	data
setos	<tibble [50x4]>
versi	<tibble [50x4]>
virgini	<tibble [50x4]>

S.L	S.W	P.L	P.W
5.1	3.5	1.4	0.2
4.9	3.0	1.4	0.2
4.7	3.2	1.3	0.2
4.6	3.1	1.5	0.2

S.L	S.W	P.L	P.W
7.0	3.2	4.7	1.4
6.4	3.2	4.5	1.5
6.9	3.1	4.9	1.5
5.5	2.3	4.0	1.3

S.L	S.W	P.L	P.W
6.3	3.3	6.0	2.5
5.8	2.7	5.1	1.9
7.1	3.0	5.9	2.1
6.3	2.9	5.6	1.8

```
n_iris <- iris %>%
  group_by(Species) %>%
  nest()
```

2 **Work with** list columns

Species	data	model
setosa	<tibble [50x4]>	<S3: lm>
versi	<tibble [50x4]>	<S3: lm>
virgini	<tibble [50x4]>	<S3: lm>

```
Call:
lm(S.L ~ ., df)

Coefs:
 (Int)  S.W  P.L  P.W
  2.3   0.6  0.2  0.2
```

```
Call:
lm(S.L ~ ., df)

Coefs:
 (Int)  S.W  P.L  P.W
  1.8   0.3  0.9  -0.6
```

```
Call:
lm(S.L ~ ., df)

Coefs:
 (Int)  S.W  P.L  P.W
  0.6   0.3  0.9  -0.1
```

```
mod_fun <- function(df)
  lm(Sepal.Length ~ ., data = df)

m_iris <- n_iris %>%
  mutate(model = map(data, mod_fun))
```

3 **Simplify** the list column

Species	beta
setos	2.35
versi	1.89
virgini	0.69

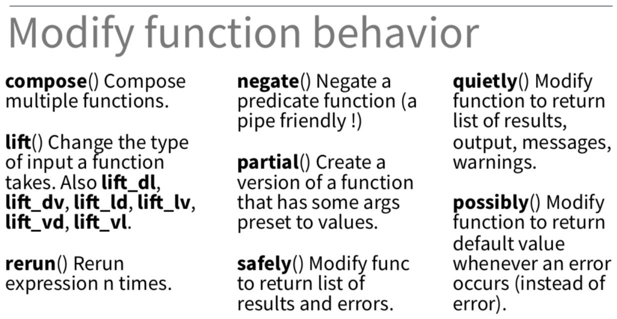
```
b_fun <- function(mod)
  coefficients(mod)[[1]]

m_iris %>% transmute(Species,
  beta = map_dbl(model, b_fun))
```

1. MAKE A LIST COLUMN - You can create list columns with functions in the **tibble** and **dplyr** packages, as well as **tidyr**'s nest()

tibble::**tribble(**…**)**   tibble::**tibble(**…**)**   dplyr::**mutate(**.data, …**)** Also **transmute()**

Adverbs: Modify function behavior



Modify function behavior

compose() Compose multiple functions.

lift() Change the type of input a function takes. Also **lift_dl**, **lift_dv**, **lift_ld**, **lift_lv**, **lift_vd**, **lift_vl**.

rerun() Rerun expression n times.

negate() Negate a predicate function (a pipe friendly !)

partial() Create a version of a function that has some args preset to values.

safely() Modify func to return list of results and errors.

quietly() Modify function to return list of results, output, messages, warnings.

possibly() Modify function to return default value whenever an error occurs (instead of error).

Learn more!

Jenny Bryan's purrr tutorial: A detailed introduction to purrr. Free online.

R for Data Science: A comprehensive but friendly introduction to the tidyverse. Free online.

RStudio Primers: Free interactive courses in the Tidyverse