

Functional programming in R

2021-10-10

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

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

```
## $char
## [1] "hello"
##
## $num
## [1] 1
##
## $fun
## function (x, ...)
## UseMethod("mean")
## <bytecode: 0x14522a838>
## <environment: namespace:base>
```

Your Turn 1

```
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

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

data frames are lists

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

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

data frames are lists

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

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

programming with functions

View source code of a function

```
mean
```

```
## function (x, ...)  
## UseMethod("mean")  
## <bytecode: 0x14522a838>  
## <environment: namespace:base>
```

```
sd
```

```
## function (x, na.rm = FALSE)  
## sqrt(var(if (is.vector(x) || is.factor(x)) x else as.double(x),  
##       na.rm = na.rm))  
## <bytecode: 0x1139d6e00>  
## <environment: namespace:stats>
```

programming with functions

functions are objects and can be assigned to variables

```
f <- mean
```

```
f
```

```
## function (x, ...)  
## UseMethod("mean")  
## <bytecode: 0x14522a838>  
## <environment: namespace:base>
```

```
identical(x = mean, y = f)
```

```
## [1] TRUE
```

dplyr::across()

use within `mutate()`
or `summarize()` to
apply function(s) to
a **selection of columns!**

EXAMPLE:

```
df %>%  
  group_by(species) %>%  
  summarise(  
    across(where(is.numeric), mean))  
)
```



species	mass_g	age_yr	range_sqmi
pika	163	2.4	0.46
marmot	1509	3.0	0.87
marmot	2417	5.6	0.62

@allison_horst

Art by Allison Horst

mutate(across())

```
mutate(  
  <DATA>,  
  across(c(<VARIABLES>), list(<NAMES> = <FUNCTIONS>))  
)
```

mutate(across())

```
mutate(  
  diamonds,  
  across(c("carat", "depth"), list(sd = sd, mean = mean)))  
)
```

mutate(across())

```
mutate(  
  diamonds,  
  across(c("carat", "depth"), list(sd = sd, mean = mean)))  
)
```

```
## # A tibble: 53,940 × 14  
##   carat cut     color clarity depth table price     x     y     z carat_sd carat_mean depth_sd dep  
##   <dbl> <ord>    <ord> <ord>  <dbl> <dbl> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  
## 1 0.23 Ideal     E      SI2     61.5    55    326  3.95  3.98  2.43  0.474  0.798  1.43  
## 2 0.21 Premium   E      SI1     59.8    61    326  3.89  3.84  2.31  0.474  0.798  1.43  
## 3 0.23 Good      E      VS1     56.9    65    327  4.05  4.07  2.31  0.474  0.798  1.43  
## 4 0.29 Premium   I      VS2     62.4    58    334  4.2    4.23  2.63  0.474  0.798  1.43  
## 5 0.31 Good      J      SI2     63.3    58    335  4.34  4.35  2.75  0.474  0.798  1.43  
## 6 0.24 Very Good J      VVS2    62.8    57    336  3.94  3.96  2.48  0.474  0.798  1.43  
## 7 0.24 Very Good I      VVS1    62.3    57    336  3.95  3.98  2.47  0.474  0.798  1.43  
## 8 0.26 Very Good H      SI1     61.9    55    337  4.07  4.11  2.53  0.474  0.798  1.43  
## 9 0.22 Fair       E      VS2     65.1    61    337  3.87  3.78  2.49  0.474  0.798  1.43  
## 10 0.23 Very Good H     VS1     59.4   61    338  4     4.05  2.39  0.474  0.798  1.43  
## # ... with 53,930 more rows
```

mutate(across(where()))

```
mutate(  
  gapminder,  
  across(where(is.numeric), list(mean = mean, median = median)))  
)
```

mutate(across(where()))

```
mutate(  
  gapminder,  
  across(where(is.numeric), list(mean = mean, median = median)))  
)  
  
## # A tibble: 1,704 × 14  
##   country   continent year lifeExp      pop gdpPercap year_mean year_median lifeExp_mean lifeExp_...  
##   <fct>     <fct>    <int>   <dbl>    <int>     <dbl>    <dbl>     <dbl>       <dbl>       <dbl>  
## 1 Afghanistan Asia      1952    28.8  8425333     779.    1980.    1980.       1980.       59.5  
## 2 Afghanistan Asia      1957    30.3  9240934     821.    1980.    1980.       1980.       59.5  
## 3 Afghanistan Asia      1962    32.0  10267083    853.    1980.    1980.       1980.       59.5  
## 4 Afghanistan Asia      1967    34.0  11537966    836.    1980.    1980.       1980.       59.5  
## 5 Afghanistan Asia      1972    36.1  13079460    740.    1980.    1980.       1980.       59.5  
## 6 Afghanistan Asia      1977    38.4  14880372    786.    1980.    1980.       1980.       59.5  
## 7 Afghanistan Asia      1982    39.9  12881816    978.    1980.    1980.       1980.       59.5  
## 8 Afghanistan Asia      1987    40.8  13867957    852.    1980.    1980.       1980.       59.5  
## 9 Afghanistan Asia      1992    41.7  16317921    649.    1980.    1980.       1980.       59.5  
## 10 Afghanistan Asia     1997    41.8  22227415    635.    1980.    1980.       1980.       59.5  
## # ... with 1,694 more rows, and 4 more variables: pop_mean <dbl>, pop_median <dbl>, gdpPercap_mean <dbl>,...  
## #   gdpPercap_median <dbl>
```

Review: tidyselect

**'Behind the scenes' workhorse for dplyr::select(),
dplyr::pull(), and tidyr::pivot_ functions**

starts_with(), ends_with(), contains(), matches(), etc.

```
# column names contain a word  
select(diabetes, ends_with("ht"))
```

```
## # A tibble: 403 × 2  
##   height weight  
##   <dbl>   <dbl>  
## 1     62    121  
## 2     64    218  
## 3     61    256  
## 4     67    119  
## 5     68    183  
## 6     71    190  
## 7     69    191  
## 8     59    170  
## 9     69    166  
## 10    63    202  
## # ... with 393 more rows
```

```
# regular expression  
select(diabetes, matches("\\"d"))
```

```
## # A tibble: 403 × 4  
##   bp.1s bp.1d bp.2s bp.2d  
##   <dbl> <dbl> <dbl> <dbl>  
## 1     118      59     NA     NA  
## 2     112      68     NA     NA  
## 3     190      92    185     92  
## 4     110      50     NA     NA  
## 5     138      80     NA     NA  
## 6     132      86     NA     NA  
## 7     161     112    161    112  
## 8       NA      NA     NA     NA  
## 9     160      80    128     86  
## 10    108      72     NA     NA  
## # ... with 393 more rows
```

```
gapminder %>%
  group_by(continent) %>%
  summarise(across(c("lifeExp", "gdpPercap"), list(med = median,
    iqr = IQR)))
```

```
gapminder %>%
  group_by(continent) %>%
  summarise(across(c("lifeExp", "gdpPercap"), list(med = median,
    iqr = IQR)))
```

A tibble: 5 × 5

	continent	lifeExp_med	lifeExp_iqr	gdpPercap_med	gdpPercap_iqr
## 1	Africa	47.8	12.0	1192.	1616.
## 2	Americas	67.0	13.3	5466.	4402.
## 3	Asia	61.8	18.1	2647.	7492.
## 4	Europe	72.2	5.88	12082.	13248.
## 5	Oceania	73.7	6.35	17983.	8072.

mutate(across()) & summarise()

Control output names with .names argument

```
gapminder %>%  
  group_by(continent) %>%  
  summarise(across(c("lifeExp", "gdpPercap"), list(med = median,  
    iqr = IQR) .names = "{.fn}_{.col}"))
```

```
## # A tibble: 5 × 5  
##   continent med_lifeExp iqr_lifeExp med_gdpPercap iqr_gdpPercap  
##   <fct>        <dbl>        <dbl>        <dbl>        <dbl>  
## 1 Africa         47.8        12.0      1192.       1616.  
## 2 Americas        67.0        13.3      5466.       4402.  
## 3 Asia           61.8        18.1      2647.       7492.  
## 4 Europe          72.2        5.88     12082.      13248.  
## 5 Oceania         73.7        6.35     17983.      8072.
```

Your Turn 2

Use starts_with() from tidyselect() to calculate the average bp columns in diabetes, grouped by gender. Name the new columns bp_ + mean

hint: {.fn} will give you the function name, and {.col} will give you the column name

Your Turn 2

```
diabetes %>%
  group_by(gender) %>%
  summarise(across(starts_with("bp"), list(mean = mean),
    na.rm = TRUE, .names = "{.col}_{.fn}"))
```



```
## # A tibble: 2 × 5
##   gender bp.1s_mean bp.1d_mean bp.2s_mean bp.2d_mean
##   <chr>     <dbl>      <dbl>      <dbl>      <dbl>
## 1 female     136.       82.5      153.       91.8
## 2 male       138.       84.5      151.       93.5
```

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

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

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

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

vectorized functions don't work on lists

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

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

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

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

`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()

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

Using map()

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

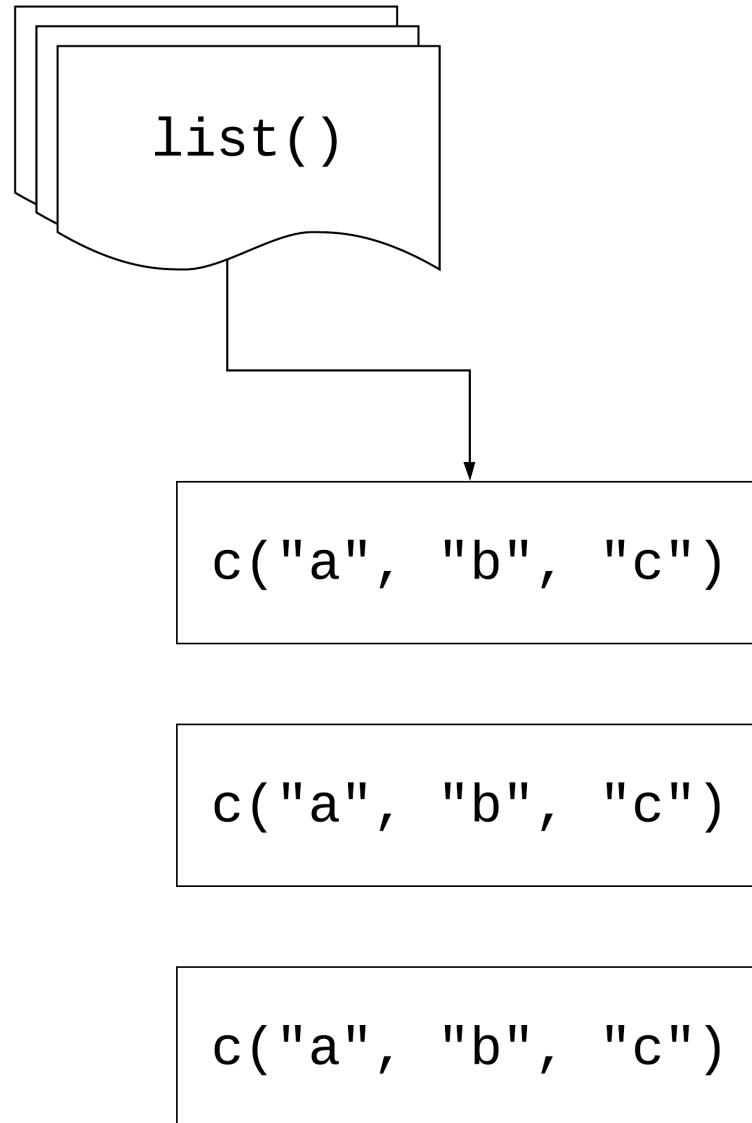
map(x_list, mean)
```

Using map()

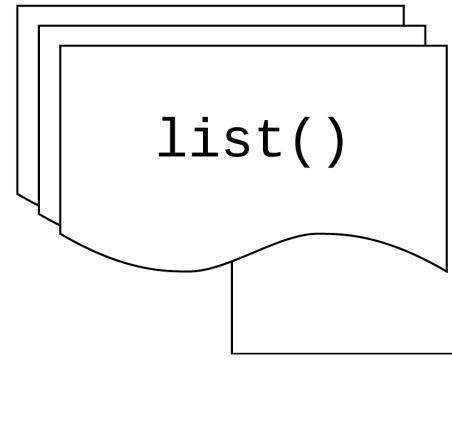
```
library(purrr)
x_list <- list(x = rnorm(10), y = rnorm(10), z = rnorm(10))

map(x_list, mean)
```

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



`map(`



`, . 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 3

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

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

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

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

Your Turn 3

```
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

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

using map() with data frames

```
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 4

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

Your Turn 4

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

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

Review: writing functions

```
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

```
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

```
.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 5

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 5

```
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 5

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

```
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 6

Do the same as #4 above but return a vector instead of a list.

Your Turn 6

```
map_chr(diabetes, class)

##      id      chol    stab.glu      hdl      ratio      glyhb      location      age
##  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "numeric"  "character"  "numeric"
##  gender      height     weight     frame     bp.1s      bp.1d      bp.2s      bp.2d
## "character" "numeric"  "numeric"  "character" "numeric"  "numeric"  "numeric"  "numeric"
##      waist      hip   time.ppn
##  "numeric"  "numeric"  "numeric"
```

Your Turn 7

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 7

```
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  FALSE  TRUE  TRUE  TRUE
## frame  bp.1s  bp.1d  bp.2s  bp.2d  waist   hip  time.ppn
## TRUE  TRUE
```

Your Turn 7

```
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        0        5        1
## frame  bp.1s    bp.1d  bp.2s  bp.2d    waist      hip time.ppn
##     12        5        5      262      262        2        2        3
```

group_map()

Apply a function across a grouping variable and return a list of grouped tibbles

```
diabetes %>%  
  group_by(gender) %>%  
  group_map(~ broom::tidy(lm(weight ~ height, data = .x)))
```

group_map()

```
diabetes %>%
  group_by(gender) %>%
  group_map(~ broom::tidy(lm(weight ~ height, data = .x)))
```

```
## [[1]]
## # A tibble: 2 × 5
##   term      estimate std.error statistic p.value
##   <chr>      <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept) -73.8      59.2     -1.25  0.214
## 2 height       3.90      0.928      4.20  0.0000383
##
## [[2]]
## # A tibble: 2 × 5
##   term      estimate std.error statistic p.value
##   <chr>      <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept) -49.7      68.9     -0.722  0.471
## 2 height       3.35      0.995      3.37  0.000945
```

group_modify()

Apply a function across grouped tibbles and return grouped tibbles

```
diabetes %>%
  group_by(gender) %>%
  group_modify(~ broom::tidy(lm(weight ~ height, data = .x)))
```



```
## # A tibble: 4 × 6
## # Groups:   gender [2]
##   gender term      estimate std.error statistic p.value
##   <chr>  <chr>     <dbl>     <dbl>     <dbl>    <dbl>
## 1 female (Intercept) -73.8      59.2     -1.25    0.214
## 2 female height       3.90      0.928      4.20    0.0000383
## 3 male   (Intercept) -49.7      68.9     -0.722    0.471
## 4 male   height       3.35      0.995      3.37    0.000945
```

Your Turn 8

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

Group diabetes by location

Use `group_modify()` with `model_lm`

Your Turn 8

```
model_lm <- function(.data, ...) {  
  mdl <- lm(chol ~ ratio, data = .data)  
  # get model statistics  
  broom::glance(mdl)  
}  
  
diabetes %>%  
  group_by(location) %>%  
  group_modify(model_lm)
```

Your Turn 8

```
## # A tibble: 2 × 13
## # Groups:   location [2]
##   location    r.squared adj.r.squared sigma statistic p.value     df logLik     AIC     BIC deviance
##   <chr>          <dbl>        <dbl>    <dbl>    <dbl>    <dbl>     <dbl> <dbl> <dbl> <dbl>      <dbl>
## 1 Buckingham  0.252       0.248    38.8     66.4  4.11e-14     1 -1009.  2025.  2034.  296206.
## 2 Louisa      0.204       0.201    39.4     51.7  1.26e-11     1 -1033.  2072.  2082.  312638.
## # ... with 2 more variables: df.residual <int>, nobs <int>
```

`map2(.x, .y, .f)`

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

`.f`: a function

Returns a list

map2(



,

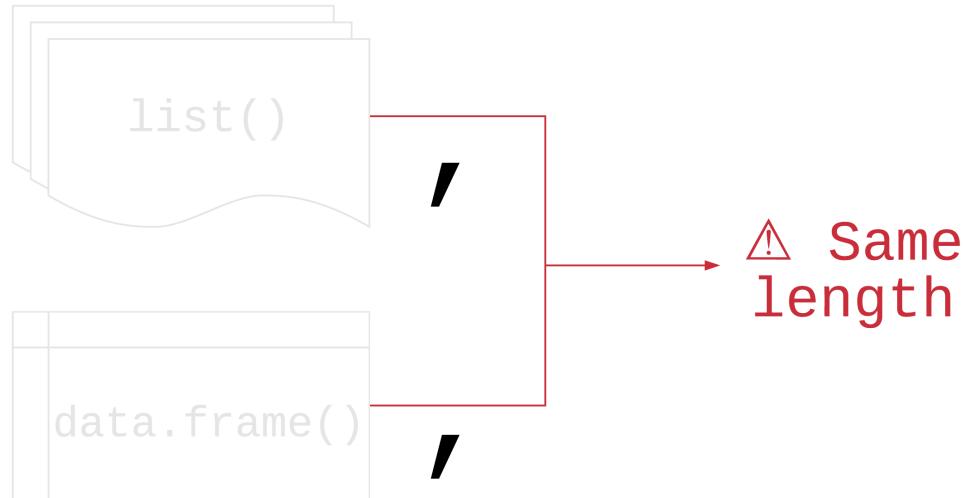


,

.f

)

map2(



.f
)

map2(



,



,

~ .f(.x, .y)

)

map2()

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

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

map2()

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

map2_db1(means, sds, rnorm, n = 1)
```

map2()

```
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 9

Split the gapminder dataset into a list by country using the split() function

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 9

```
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 9

```
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 9

```
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 9

```
## $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!)

group_walk()

Use group_walk() for side effects across groups

```
temp <- "temporary_folder"  
fs::dir_create(temp)  
gapminder %>%  
  group_by(continent) %>%  
  group_walk(  
    ~ write_csv(  
      .x,  
      file = file.path(temp,  paste0(.y$continent,  ".csv"))  
    )  
  )
```

group_walk()

Use group_walk() for side effects across groups

```
## temporary_folder  
## └── Africa.csv  
## └── Americas.csv  
## └── Asia.csv  
## └── Europe.csv  
## └── Oceania.csv
```

Your turn 10

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 10

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

ggsave_gapminder <- function(variable) {
  # we're using `aes_string()` so we don't need the
  # curly-curly syntax
  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 10

```
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 $\sim f(.x)$

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

```
x <- rnorm(10)
y <- map(x, mean)
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```
x <- rnorm(10)
y <- vector("list", length(x))
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Loops vs functional programming

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Loops vs functional programming

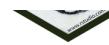
```
x <- rnorm(10)
y <- map(x, mean)
```

```
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.

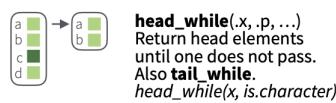
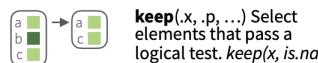
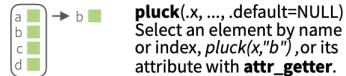
—Jenny Bryan

Working with lists and nested data

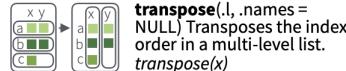


Work with Lists

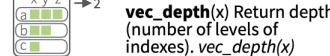
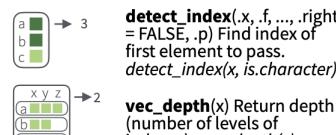
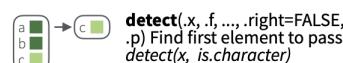
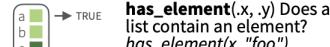
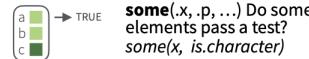
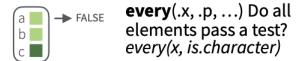
FILTER LISTS



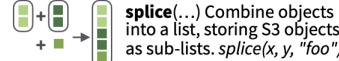
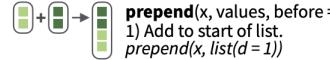
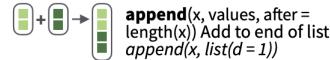
RESHAPE LISTS



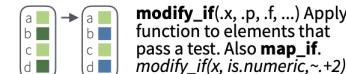
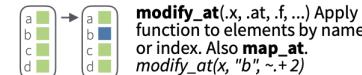
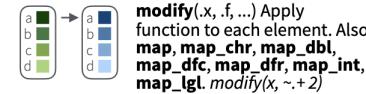
SUMMARISE LISTS



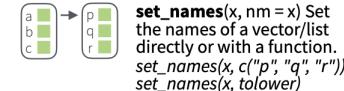
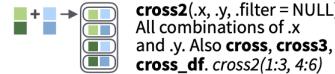
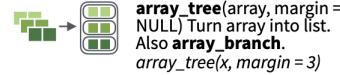
JOIN (TO) LISTS



TRANSFORM LISTS



WORK WITH LISTS



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	<ibble [50 x 4]>
versicolor	<ibble [50 x 4]>
virginica	<ibble [50 x 4]>

n_iris

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()`.

"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]]

List Column Workflow

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

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

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

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

`tibble::tribble(...)`

2 Work with list columns

Species	data	model
setosa	<tibble [50 x 4]>	Call: lm(S.L ~ ., df)
versi	<tibble [50 x 4]>	Coefs: (int) S.W P.L P.W
virgini	<tibble [50 x 4]>	2.3 0.6 0.2 0.2
		versi <tibble [50 x 4]>
		Call: lm(S.L ~ ., df)
		Coefs: (int) S.W P.L P.W
		virgini <tibble [50 x 4]>
		Call: lm(S.L ~ ., df)
		Coefs: (int) S.W P.L P.W
		1.8 0.3 0.9 -0.6

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

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

`tibble::tribble(...)` 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