



purrr beyond map()

a.k.a. fun with functional programming in R

```
result <- purrr::modify(.x = , .f = )
```



 Hendrik van Broekhuizen

 Predictive Insights

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 hendrik@predictiveinsights.net

 [@hendrikvanb](https://twitter.com/hendrikvanb)

The purrr package

what and why?



definition



A complete and consistent functional programming toolkit for R
- *help(purrr)*



objective



... to give you similar expressiveness to a classical FP language, while allowing you to write code that looks and feels like R
- *purrr 0.1.0*

purrr: what is it good for?

Absolutely ~~nothing~~ ~~everything~~ lots of stuff

Iterative tasks

- `lapply`++
 - more consistent, more general, more powerful

Working with lists

- Yes, even complex, nested lists
- It's lists, all the way down

Creating consistent, robust functions/routines

- Consistent syntax
- Fail loudly
- Nice error handling

Bringing some `tidyverse`-esque style to `data.table`

- `modify_if`, `modify_at`

The obligatory preamble

Making sure we are all on the same page



Disclaimer

- *purrr* fantastic \neg *purrr* expert
- 15min \neq enough time

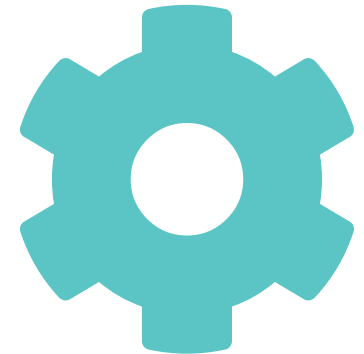
Admissions

- I'm an *extreme centrist* w.r.t. *tidyverse* and *data.table*
- I love to `%>%`
- I often find it useful to explicitly prefix functions with their namespace

Setup

- Working in RStudio in an *.Rproj* context
- Using same set of packages throughout

```
library(data.table)
library(tidyverse)
library(lubridate)
```



Some tips

useful things to keep in mind when using purrr

When not to use `map()`

- `lapply()` is the base equivalent to `map()` (sans `purrr` helpers support)
 - if you're only using `map()` from purrr, you can skip the additional dependency and use `lapply()` directly
- there is no need to map if the operation is already appropriately vectorised

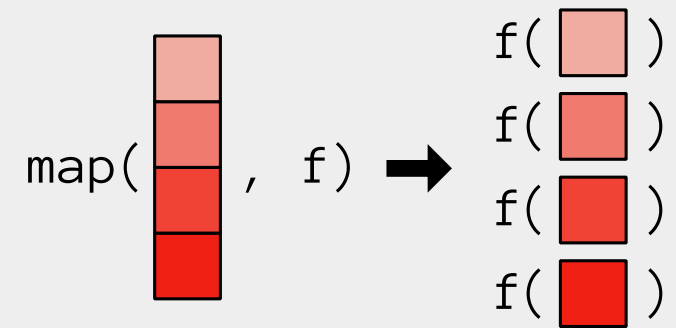
Avoiding nasty surprises

- `map*()` functions always return output of the same length as the input
- a data frame is simply a list of [consistently typed] vectors of equal length
 - lists vs atomic vectors vs vectors

An unsolicited piece of advice

- use inline anonymous functions instead of `purrr`'s formula syntax

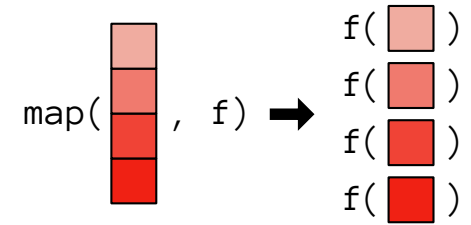
A `map()` primer



map()

Apply to all

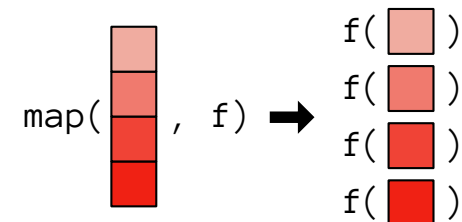
- | `map(.x, .f)`
- | **i** call function `.f` once for each element of vector `.x`;
- | return the result as a list



map()

Apply to all

- | `map(.x, .f)`
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Example:

Get the square of each number from 1 to 5

```
# function to get square of number
my_square <- function(x) x^2

# get square of each number 1:5 and output as list
res1 <- 1:5 %>% map(my_square)           # direct call
res2 <- 1:5 %>% map(~my_square(.))       # for backward compatibility
res3 <- 1:5 %>% map(~my_square(.x))      # formula
res4 <- 1:5 %>% map(function(x) my_square(x)) # inline anonymous function

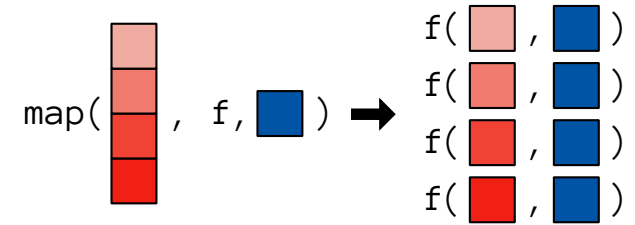
# test equivalence
identical(res1, res2) & identical(res2, res3) & identical(res3, res4)
```

[1] TRUE

Passing arguments with . . .

Many ways to do to the same thing

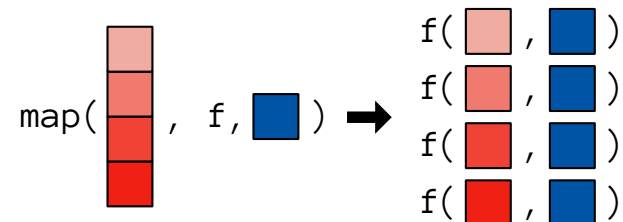
i `map(.x, .f, ...)`
passes arguments specified in ... along



Passing arguments with ...

Many ways to do the same thing

i `map(.x, .f, ...)`
passes arguments specified in ... along



Example:

Use `paste()` to add 'min' as suffix to each number from 1 to 5

```
# pass arguments along
spec1 <- 1:5 %>% map(paste, 'min')

# formula specification (two variants)
spec2 <- 1:5 %>% map(~paste(., 'min'))
spec3 <- 1:5 %>% map(~paste(.x, 'min'))

# inline anonymous function specification
spec4 <- 1:5 %>% map(function(x) paste(x, 'min'))

# test equivalence
list(spec2, spec3, spec4) %>% map_lgl(identical, y = spec1)
```

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

Passing arguments: via `...` vs in function

A seemingly subtle, yet important difference

Not all that seems vectorised is...

- `map()` is only vectorised over its first argument so arguments passed to `map()` after `.f` will be
 - passed along as is and
 - evaluated once

What is that supposed to mean?

- Has implications if you pass arguments to function via `...`
 - errors if you pass vectors as arguments to functions that do not accept vectors as arguments
 - potentially wrong results even if arguments specified correctly

Passing arguments: via `...` vs in function

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 - potentially wrong results even if arguments specified correctly

E.g.:

```
# function that multiplies input (arg1) by specified constant (arg2)
temp_func <- function(x, constant = 2) {
  glue::glue('{x} x {constant} = {x*constant}')
```



```
# method 1: pass parameterised arg2 directly to map_chr
1:5 %>% map_chr(temp_func, constant = sample(1:10, 1))
```



```
# method 2: pass parameterised arg2 into inline anonymous function
1:5 %>% map_chr(function(x) temp_func(x, constant = sample(1:10, 1)))
```

```
[1] "1 x 2 = 2"  "2 x 2 = 4"  "3 x 2 = 6"  "4 x 2 = 8"  "5 x 2 = 10"
[1] "1 x 8 = 8"  "2 x 1 = 2"  "3 x 7 = 21" "4 x 7 = 28" "5 x 7 = 35"
```

map_*()

Dictating the output format

`map_*(.x, .f, ...)`



call function `.f` once for each element of vector `.x`;
return the result as an atomic vector of type `*`; error if
impossible

- `map_chr(.x, .f)`: character
- `map_lgl(.x, .f)`: logical
- `map_dbl(.x, .f)`: real
- `map_int(.x, .f)`: integer
- `map_dfr(.x, .f)`: data frame (`bind_rows`)
- `map_dfc(.x, .f)`: data frame (`bind_cols`)

map_*()

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- `map_dfr(.x, .f)`: data frame (`bind_rows`)
- `map_dfc(.x, .f)`: data frame (`bind_cols`)

Examples:

```
1:5 %>% map_chr(paste, 'min') %>% class()
```

```
[1] "character"
```

```
1:5 %>% map_lgl(function(x) x < 3) %>% class()
```

```
[1] "logical"
```

```
1:5 %>% map_int(function(x) x * 2L) %>% class()
```

```
[1] "integer"
```

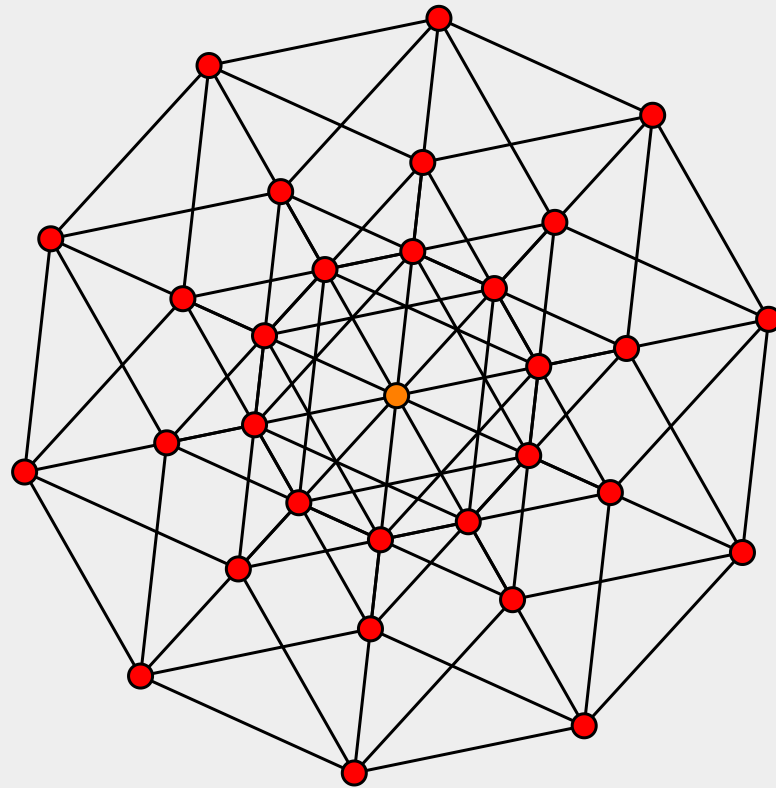
```
1:5 %>% map_df(function(x) data.frame(value = x)) %>% class()
```

```
[1] "data.frame"
```

```
1:5 %>% map_dfc(function(x) data.table(value = x)) %>% class()
```

```
[1] "data.table" "data.frame"
```

Map variants



walk() and modify()

map() has siblings...

| walk(.x, .f, ...)

| ⓘ call function .f once for each element of .x; return
| nothing

| modify(.x, .f, ...)

| ⓘ call function .f once for each element of .x; return the
| result as an object of the same type as .x

walk() and modify()

map() has siblings...

| walk(.x, .f, ...)

i call function .f once for each element of .x; return nothing

E.g.:

```
1:5 %>% purrr::walk(paste, 'min')
```

```
result <- 1:5 %>%  
  purrr::walk(function(x) x ^ 2)
```

```
print(result)
```

```
[1] 1 2 3 4 5
```

| modify(.x, .f, ...)

i call function .f once for each element of .x; return the result as an object of the same type as .x

E.g.:

```
# obviously a character vector  
x <- c('1', '2', '3', '4', '5')
```

```
# try to convert each element to integer using map_dbl  
x %>% purrr::map_dbl(as.integer)
```

```
[1] 1 2 3 4 5
```

```
# try to convert each element to integer using modify  
x %>% purrr::modify(as.integer)
```

```
[1] "1" "2" "3" "4" "5"
```

Why `walk()`? Why `modify()`?

what's the point?

`walk(.x, .f, ...)`

- call function `.f` once for each element of `.x`; return nothing



`modify(.x, .f, ...)`

- call function `.f` once for each element of `.x`; return the result as an object of the same type as `.x`



Just do stuff

- Some functions just need to do stuff, not necessarily return stuff
 - E.g.: `cat()`, `message()`, `saveRDS()`, etc
- Particularly useful for disk I/O operations
- Allows input "passthrough"

Change the content; keep the wrapper

- Some functions just need to change stuff, not necessarily create stuff
- Not everything needs to be coerced
 - What if input is already of the type we want as output?
 - Type preservation can be essential
- Particularly useful are the `modify_if()` and `modify_at()` variants

map() variants cheatsheet

Basic rules & the matrix of understanding

map variant rules:

1. `map()` returns list `map_*()` returns vector of type specified
2. `modify()` returns same type as input
3. `walk()` returns nothing
4. Iterate over two inputs with `map2()`, `walk2()`, `modify2()`
5. Iterate over input and index with `imap()`, `imodify()`, `iwalk()`
6. Iterate over any number of inputs with `pmap()` and `pwalk()`

map variant matrix:

- map family of functions has orthogonal input and outputs
- can organise all the family into a matrix, with inputs in the rows and outputs in the columns

arguments	list	atomic	preserve type	nothing
one argument	<code>map()</code>	<code>map_lgl()</code> , ...	<code>modify()</code>	<code>walk()</code>
two arguments	<code>map2()</code>	<code>map2_lgl()</code> , ...	<code>modify2()</code>	<code>walk2()</code>
one argument + index	<code>imap()</code>	<code>imap_lgl()</code> , ...	<code>imodify()</code>	<code>iwalk()</code>
n arguments	<code>pmap()</code>	<code>pmap_lgl()</code> , ...	NA	<code>pwalk()</code>

map() & map_*()

Some practical illustrations and applications

Examples:

scripts/map_family.R

1. Try some specs
use `map()` to fit multiple models to the same data
2. A bit of class
use `map_*()` to iterate over columns of a tibble and extract each's class
3. The biggest year for hits
use `map_*()` inside a tibble to create a new column from an existing list column
4. Forgetting the bad years
use `map_*()` to filter a tibble based on a condition applied to a list column
5. Read it in; build it up
use `map_dfr()` to build a single tibble from multiple constituent csv files on disk
6. A decade of hits
use `map_dfr()` to build a nested df by iterating over a vector and applying a parameterised function
7. Which spec is best?
use `map_dfr()` to fit multiple models to the same data and build a tidy df with results

modify() & walk()

Some practical illustrations and applications

modify() examples:

scripts/map_family.R

1. Let's call a spade a spade
conditionally modify a vector using `modify_if()`
2. Back to the future
use `modify_at()` to target and modify specific vector elements
3. Double the hits, tripple the misses
complex conditional modification of a vector/(list column) using `modify()`

walk() examples:

scripts/map_family.R

1. The mystery of the missing classes
use `walk()` to iterate over columns of a tibble and output each's class

`*walk_*`()

Iteratively write data to disk using `purrr::pwalk()`

Example:

For each manufacturer in the `mpg` dataset, write a `.csv` file to disk containing only the data for that manufacturer

`*walk_*`()

Iteratively write data to disk using `purrr::pwalk()`

Example:

For each manufacturer in the `mpg` dataset, write a `.csv` file to disk containing only the data for that manufacturer

```
# check for files (show that there are none)  
list.files('data/mpg')  
character(0)
```

`*walk_*`()

Iteratively write data to disk using `purrr::pwalk()`

Example:

For each manufacturer in the `mpg` dataset, write a `.csv` file to disk containing only the data for that manufacturer

```
# check for files (show that there are none)
list.files('data/mpg')

character(0)

# create files by taking the mpg df %>% collapsing the data for each manufacturer into a list column %>% walking
# over the two columns in the df and for each pair (i.e. row of manufacturer and data values) doing: {create path
# variable to point to the path where the data should be written %>% write the data to disk in .csv format}
mpg %>%
  group_nest(manufacturer, keep = T) %>%
  purrr::pwalk(function(manufacturer, data) {
    path <- file.path('data/mpg', glue::glue('df_{manufacturer}.csv'))
    write_csv(data, path)
  })
```


walk_

Iteratively write data to disk using `purrr::pwalk()`

Example:

For each manufacturer in the `mpg` dataset, write a `.csv` file to disk containing only the data for that manufacturer

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# variable to point to the path where the data should be written %>% write the data to disk in .csv format}
mpg %>%
  group_nest(manufacturer, keep = T) %>%
  purrr::pwalk(function(manufacturer, data) {
    path <- file.path('data/mpg', glue::glue('df_{manufacturer}.csv'))
    write_csv(data, path)
  })

# check for files again (show that there are now files)
list.files('data/mpg') %>% {c(head(., 3), tail(., 3))}

[1] "df_audi.csv"           "df_chevrolet.csv"    "df_dodge.csv"       "df_subaru.csv"      "df_toyota.csv"
"df_volkswagen.csv"
```

map() variants

Some practical illustrations and applications

Examples:



`scripts/map_variants.R`

1. One year at a time
use `pwalk()` to create objects from a tibble

I'm intrigued...

where can I learn more?

Reference (R/Rstudio)

- `help(package = purrr)`
-  to show function help
-  to inspect function

Reference (online)

- [purrr cheatsheet](#)
- [purrr reference](#)

Learning and understanding

- Jenny Bryan's [purrr tutorial](#)
- Hadley Wickham's [Advanced R Chapter 9: Functionals](#)