INTRODUCTION TO

PURRR

WELCOME R-LADIES!

WANT TO PLAY ALONG?

CODE AVAILABLE AT
GITHUB.COM/
JENNIFERTHOMPSON/
RLADIESINTROTOPURRR

install.packages("tidyverse")
install.packages("viridis")

WILL GET YOU SET UP

OPTIONAL: TO RUN **ALL** THE CODE, YOU'LL ALSO NEED A DATA.WORLD ACCOUNT + API TOKEN, AND

install.packages("data.world")

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R-LADIES NASHVILLE • NOVEMBER 2017

“

ITERATION:

DOING THE SAME* THING TO A BUNCH OF THINGS

**ISH*

— Jennifer Thompson

”

AUDIENCE PARTICIPATION!

WHAT ARE SOME EXAMPLES?

WAYS TO ITERATE IN R

AUDIENCE PARTICIPATION!

HOW DO **YOU** ITERATE?

- **Copy & paste**
  - PROS: easy (in the short run)
  - CONS: hard to maintain, edit
- **for loops**
  - PROS: easy to conceptualize, write
  - CONS: inefficient
- **lapply**
  - PROS: faster than for loop; base R -> more stable, fewer dependencies
  - CONS: often need to do something else after you iterate (eg, do.call(rbind, lapply(…))
- **apply**
  - PROS: working with rows/cols in a data.frame
  - CONS: syntax & defining functions can be tricky
- **mapply, sapply, tapply, vapply**
  - PROS: I'm sure there a
  - CONS: mystifying synt

MY PERSONAL EXPERIENCE

doctordisruption.com

REASONS TO USE PURRR VS BASE R

- Consistent, readable syntax (compare to apply vs lapply vs mapply vs…)
- More efficient than for loops
- Plays nicely with pipes %>%
- Returns the output you expect (type-stable)
- Ease of making changes
- Flexibility
- Particularly excellent if you work with list-columns, JSON, other non-strictly-rectangular data

PREAMBLE:
STOP WORRYING AND

LOVE LISTS

- Lists in R are collections of elements - that's it
- Each element can be any length and any type… even another list (it's lists all the way down…)
- Totally valid example:

```
list("a" = 1:10,           ## numeric vector of length 10
     "b" = list(1:10),     ## list of length 1; element 1 = vector of length 10
     "c" = LETTERS[1:10]) ## character vector of length 10
```

- With such flexibility comes both great power & great complexity
- purrr works really well with lists by providing ways to:
  - iterate quickly over lists comprising elements of the same type
  - quickly extract elements of complicated lists

MAP(): WHERE IT'S AT

(ALONG WITH ITS VARIANTS)

- Let us do the same (or similar) things to a list of things, and know what kind of output to expect
- Several variants, depending on how many combinations you're iterating over and what type of output you want
- Different combinations:
  `map()` (one thing), `map2()` (two things), `pmap()` (infinite number of things)
- Different outputs:
  `map()` (list), `map_chr()`, `map_dbl()`, `map_int()`, `map_lgl()`, `map_df()`

THEY ALL WORK THIS WAY:

Two sets of arguments:

1. **What we're iterating over**
   Specified differently depending on which map() we're using
2. **What we're doing each time**
   *Always specified as **.f***
   Can be built-in, user-defined, or anonymous (defined within the map() call itself)

```
map(.x = …, .f = …)

map2(.x = …, .y = …, .f = …)

pmap(.l = list(a1 = …, a2 = …, …),
     .f = …)
```

MAP EXAMPLES

+ USING ANONYMOUS FUNCTIONS IN PURRR

```
v1 <- v2 <- 1:10

map(v1, ~ . * 3)
```

"this is what I want to do to each element"

"this is an anonymous function"

"this is where the thing I'm iterating over goes"

```
[[1]]
[1] 3

[[2]]
[1] 6
…

[[10]]
[1] 30
```

Great if we want to continue iterating!

If we *really* want a new vector:

```
map_dbl(v1, ~ . * 3)
[1]  3  6  9 12 15 18 21 24 27 30
```

Examples of other `map` variants:

```
map_chr(v1, ~ LETTERS[.])
 [1] "A" "B" "C" "D" "E" "F" "G" "H" "I" "J"
```

```
map2_dbl(v1, v2, sum)
[1]  2  4  6  8 10 12 14 16 18 20
```

```
map_lgl(v1, is.numeric)
 [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE…
```

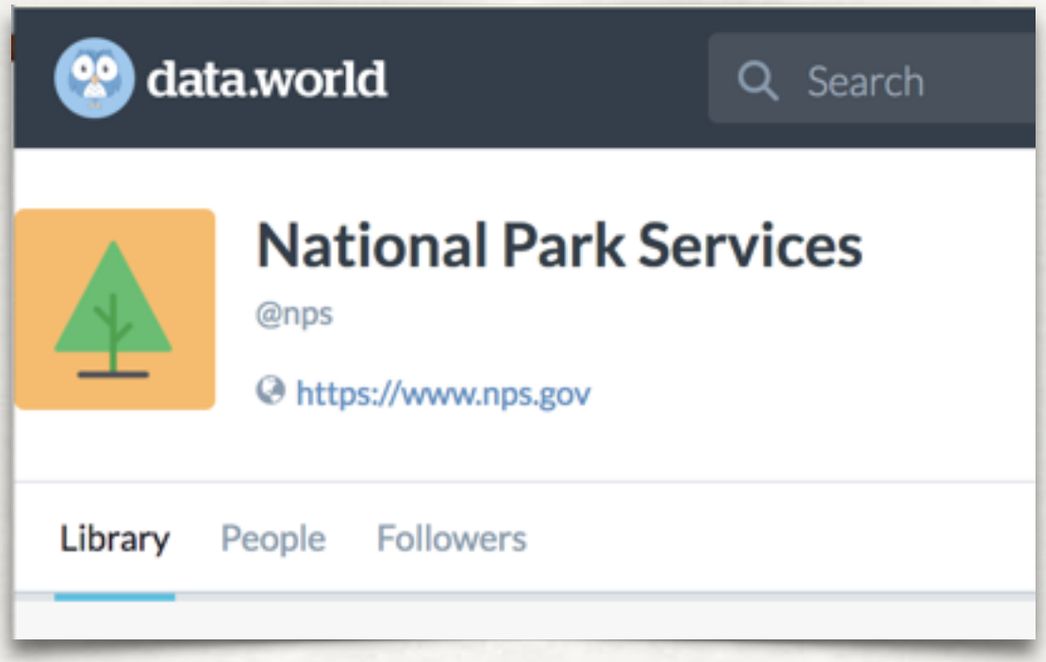
EXAMPLE TIME!

PLAY ALONG IF YOU LIKE
GITHUB.COM/JENNIFERTHOMPSON/RLADIESINTROTOPURRR

- **Goal**: Show lots of purrr's capabilities, give you ideas about how you can use it
- **Not goals**:
  - Write most efficient code possible
  - Complex statistical analysis
- **What we'll do**:
  1. Extract data stored in multiple files and combine it into 3 datasets
  2. Fit the same model to three different outcomes
  3. Check assumptions for those models
  4. If needed, update the model
  5. Visualize our model results

MOTIVATING DATA

HAPPY 101ST BIRTHDAY, NATIONAL PARKS SERVICE!



AUDIENCE PARTICIPATION!

TO CODE ALONG WITH THIS SECTION, YOU'LL NEED A DATA.WORLD ACCOUNT AND AN API TOKEN

ALTERNATELY: PURRR_DATA.RDATA

data.world/nps

We'll look at annual total recreation, tent camping, and backcountry camping visits from the years 2007-2016.

We'll also use the Glossary to restrict our data to only national parks.

TOTAL RECREATIONAL VISITS

PRETTY SURE THIS MEANS EVERYBODY

10 files

Recreation_Visits_2007.csv
Request more info

	parkname	# rank	# value	# percentoftotal
1	Blue Ridge PKWY	1	17,352,286	6.3%
2	Golden Gate NRA	2	14,397,313	5.22%
3	Great Smoky Mountains NP	3	9,372,253	3.4%
4	Gateway NRA	4	8,813,204	3.2%
5	Lake Mead NRA	5	7,622,139	2.77%

Showing 1-5 of 359 rows, 4 columns See all

Recreation_Visits_2008.csv
Request more info

	parkname	# rank	# value	# percentoftotal
1	Blue Ridge PKWY	1	16,309,307	5.91%
2	Golden Gate NRA	2	14,554,750	5.3%
3	Gateway NRA	3	9,431,021	3.43%
4	Great Smoky Mountains NP	4	9,044,010	3.29%
5	Lake Mead NRA	5	7,601,863	2.77%

Showing 1-5 of 360 rows, 4 columns See all

Recreation_Visits_2009.csv
Request more info

	parkname	# rank	# value	# percentoftotal
1	Blue Ridge PKWY	1	15,936,316	5.58%
2	Golden Gate NRA	2	15,036,372	5.27%

- Each year's data is stored as a separate CSV file
- Each file has the same columns, and same name, except for the year
- Datasets for tent campers, backcountry campers are formatted the same way
- This seems like a prime target for…

AUDIENCE PARTICIPATION!

1. FILL IN THE BLANK

2. WHAT ARE WAYS YOU MIGHT HAVE DONE THIS WITHOUT PURRR?

USING MAP + USER-DEFINED FUNCTIONS

STEP 1: WRITE FUNCTION

```
download_nps_year <- function(
  year = 2007:2016,
  table_prefix,
  url
){
  data.world::query(
    data.world::qry_sql(
      sprintf(
        "SELECT * FROM %s_%s",
        table_prefix, year
      )
    ),
    dataset = url
  ) %>%
    ## As long as we're customizing…
    select(parkname, value) %>%
    mutate(year = year)
}
```

allows us to do the same for tent, backcountry data

STEP 2: EXTRACT EACH DATASET

```
## Download recreation data
url_recvisits <-
  "https://data.world/nps/annual-park-ranking-recreation-visits"
rec_visits <- map_df(
  .x = 2007:2016,
  .f = download_nps_year,
  table_prefix = "recreation_visits",
  url = url_recvisits
)
```

what we're iterating over

what we're doing

what stays the same each time

```
## Same thing for backcountry, tent campers
## Download tent camper data
url_tent <-
  "https://data.world/nps/annual-park-ranking-tent-campers"
tent_visits <- map_df(
  .x = 2007:2016,
  .f = download_nps_year,
  table_prefix = "tent_campers",
  url = url_tent
)

## Download backcountry data
url_back <-
  "https://data.world/nps/annual-park-ranking-backcountry-campers"
back_visits <- map_df(
  .x = 2007:2016,
  .f = download_nps_year,
  table_prefix = "backcountry_campers",
  url = url_back
)
```

WHAT'D WE GET?

TOTAL RECREATIONAL VISITS

```
dplyr::sample_n(rec_visits, size = 10)
```

parkname <chr>	value <int>	year <int>
Fort Stanwix NM	86678	2015
Pictured Rocks NL	593587	2012
Klondike Gold Rush NHP Alaska	975043	2007
Jimmy Carter NHS	62057	2014
Pipestone NM	70748	2015
Cowpens NB	206740	2015
Cumberland Island NS	91996	2010
Lassen Volcanic NP	536068	2016
Cape Hatteras NS	2237378	2007
Channel Islands NP	360806	2007

1-10 of 20 rows Previous 1 2 Next

We're skipping some data management which

1. *Restricts all our data to national parks only*
2. *Determines the region each park is in*

CREATE THE FINAL LIST THAT STARTS IT ALL

This `map` *call iterates over our three separate datasets, merges park region onto each, and gives us a* ***list*** *as our final result*

```
datalist <- map(
  ## Initial list = all three datasets
  .x = list(rec_visits, tent_visits, back_visits),
  ## For each, reduce() uses left_join to merge on state/region by parkname
  .f = ~ reduce(list(., park_index), left_join, by = "parkname")
)
```

particularly handy if you have >2 data.frames to merge!

AUDIENCE PARTICIPATION!

IF YOU'RE USING PURRR_DATA.RDATA, JUMP IN HERE!

```
> head(datalist[[1]])
# A tibble: 6 x 7
             parkname  value  year              name  type location                 on
                <chr>  <int> <int>             <chr> <chr>    <chr>              <fctr>
1     Kings Canyon NP 580129  2007     Kings Canyon    NP       CA    Pacific NW
2   Virgin Islands NP 571382  2007   Virgin Islands    NP       VI    Eastern US
3 Petrified Forest NP 563590  2007 Petrified Forest    NP       AZ Intermountain
4     Capitol Reef NP 554907  2007     Capitol Reef    NP       UT Intermountain
5       Mesa Verde NP 541102  2007       Mesa Verde    NP       CO Intermountain
6         Biscayne NP 517442  2007         Biscayne    NP       FL    Eastern US
```

LET'S RUN SOME MODELS!

PREDICT # VISITORS BY YEAR, REGION, INTERACTION

datalist: list of data.frames


```
map(datalist, ~ lm(value = year * region, data = .))
```

orgmod_list: list of lm fits

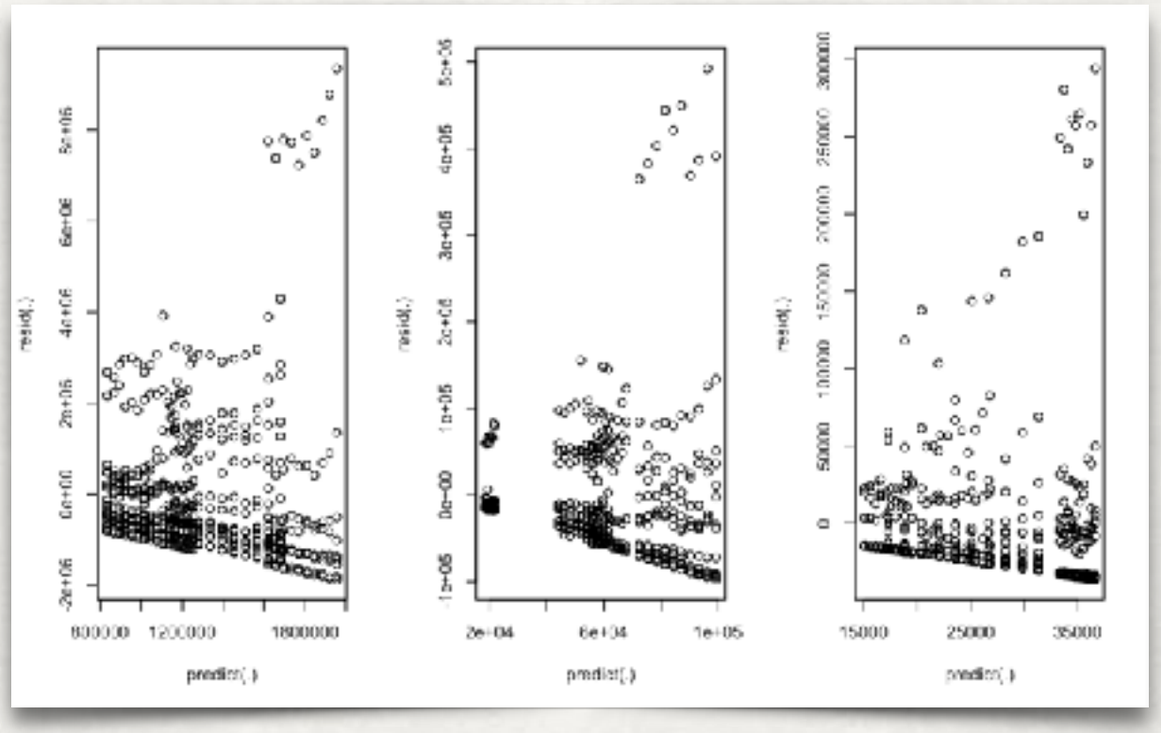
NO ERRORS MEANS WE'RE GOOD, RIGHT?

MANY OF US ARE STATISTICIANS
WE KNOW IT ISN'T THAT EASY

- **Goal**: Check model assumptions by looking at residual vs fitted plots
- **Strategy**: Use `purrr::walk()` to iterate over all our model fits, extract residuals and fitted values, and plot them

`walk` is very similar to **`map`**, but we use `walk` when we want **side effects** - printed output, plots, saved files, etc - rather than an **object** returned

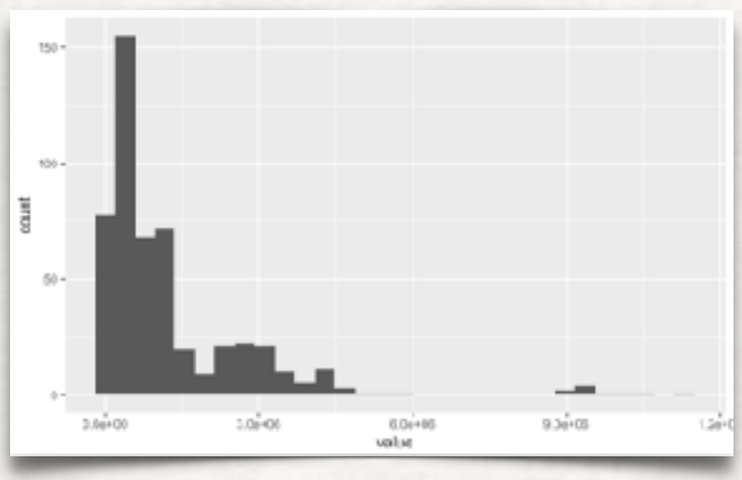
```
par(mfrow = c(1, 3))
walk(
  orgmod_list,
  ~ plot(resid(.) ~ predict(.))
)
```

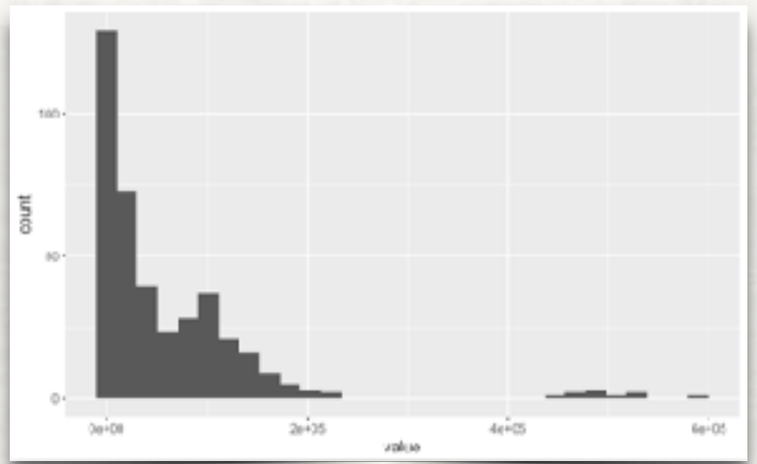


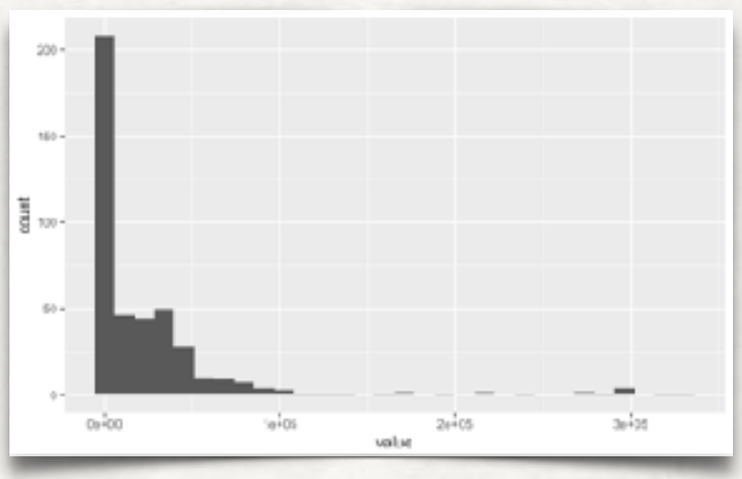
USE PURRR TO FIX IT

Diagnose the problem: Use **`walk`** to look at the distribution of our outcome

```
walk(
  datalist,
  ~ print(ggplot(data = ., aes(x = value)) + geom_histogram())
)
```







Perhaps a log transformation would be helpful?

USE PURRR TO FIX IT

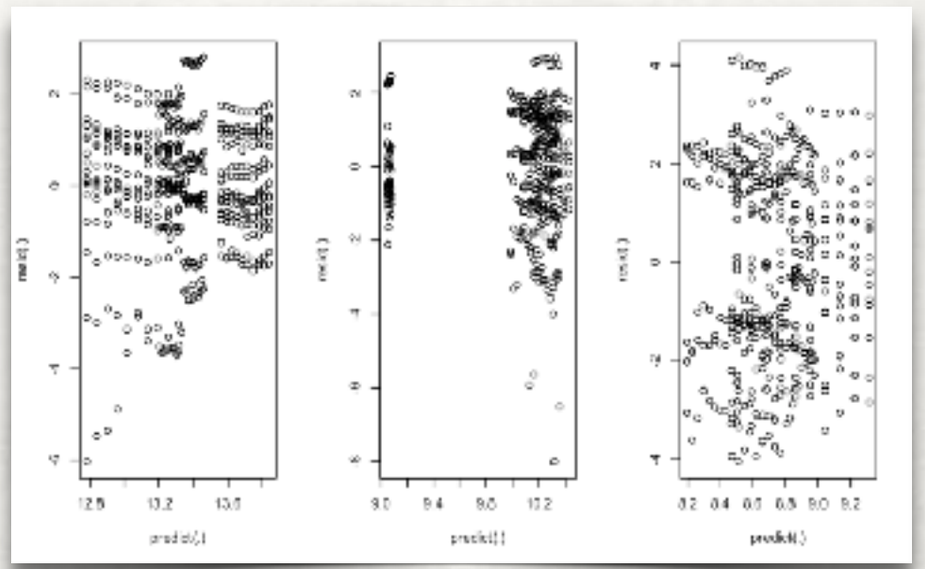
Use **map** (and dplyr) to transform our outcome variable in place

```
datalist <- datalist %>%
  map(~ dplyr::mutate_at(.x, "value", log))
```

Use **map** to refit the linear model with our transformed outcome, then recheck RP plots

```
logmod_list <-
  map(datalist, ~ lm(value ~ year * region, data = .))

par(mfrow = c(1, 3))
walk(
  logmod_list,
  ~ plot(resid(.) ~ predict(.))
)
```



TIME FOR SOME NUMBERS

Let's quickly look at the R^2 for each of our models. Know how we can do that?

AUDIENCE PARTICIPATION!

HOW CAN WE DO THAT?

`map_dbl!`

One-line method:

```
round(map_dbl(logmod_list, ~ summary(.)$adj.r.squared), 2)
```

Pipe method:

```
logmod_list %>%
  map(summary) %>%
  map_dbl(.f = "adj.r.squared") %>%
  round(2)
```

From each element of `.x`, take the element named "`adj.r.squared`"

Either way:

```
[1] 0.03 0.05 0.00
```

VISUALIZE RESULTS

For each model, we're going to:

- Create a data.frame with predicted values for each year and region
- Plot visitors over time, faceted by region
- Save those plots

Points to emphasize:

- `purrr::cross` for getting all combinations of things
- `purrr::pluck` for extracting elements from a list
- using `map` in a pipeline, starting with one list and taking it through multiple steps

VISUALIZATION PREP

Create a data.frame of all possible combinations of year and region

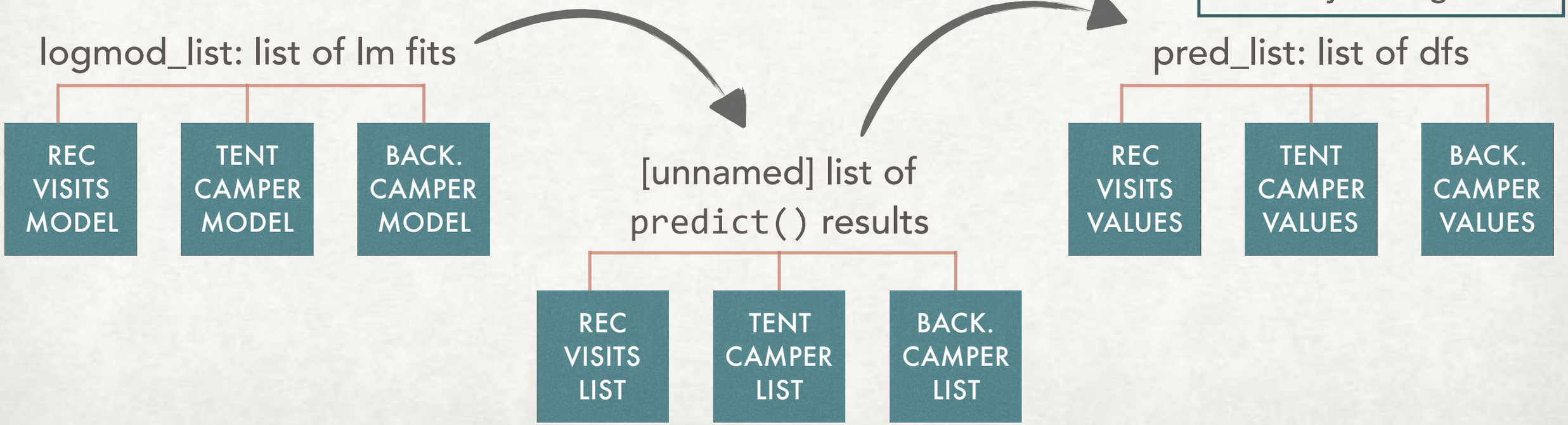
```
preddata <- cross_df(
  .l = list("year" = unique(pluck(datalist, 1, "year")),
            "region" = levels(datalist[[1]]$region))
)
```

For each visit type, create data.frame with predicted # for each year/region

```
pred_list <- logmod_list %>%
  map(.f = predict, newdata = preddata, se.fit = TRUE) %>%
  map(~ data.frame(fit = pluck(., "fit"), se = .$se.fit) %>%
          mutate(lcl = fit - qnorm(0.975) * se,
                 ucl = fit + qnorm(0.975) * se)) %>%
  ## Add year and region onto each
  map(dplyr::bind_cols, preddata)
```

List of lm fits ->
List of lists! ->
List of data.frames we transformed ->

List of data.frames we added year/region to



VISUALIZATION PREP

AUDIENCE PARTICIPATION!

We want to make very similar charts for each type of visitor, but we want a few things to be different. What do you think we should do first?

Write a function!

```
plot_predicted <- function(df, vscale, maintitle){
  ## Make sure df has all the columns we need
  if(!all(c("fit", "se", "lcl", "ucl", "year", "region") %in% names(df))){
    stop("df should have columns fit, se, lcl, ucl, year, region")
  }

  ## Create a plot faceted by region
  p <- ggplot(data = df, aes(x = year, y = fit)) +
    facet_wrap(~ region, nrow = 2) +
    geom_ribbon(aes(ymin = lcl, ymax = ucl, fill = region), alpha = 0.4) +
    geom_line(aes(color = region), size = 2) +
    scale_fill_viridis(option = vscale, discrete = TRUE, end = 0.75) +
    scale_colour_viridis(option = vscale, discrete = TRUE, end = 0.75) +
    labs(title = maintitle,
         x = NULL, y = "Log(Visitors)") +
    theme(legend.position = "none")

  return(p)

}
```

Three things can change; everything else remains constant

VISUALIZE RESULTS

THREE ARGUMENTS = BREAK OUT THE BIG GUNS

Time for some **parallel mapping!**

First, let's set up a list of arguments.

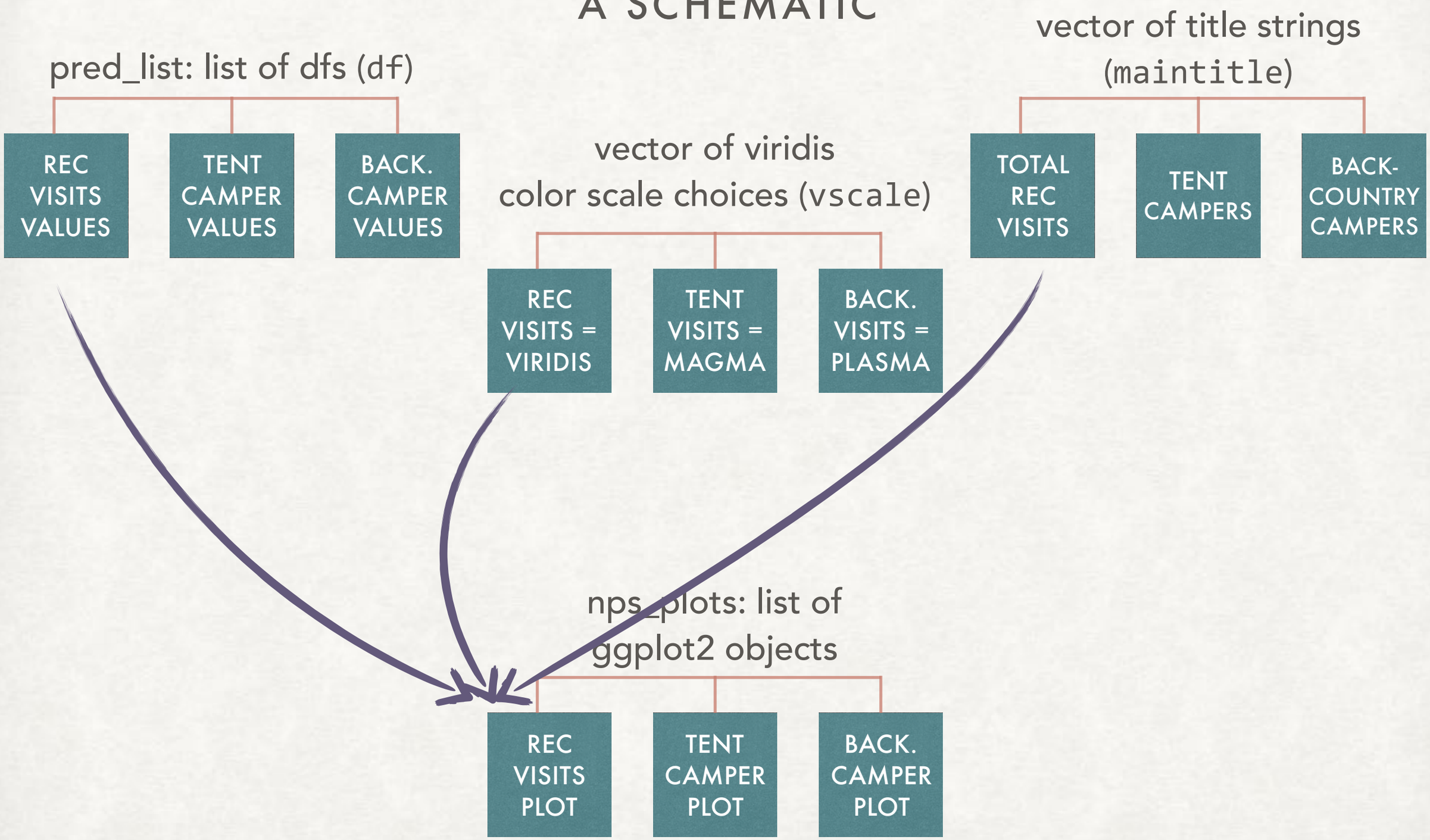
```
plot_args <- list(
  "df" = pred_list,
  "vscale" = c("D", "A", "C"),
  "maintitle" = c("Total Recreational Visits",
                  "Tent Campers",
                  "Backcountry Campers")
)
```

Once our plotting function is written and our arguments are set up, we can get all our plots with one line:

```
nps_plots <- pmap(plot_args, plot_predicted)
```

WHAT JUST HAPPENED?

A SCHEMATIC



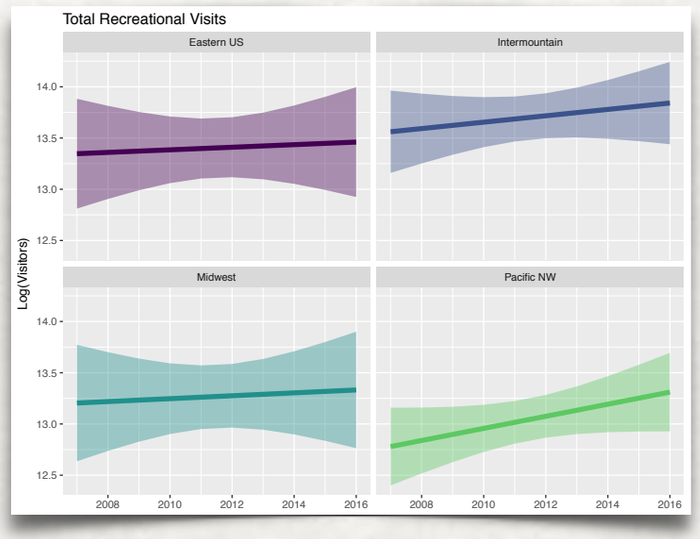
BUT... BUT... WHERE ARE THE PLOTS?!

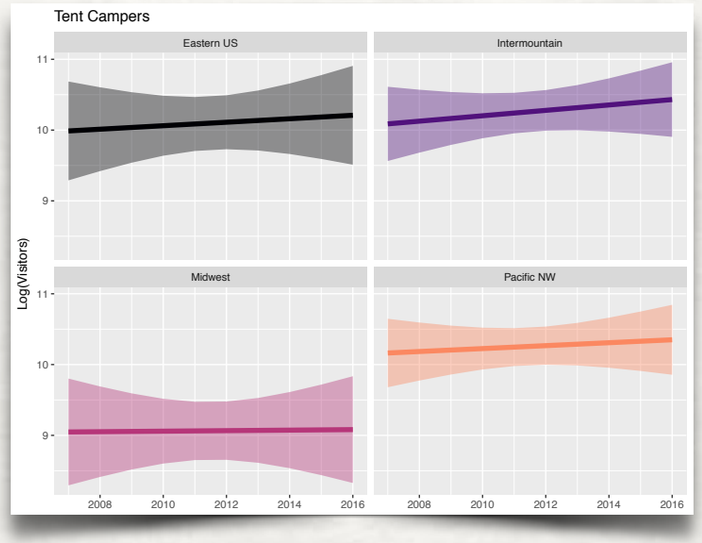
THEY ARE MERELY OBJECTS IN THE SKY FOR NOW

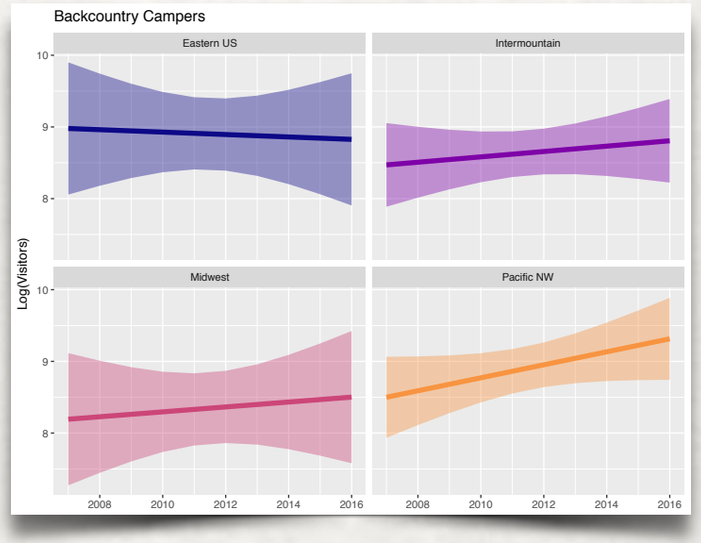
AUDIENCE PARTICIPATION!

Remember, `map` functions return objects; in order to see our plots, we have to *print* them somehow. How can we do that?

```
walk2(.x = c("rec.pdf", "tent.pdf", "backcountry.pdf"),
      .y = nps_plots,
      ggsave,
      width = 8, height = 6)
```







BONUS MATERIAL

You *may* have been thinking - "given my newfound knowledge of `pmap`, couldn't we have extracted that data in one step instead of copying and pasting *almost* the same thing?"

YES. Yes we could.

```
showoff <- pmap_df(
  .l = list(
    "year" = rep(2007:2016, 3),
    "table_prefix" = c(rep("recreation_visits", 10),
                       rep("tent_campers", 10),
                       rep("backcountry_campers", 10)),
    "url" = c(rep(url_recvisits, 10),
              rep(url_tent, 10),
              rep(url_back, 10))
  ),
  .f = download_nps_year
)
```

(This creates one big data frame; we'd probably want to add a line to download_nps_year to add the visitor type as well as the year.)

BUT WAIT! THERE'S MORE!

RANDOM PURRR THINGS THAT YOU MIGHT LIKE

- `partial`, for when you want to create a partially specified version of a function (eg, `q25 <- partial(quantile, probs = 0.25, na.rm = TRUE)`)
- `flatten`, for removing hierarchies from a list
- `safely, quietly, possibly` - can be helpful especially when writing functions or packages
- `invoke, modify`
- List-columns can be your friend if you want to store complex data, results, etc in a tidy way; purrr functions can be really helpful when working with these. Jenny Bryan's tutorial is a great resource here.

```
> dplyr::starwars %>% select(name, height, hair_color, skin_color, films, vehicles)
# A tibble: 87 x 6
                 name height    hair_color  skin_color     films  vehicles
                <chr>  <int>         <chr>       <chr>    <list>    <list>
 1    Luke Skywalker    172         blond        fair <chr [5]> <chr [2]>
 2             C-3PO    167          <NA>        gold <chr [6]> <chr [0]>
 3             R2-D2     96          <NA> white, blue <chr [7]> <chr [0]>
 4       Darth Vader    202          none       white <chr [4]> <chr [0]>
 5       Leia Organa    150         brown       light <chr [5]> <chr [1]>
```

PURRR RESOURCES

FOR THE CURIOUS

cafepress.com

- Official page: purrr.tidyverse.org
- RStudio cheatsheet (under "Apply Functions")
- R for Data Science: Lists & iteration
- DataCamp: Writing Functions in R
- Charlotte Wickham's purrr tutorial
- Jenny Bryan's purrr tutorial; particularly great if you love the idea of list-columns
- Hadley Wickham on purrr vs *apply
- Fun use cases:
  - A roundup of blog posts curated by Mara Averick
  - Peter Kamerman on bootstrap CIs with purrr
  - Ken Butler on handling errors with safely/possibly

THANK YOU & HAPPY PURRR-ING

photo: Nick Strayer, of his cat Flumpert, via Lucy
bad cropping by me