# 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")

JENNIFER THOMPSON, MPH @JENT103

R-LADIES LOUISVILLE **INAUGURAL** MEETUP 🎉

APRIL 2018

“

”

“

ITERATION:

”

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# ITERATION:

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AUDIENCE PARTICIPATION!

WHAT ARE SOME EXAMPLES?

# WAYS TO ITERATE IN R

doctordisruption.com

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HOW DO **YOU** ITERATE?

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  - PROS: easy (in the short run)
  - CONS: hard to maintain, edit

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  - 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(…)))`

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- **mapply, sapply, tapply, vapply**
  - PROS: efficient at their specific purposes
  - CONS: mystifying, inconsistent syntax

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# 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:**

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- 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

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## 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)*

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```
map(.x = …, .f = …)

map2(.x = …, .y = …, .f = …)

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

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[1] 3

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Great if we want to continue iterating!

If we *really* want a new vector:

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

# EXAMPLE TIME!

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GITHUB.COM/JENNIFERTHOMPSON/RLADIESINTROTOPURRR

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- **Not goals:**
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- **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

## IT'S ALMOST NATIONAL PARK WEEK!

**AUDIENCE PARTICIPATION!**

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ALTERNATELY: PURRR_DATA.RDATA

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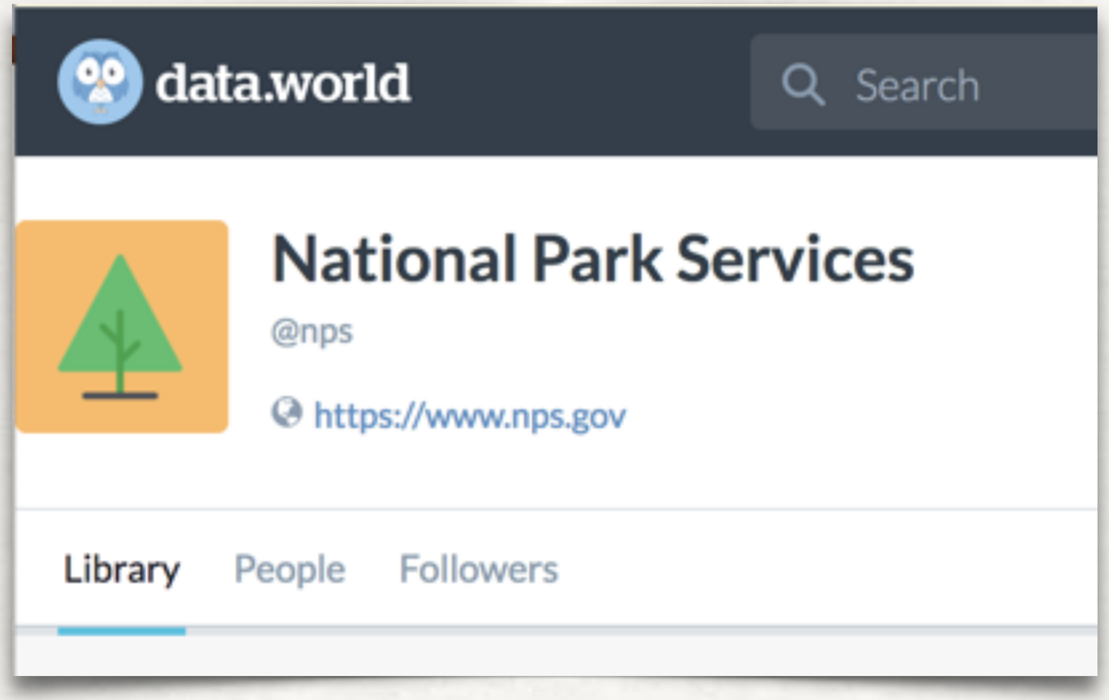


# data.world/nps

*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.*

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# TOTAL RECREATIONAL VISITS

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10 files

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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**
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| 1 | Blue Ridge PKWY | 1 | 16,309,307 | 5.93% |
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| 3 | Gateway NRA | 3 | 9,431,021 | 3.43% |
| 4 | Great Smoky Mountains NP | 4 | 9,044,010 | 3.29% |
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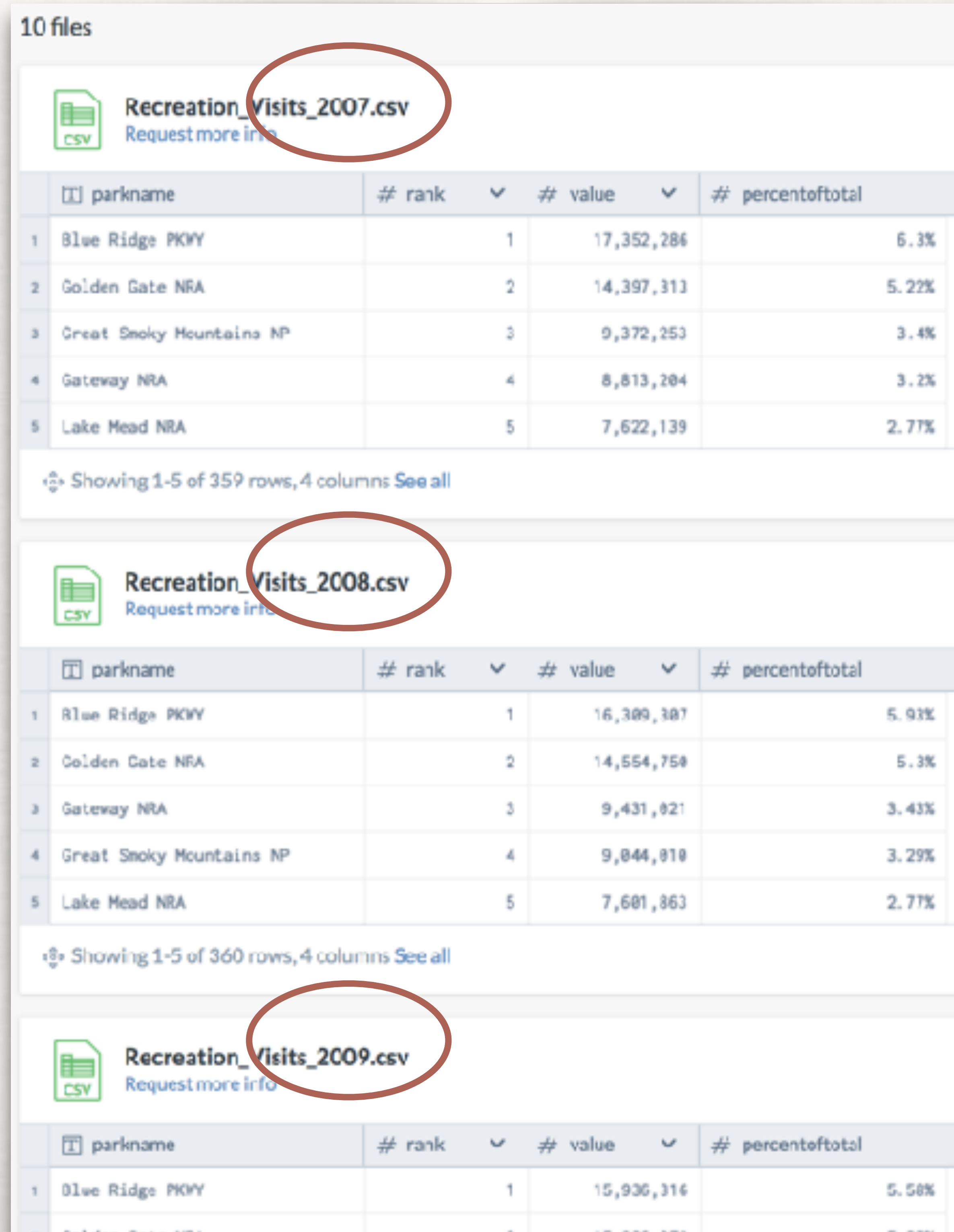
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**AUDIENCE PARTICIPATION!**

1. FILL IN THE BLANK

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

# USING MAP + USER-DEFINED FUNCTIONS

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## STEP 1: WRITE FUNCTION

```
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  table_prefix,
  url
){
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        "SELECT * FROM %s_%s”,
        table_prefix, year
      )
    ),
    dataset = url
  ) %>%
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}
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# USING MAP + USER-DEFINED FUNCTIONS

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what we’re iterating over

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```
## 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
)
```

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what we’re iterating over

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```
## Same thing for backcountry, tent campers
```

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## Download tent camper data
url_tent <-
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tent_visits <- map_df(
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  .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 |
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1-10 of 20 rows    Previous 1 2 Next

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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

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*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),
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  .f = ~ purrr::reduce(list(., park_index), left_join, by = "parkname")
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particularly handy if you have >2 data.frames to merge!

```
> head(datalist[[1]])
# A tibble: 6 x 7
             parkname  value  year                name  type location       region
                <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
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**AUDIENCE PARTICIPATION!**

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

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# LET'S RUN SOME MODELS!

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- REC VISITS DATA
- TENT CAMPER DATA
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map(datalist, ~ lm(value = year * region, data = .))
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```
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```

`orgmod_list`: list of `lm` fits

- REC VISITS MODEL
- TENT CAMPER MODEL
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par(mfrow = c(1, 3))
walk(
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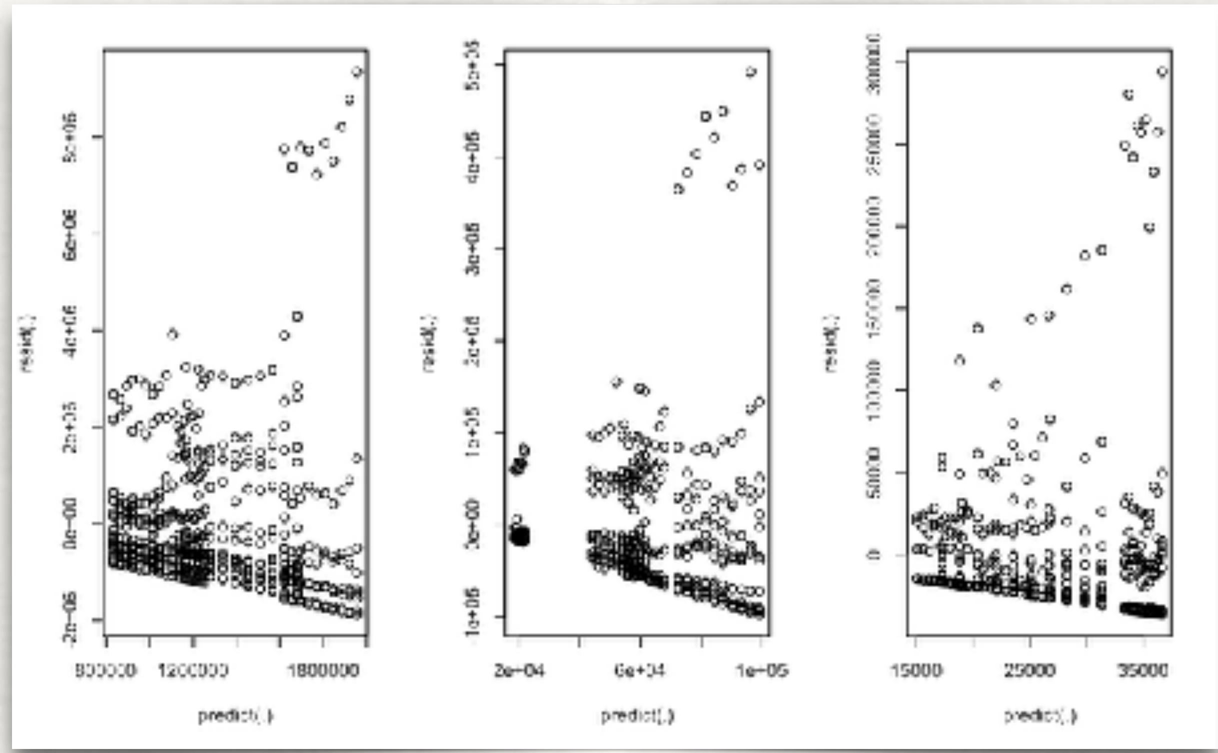
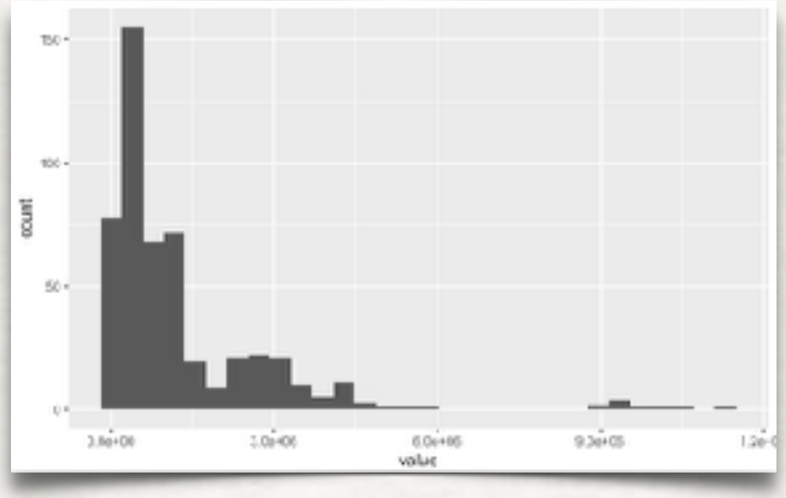
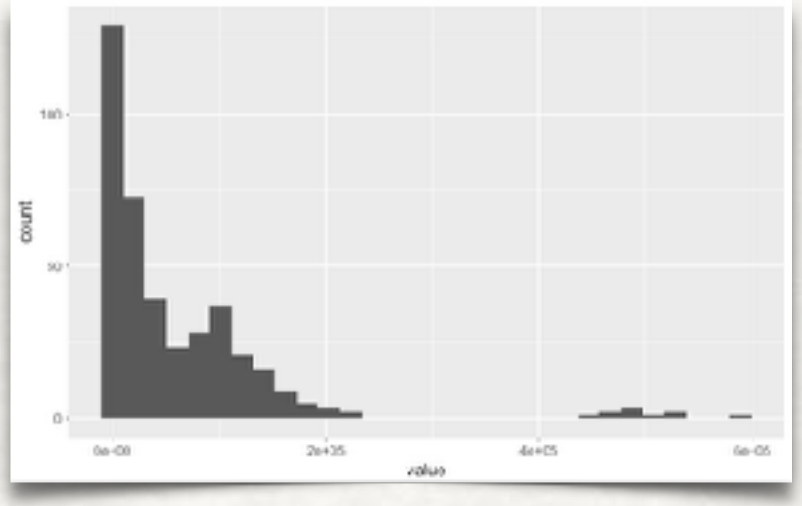


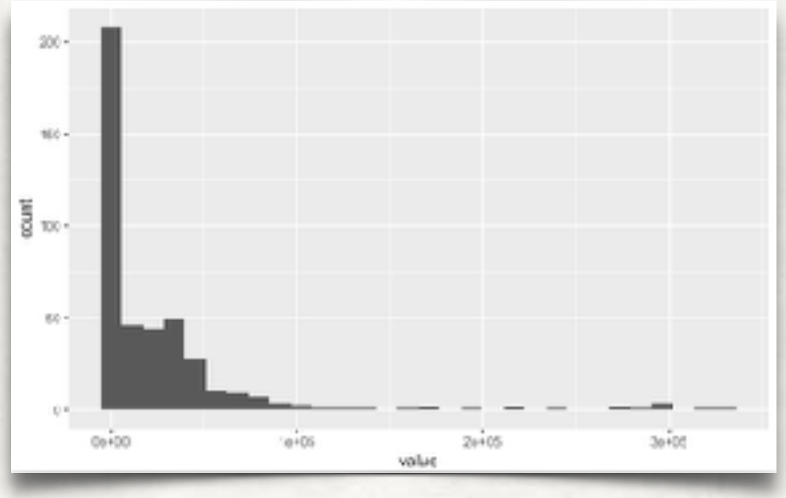
# USE PURRR TO FIX IT

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?

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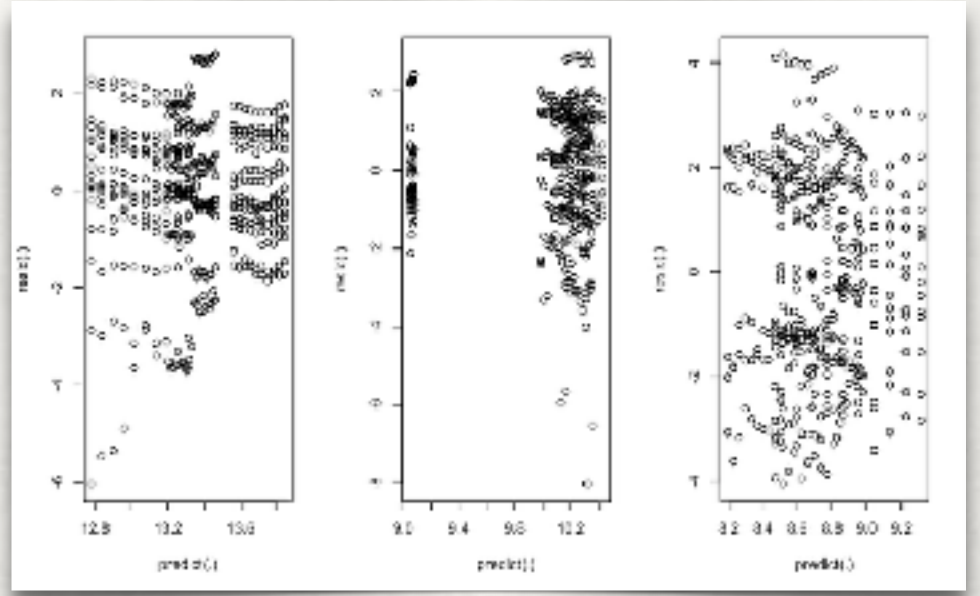

# TIME FOR SOME NUMBERS

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

**AUDIENCE PARTICIPATION!**

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One-line method:

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

```
logmod_list %>%
  map(summary) %>%
  map_dbl(.f = “adj.r.squared") %>%
  round(2)
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From each element of .x, take the element named "adj.r.squared"

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Either way:

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

# VISUALIZE RESULTS

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For each model, we're going to:

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Points to emphasize:

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

# VISUALIZATION PREP

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

```
preddata <- cross_df(
  .l = list("year" = unique(pluck(datalist, 1, "year")),
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For each visit type, create data.frame with predicted # for each year/region

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pred_list <- logmod_list %>%
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# VISUALIZATION PREP

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

```
preddata <- cross_df(
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```

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List of lm fits ->

List of lists! ->

List of data.frames we transformed ->

List of data.frames we added year/region to

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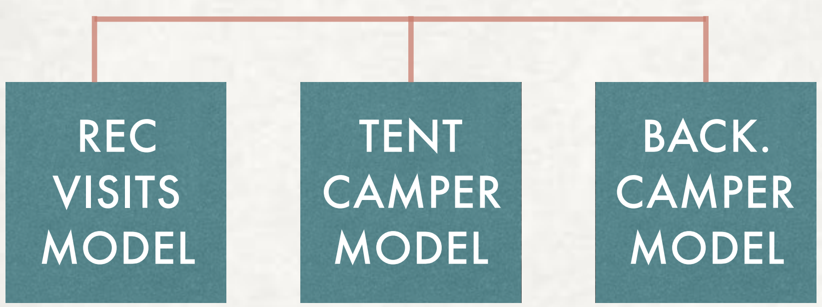
`logmod_list`: list of lm fits



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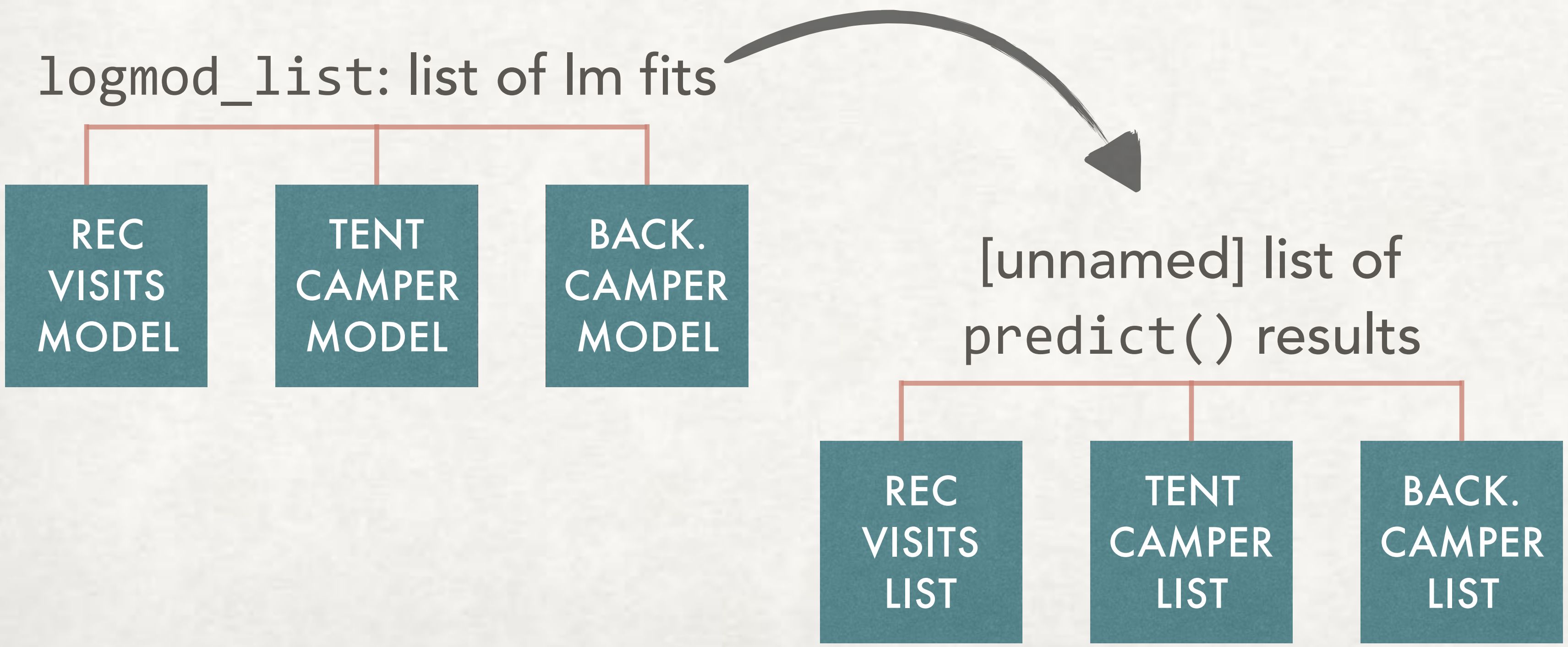

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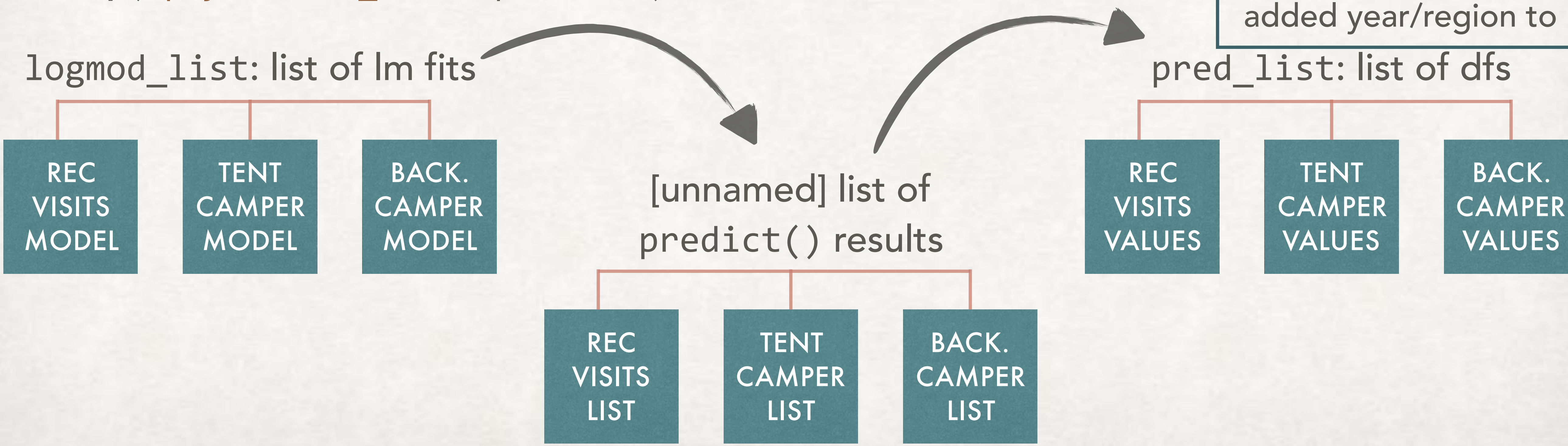

# VISUALIZATION PREP

**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?

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**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)

}
```

# VISUALIZATION PREP

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    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.

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plot_args <- list(
```

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Time for some **parallel mapping!**

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

```
plot_args <- list(
  "df" = pred_list,
```

# 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"),
```

# 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",
```

# VISUALIZE RESULTS

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

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

# VISUALIZE RESULTS

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                  "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

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## A SCHEMATIC

`pred_list`: list of dfs (`df`)

- REC VISITS VALUES
- TENT CAMPER VALUES
- BACK. CAMPER VALUES

vector of viridis color scale choices (`vscale`)

- REC VISITS = VIRIDIS
- TENT VISITS = MAGMA
- BACK. VISITS = PLASMA

vector of title strings (`maintitle`)

- TOTAL REC VISITS
- TENT CAMPERS
- BACK-COUNTRY CAMPERS

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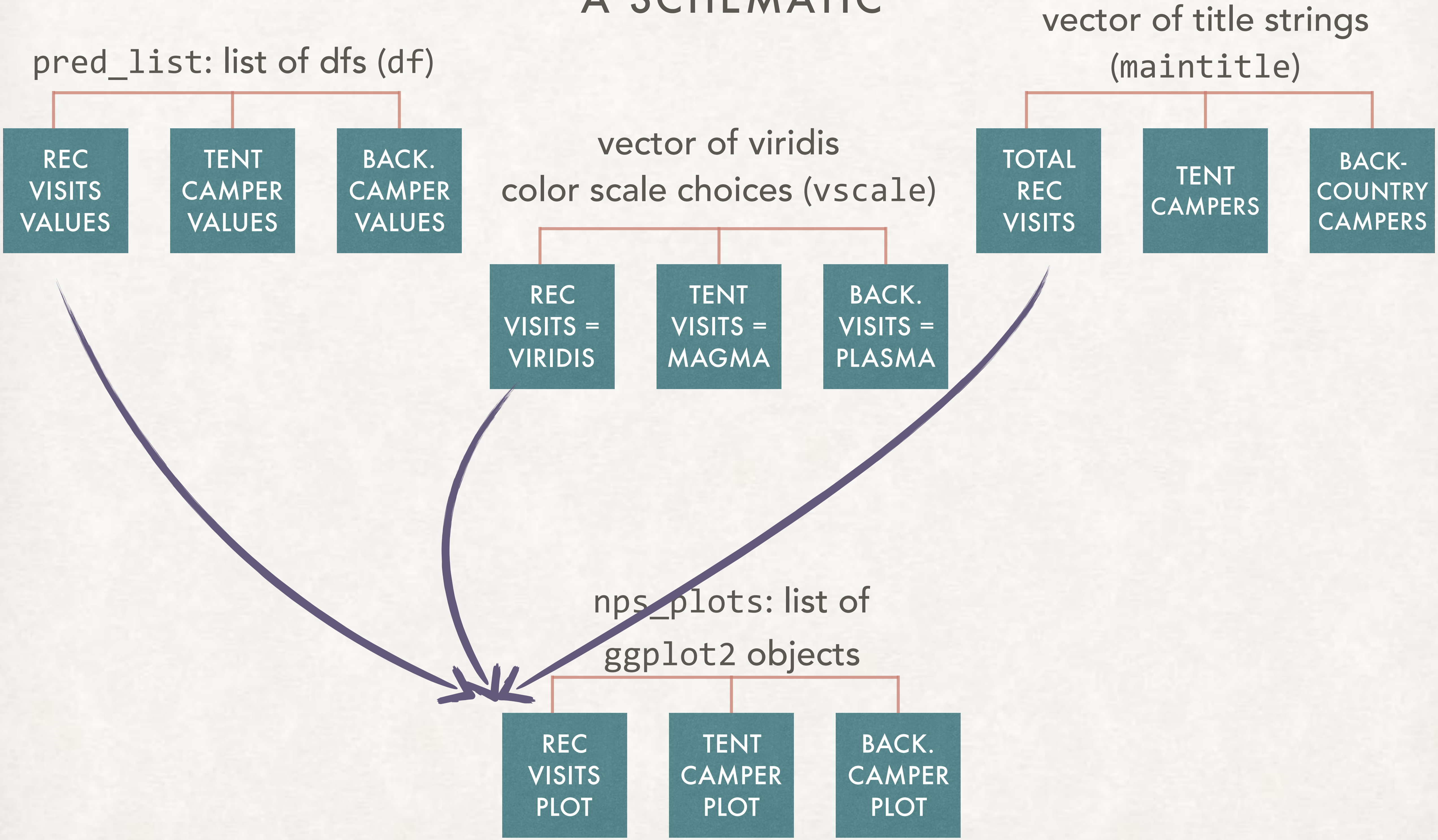
`nps_plots`: list of `ggplot2` objects

- REC VISITS PLOT
- TENT CAMPER PLOT
- BACK. CAMPER PLOT

# WHAT JUST HAPPENED?

## A SCHEMATIC



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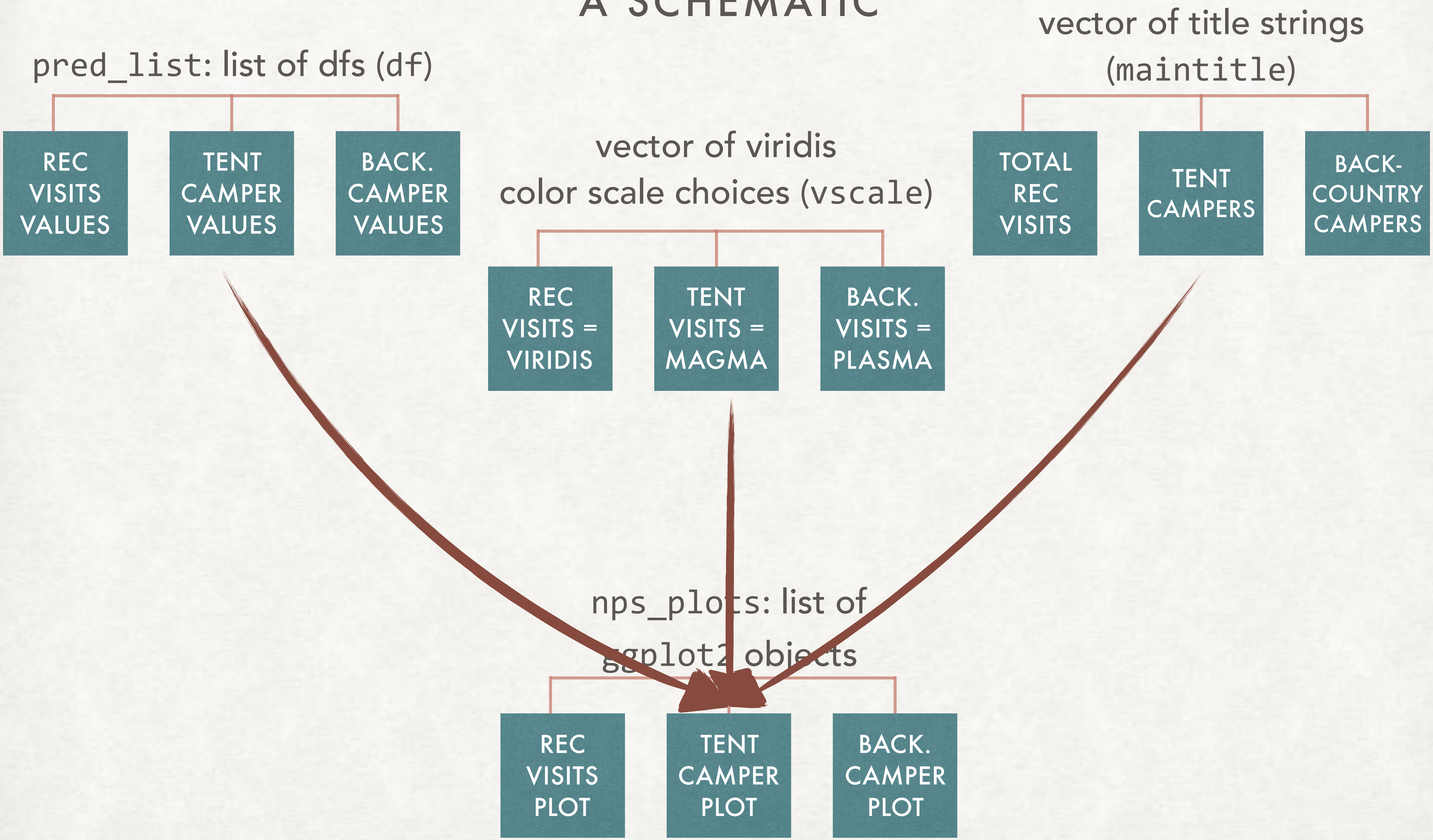

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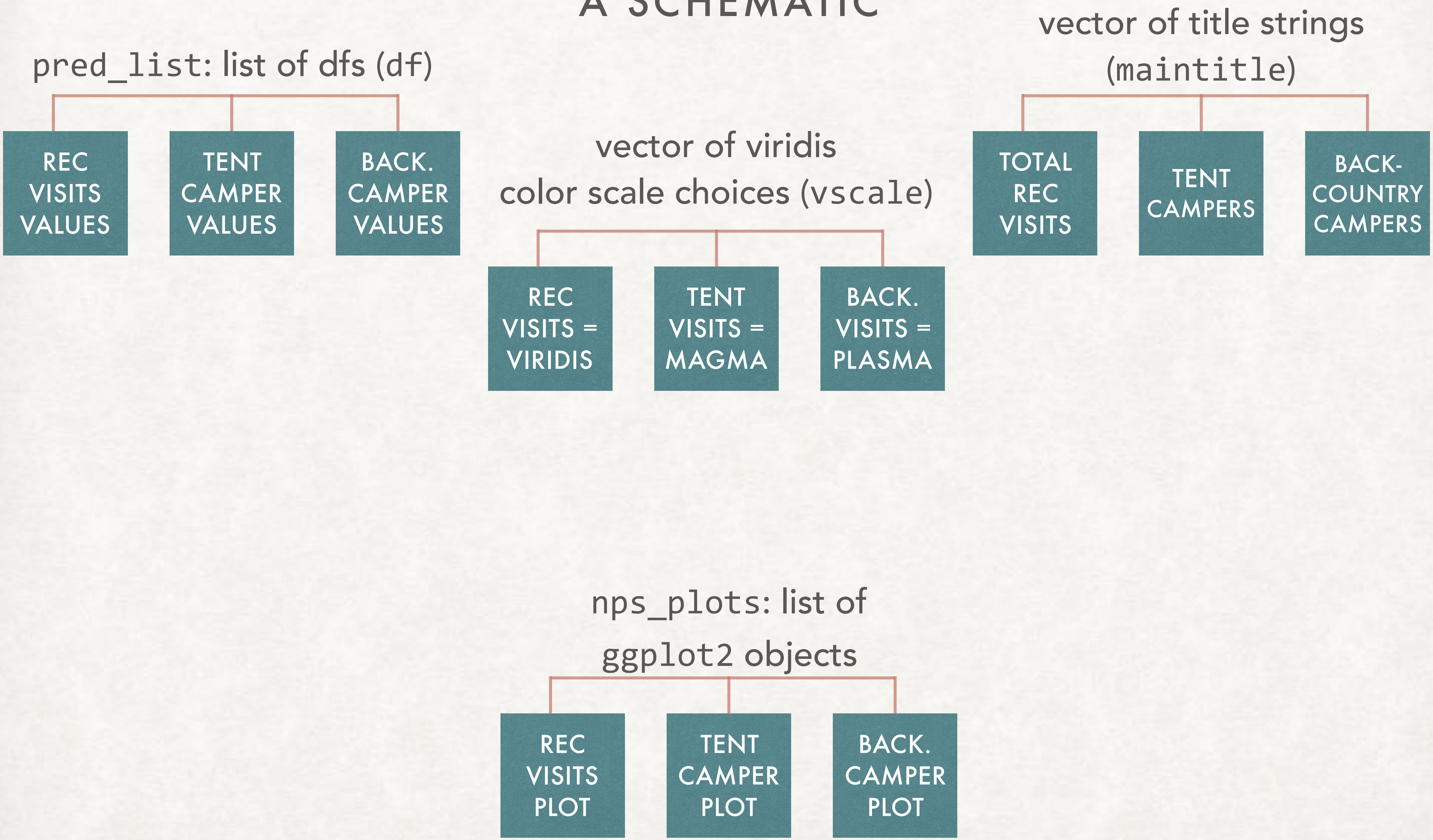

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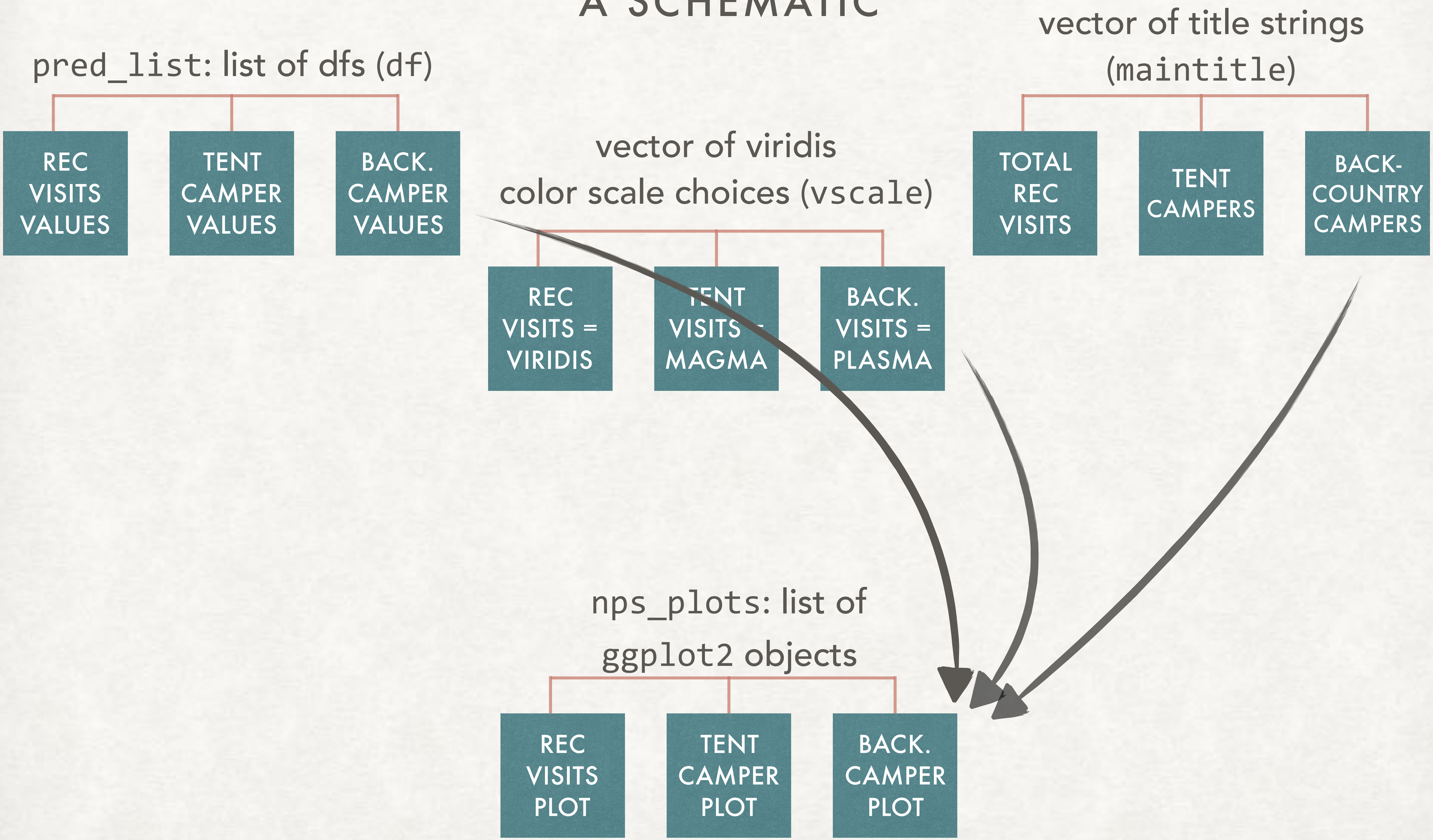

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pred_list: list of dfs (df)

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nps_plots: list of ggplot2 objects

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# 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?

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

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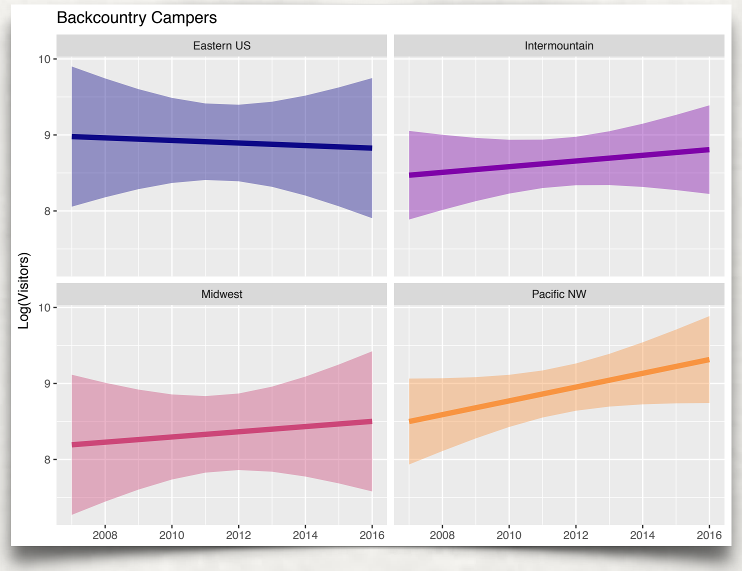

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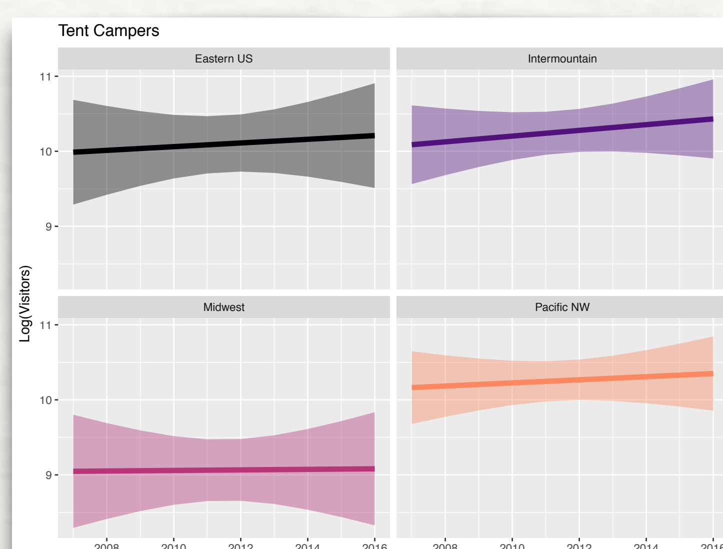


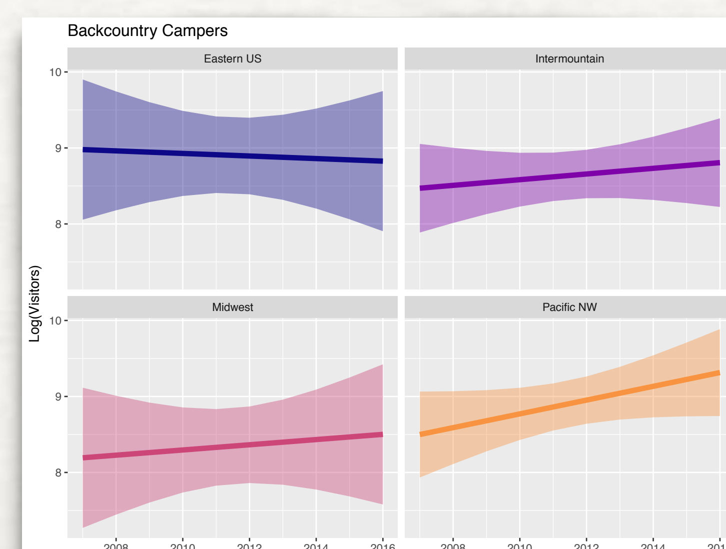

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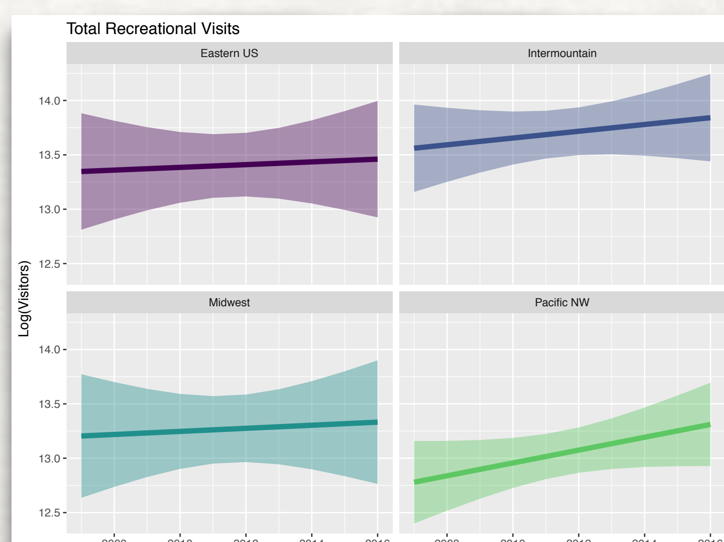


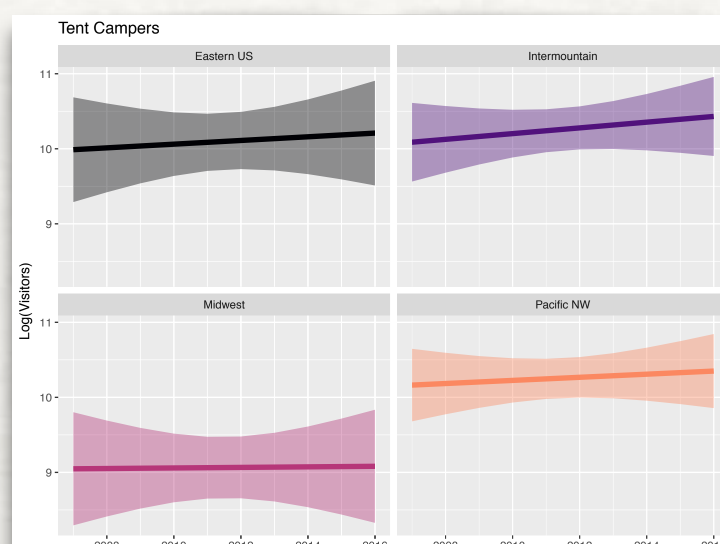


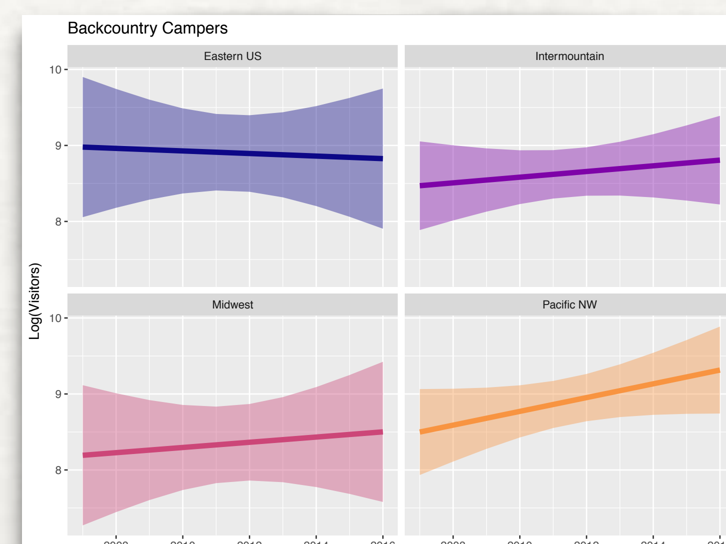

# BONUS MATERIAL

You *may* have been thinking: “given my newfound knowledge of `pmap()`, couldn’t we have extracted that data in one step instead of copying & 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.

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```
> 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 D'Agostino McGowan*
*bad cropping by me*