

INTRODUCTION TO PURRR

WELCOME R-LADIES!

WANT TO PLAY ALONG?

CODE AVAILABLE AT
[GITHUB.COM/
JENNIFERTHOMPSON/
RLADIESINTROTOPURRR](https://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: efficient at their specific purposes
 - CONS: mystifying, inconsistent syntax



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!

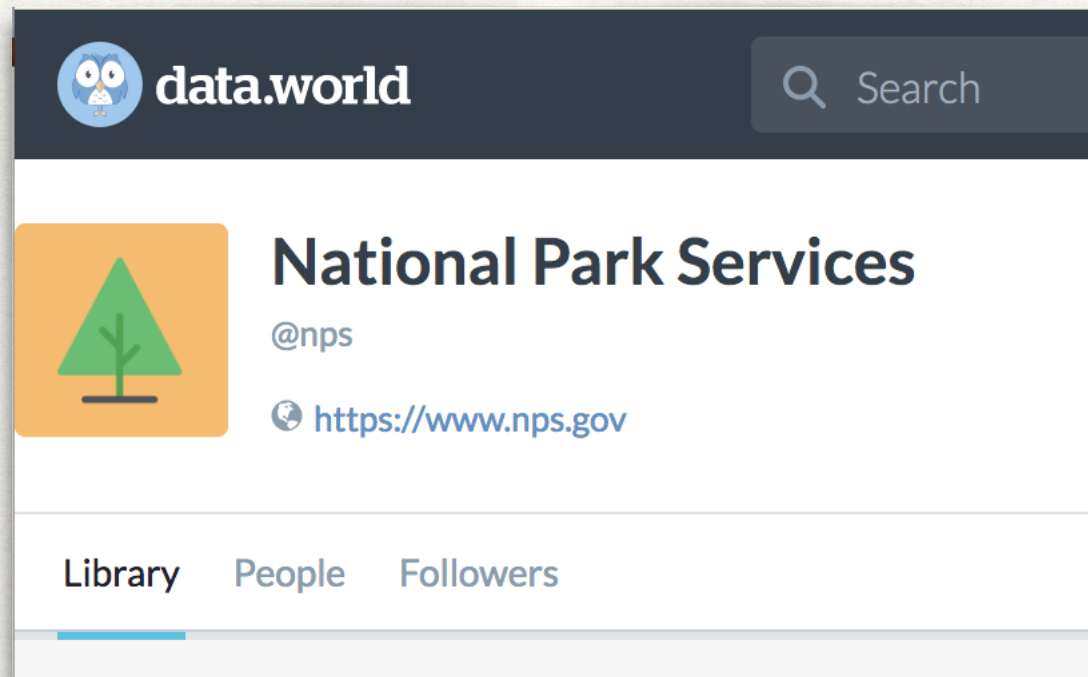
PLAY ALONG IF YOU LIKE

[GITHUB.COM/JENNIFERTHOMPSON/RLADIESINTROTOPURRR](https://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!



data.world/nps

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

AUDIENCE PARTICIPATION!

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


ALTERNATELY:
PURRR_DATA.RDATA

*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	5.93%
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, ← what we're iterating over
  .f = download_nps_year, ← what we're doing
  table_prefix = "recreation_visits",
  url = url_recvisits
)
  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 = ~purrr::reduce(list(., park_index), left_join, by = "parkname")  
)  
  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

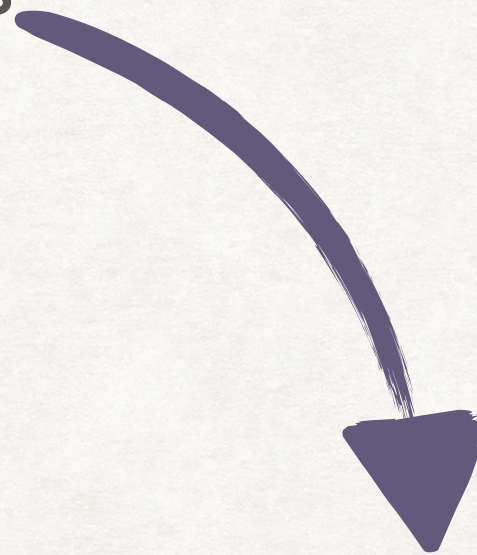
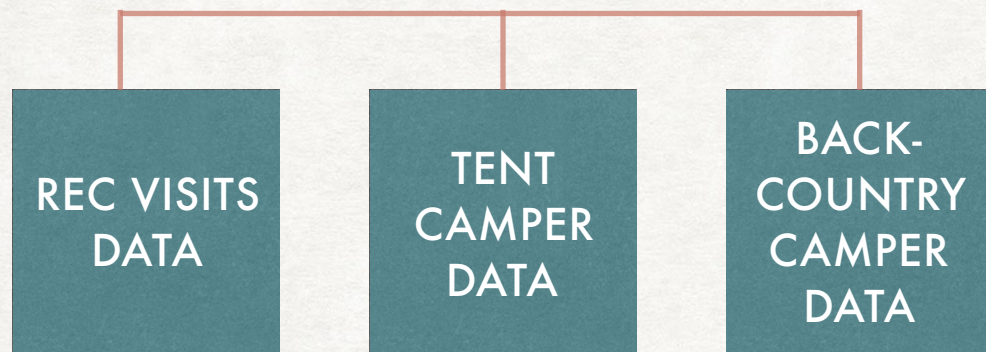
**AUDIENCE
PARTICIPATION!**

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

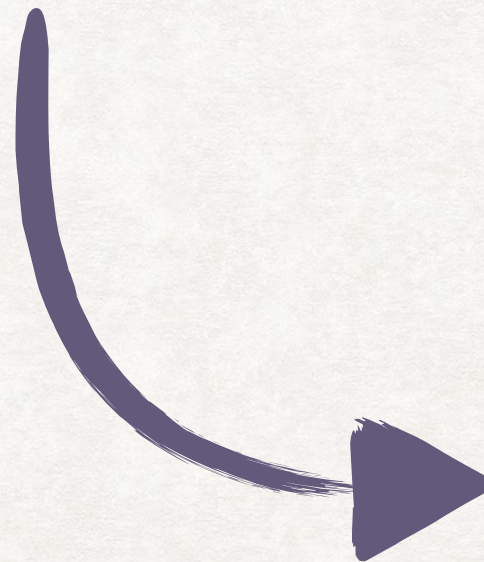
LET'S RUN SOME MODELS!

PREDICT # VISITORS BY YEAR, REGION, INTERACTION

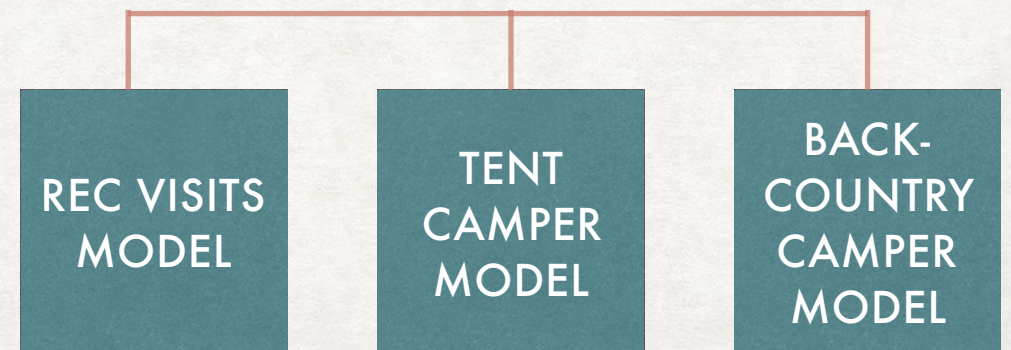
datalist: list of data.frames



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



orgmod_list: list of lm fits



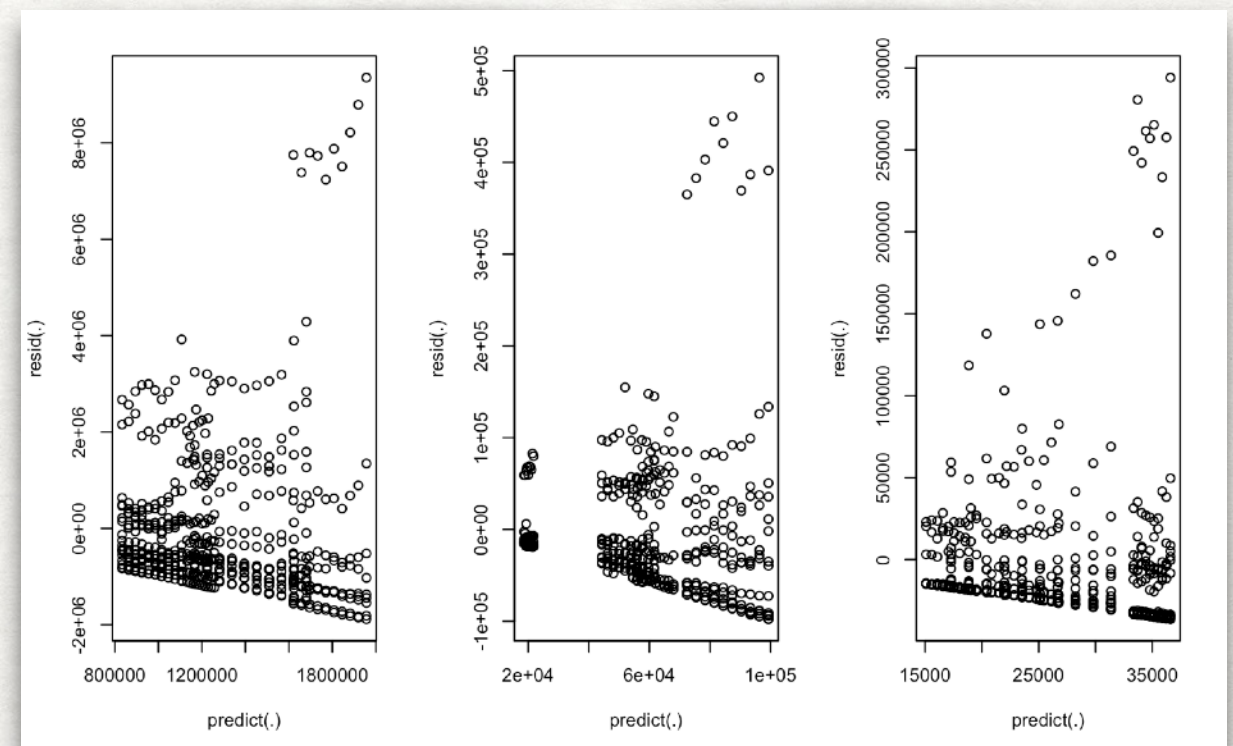
NO ERRORS MEANS WE'RE GOOD, RIGHT?

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

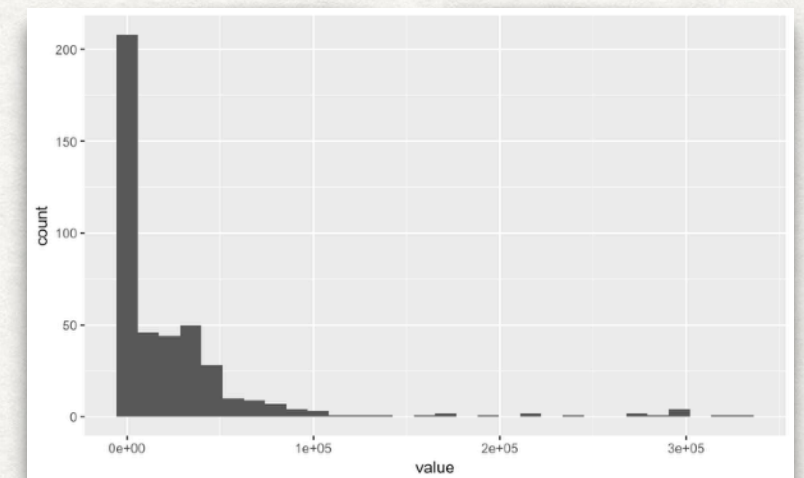
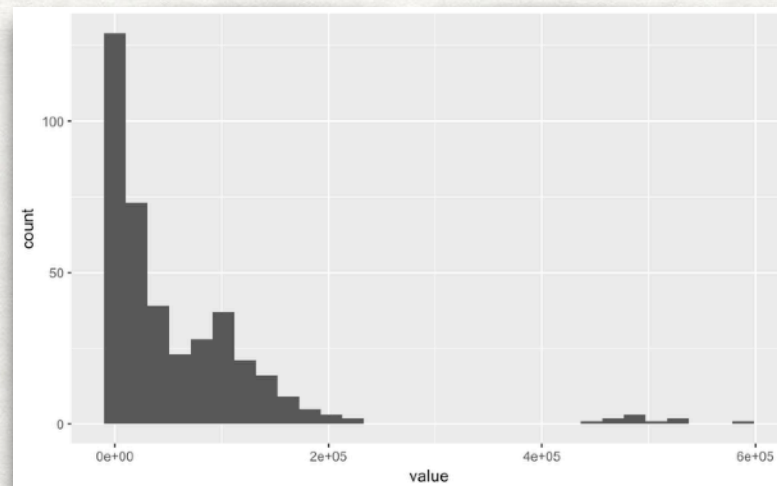
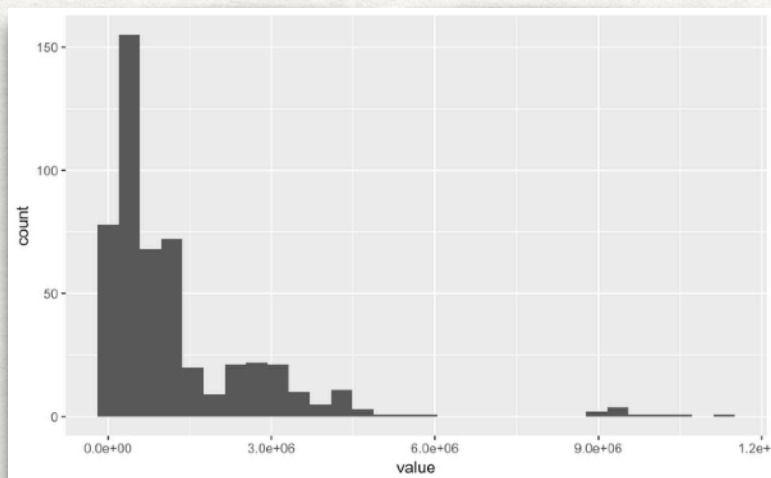
```
par(mfrow = c(1, 3))  
walk(  
  orgmod_list,  
  ~ plot(resid(.), predict(.))  
)
```



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

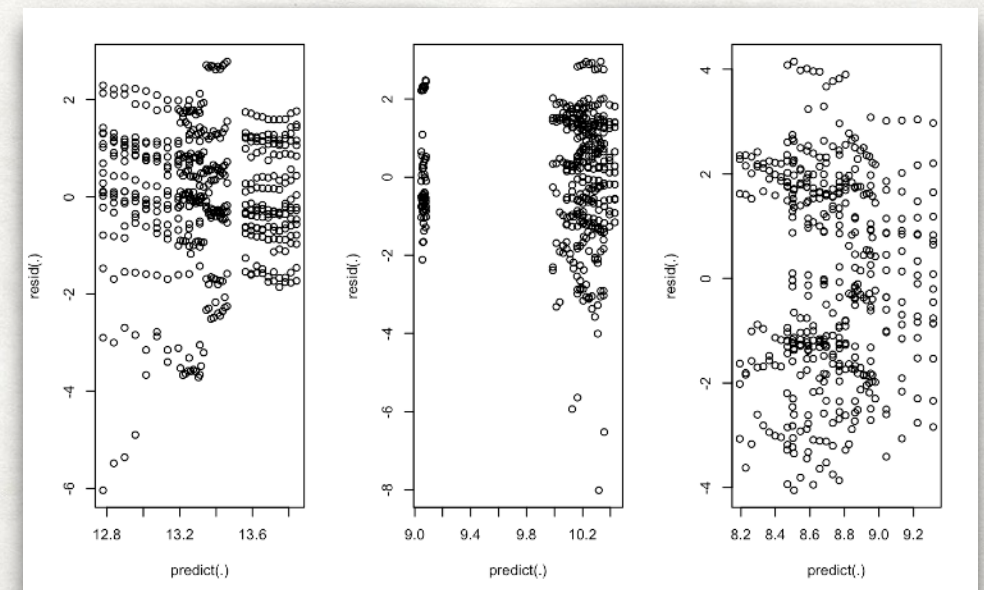
Use `map()` (and `dplyr`) to transform our outcome variable in place

```
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_db1!

One-line method:

```
round(map_db1(logmod_list, ~ summary(.)$adj.r.squared), 2)
```

Pipe method:

```
logmod_list %>%
```

```
map(summary) %>%
```

```
map_db1(.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 `purrr::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

logmod_list: list of lm fits

REC
VISITS
MODEL

TENT
CAMPER
MODEL

BACK.
CAMPER
MODEL

[unnamed] list of
predict() results

REC
VISITS
LIST

TENT
CAMPER
LIST

BACK.
CAMPER
LIST

pred_list: list of dfs

REC
VISITS
VALUES

TENT
CAMPER
VALUES

BACK.
CAMPER
VALUES

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.

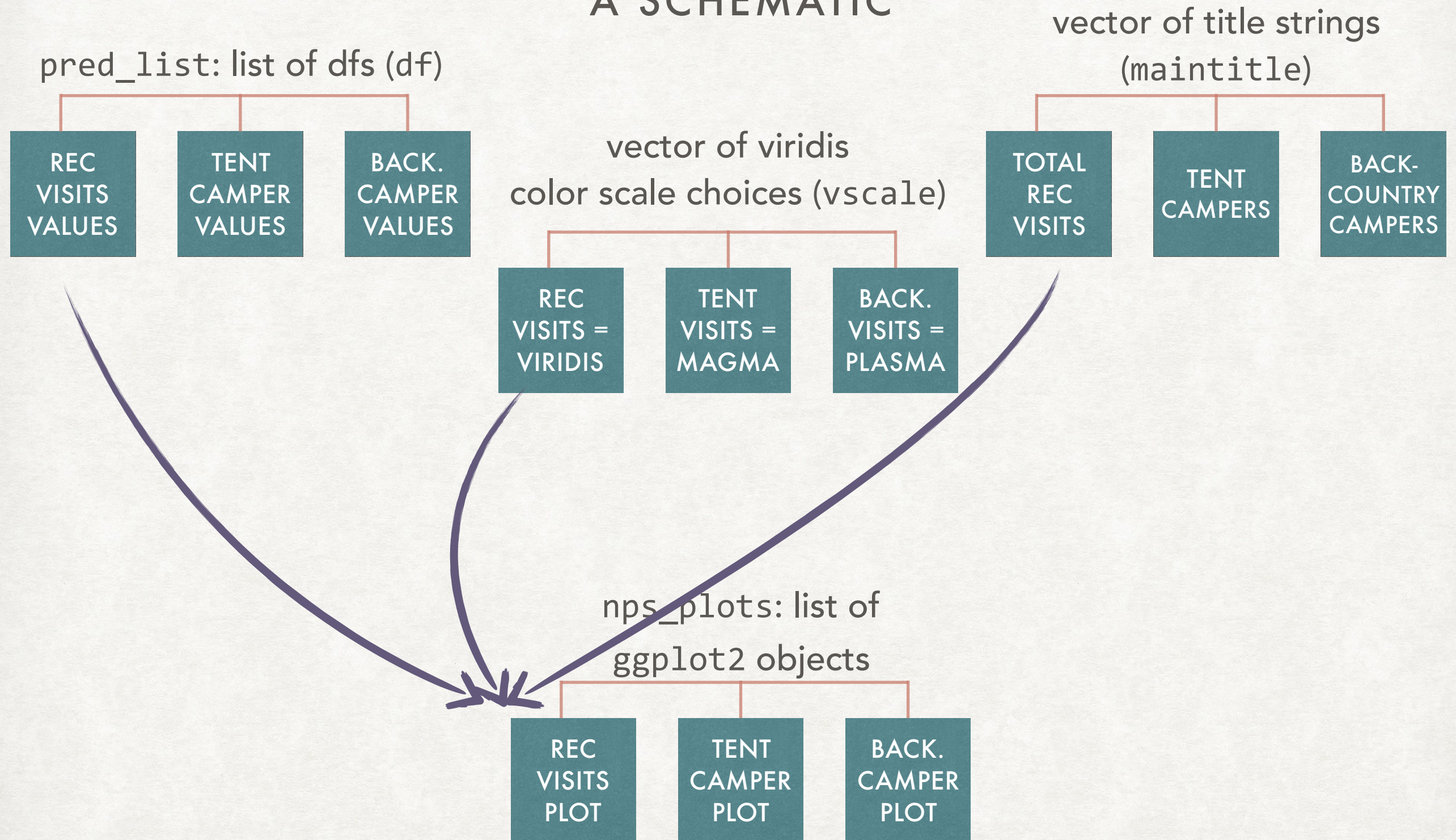
```
plot_args <- list(  
  "df" = pred_list,  
  "vscale" = c("D", "A", "C"),  
  "maintitle" = c("Total Recreational Visits",  
                  "Tent Campers",  
                  "Backcountry Campers")  
)
```

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



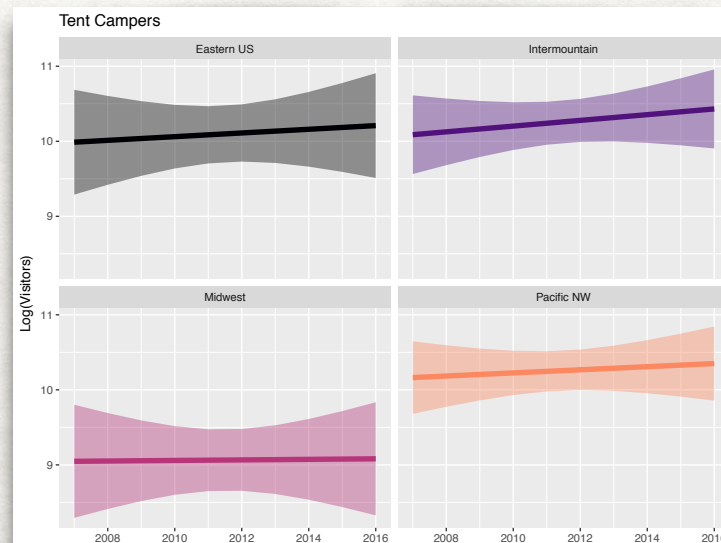
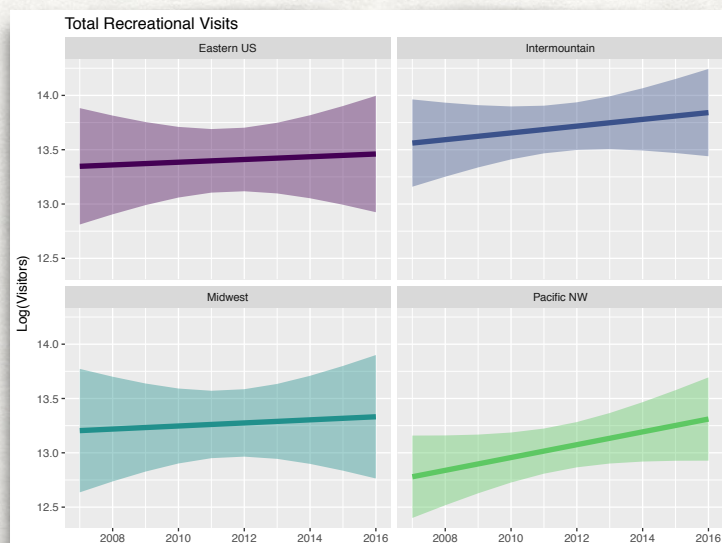
BUT... BUT... WHERE ARE THE PLOTS?!

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 & 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

- 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](#)



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THANK
YOU &
HAPPY
PURRR-
ING



*photo: Nick Strayer, of his cat Flumpert, via Lucy D'Agostino McGowan
bad cropping by me*