INTRODUCTION TO PURRR

WELCOME!

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
AXIAL HEALTHCARE ◆ NOVEMBER 30, 2017

“

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ITERATION:

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DOING THE SAME* THING TO A BUNCH OF THINGS

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— *Jennifer Thompson*

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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
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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

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STOP WORRYING AND

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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

MAP(): WHERE IT'S AT

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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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map(v1, ~ . * 3)
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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_dbl(v1, ~ . * 3)
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Examples of other `map` variants:

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

EXAMPLE TIME!

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  - Write most efficient code possible
  - Complex statistical analysis

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- **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

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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

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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

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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

```
download_nps_year <- function(
  year = 2007:2016,
  table_prefix,
  url
){
  data.world::query(
    data.world::qry_sql(
      sprintf(
        "SELECT parkname, value FROM %s_%s",
        table_prefix, year
      )
    ),
    dataset = url
  ) %>%
   ## Add a year variable
   mutate(year = year)
}
```

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STEP 2: EXTRACT EACH DATASET

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STEP 1: WRITE FUNCTION

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download_nps_year <- function(
  year = 2007:2016,
  table_prefix,
  url
){
  data.world::query(
    data.world::qry_sql(
      sprintf(
        "SELECT parkname, value FROM %s_%s",
        table_prefix, year
      )
    ),
    dataset = url
  ) %>%
   ## Add a year variable
   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
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USING MAP + USER-DEFINED FUNCTIONS

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what we're iterating over

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what we're iterating over

what we're doing

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)
```

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>
Big Thicket NPRES	140489	2010
City of Rocks NRES	92484	2010
Glacier Bay NP & PRES	551353	2015
Rock Creek Park	1883457	2010
Rocky Mountain NP	4517585	2016
Bryce Canyon NP	2365110	2016
Cedar Breaks NM	493147	2011
Little River Canyon NPRES	197693	2008
Hopewell Furnace NHS	52870	2012
Fredericksburg & Spotsylvania NMP	899936	2010

1-10 of 10 rows

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1-10 of 10 rows

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 = ~ reduce(list(., park_index), left_join, by = "parkname")
)
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)
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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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# A tibble: 6 x 7
            parkname  value  year             name  type location          on
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LET'S RUN SOME MODELS!

PREDICT # VISITORS BY YEAR, REGION, INTERACTION

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

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- **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

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```
par(mfrow = c(1, 3))
walk(
  orgmod_list,
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)
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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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Use `map` (and dplyr) to transform our outcome variable in place

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datalist <-
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```

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

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

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walk(
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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!

HOW CAN WE DO THAT?

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One-line method:

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

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```
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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```

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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:

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

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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

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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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)
```

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

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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

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  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?

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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)

}
```

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  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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```

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

VISUALIZE RESULTS

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```
plot_args <- list(
  "df" = pred_list,
  "vscale" = c("D", "A", "C"),
```

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

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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")
```

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VISUALIZE RESULTS

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                  "Tent Campers",
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)
```

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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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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```

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.

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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