Final results for the 2021 USMS ePostal National Championships have been posted. We'll take a look at them using some basic summary stats and charts, then work up the data from inclusion in Shiny application built to present it interactively.

If you'd like to just skip to playing with the app and not bother about working up the data the app is available here.

This will be a tutorial style post, where I'll prioritize making the code clear and readable, while perhaps sacrificing efficiency. No building functions and them `map`ping them like I sometimes do.

With that in mind let's grab some packages. We'll use `readr` to actually read in the data set. Then `dplyr` and `stringr` to work it up and finally `ggplot2` and `flextable` to present it at various points throughout the article.

```
library(readr)
library(dplyr)
library(stringr)
library(ggplot2)
library(flextable)


flextable_style <- function(x) {
  x %>%
    flextable() %>%
    bold(part = "header") %>% # bolds header
    bg(bg = "#D3D3D3", part = "header") %>%  # puts gray background
behind the header row
    autofit()
}
```

I've already collected the data from USMS, wrestled it into a .csv file and hosted that on Github (you're all very welcome). We can grab it directly with `read_csv`.

```
Postal <- read_csv("https://raw.githubusercontent.com/gpilgrim2670/MastersPostal/
master/Postal_Raw.csv")
```

Last year I did a big analysis of the 2020 ePostal results and another on the ePostal over the past two+ decades. Rather than just repurposing all that code (which you're welcome to do if you'd like) we'll just take a quick look at the 2021 results before working up all the data, from all the years for the Shiny app.

How Many People Participated This Year?

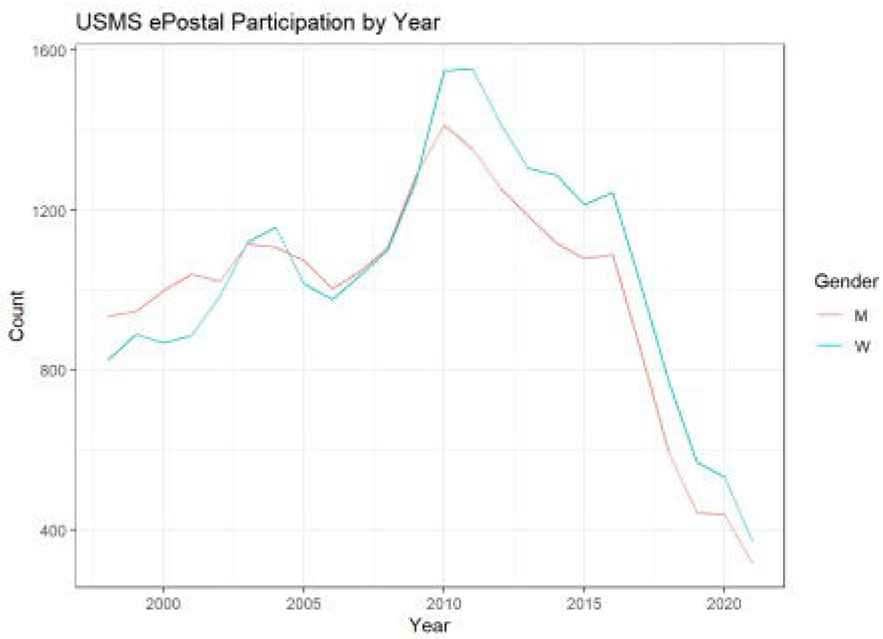
```
Postal %>%
  filter(Year == "2021") %>%
  group_by(Gender) %>%
  summarise(Count = n()) %>%
  flextable_style()
```

Gender Count

Gender	Count
M	317
W	372

How Does That Compare to Previous Years?

```
Postal %>%
  group_by(Year, Gender) %>%
  summarise(Count = n()) %>%
  ggplot() +
  geom_line(aes(x = Year, y = Count, color = Gender)) +
  theme_bw() +
  labs(title = "USMS ePostal Participation by Year")
```



It's fewer people. Probably COVID, and the general trends discussed here. Moving on.

Shiny App

Cleaning Data for a Shiny App

The data we've already downloaded and named `Postal` contains the as-reported results from all ePostals from 1998 through 2021. Let's take a look.

```
names(Postal)
## [1] "Place"           "Name"            "Age"             "USMS_ID"
## [5] "Distance"        "Club"            "Gender"          "Year"
## [9] "National_Record"
```

Pretty self explanatory column names, and quite a bit of information. There's more though that we can tease out.

I'd like to add to `Postal` in the following ways:

1. Age groups. The ePostal is scored by age group, 18-24 and then by 5 year windows thereafter (25-29 etc.)
2. Athlete's relative place within their age and gender category by year
3. An athlete's average 50 split, based on distance traveled and assuming a 25 yard pool
4. Cleaning up USMS identification to identify athletes across years
5. Club sizes. USMS defines club sizes and scores based on those sizes, both by gender and total size by year
6. Summary stats for clubs by year
   - Total distance swam
   - Club rankings by gender
   - Average distance traveled and 50 split by gender
   - Average age by gender

Since this is headed for a Shiny app, where it will be displayed the goal will be to make information readable, which will involve some sacrifices. For example an athlete's relative place will be a string in the form of "Athlete place of Total place" (i.e. "1 of 54") rather than just a naked numeric.

Age Groups

Since we already have an `Age` column making an age group column is a simple matter of using `dplyr::case_when` to match the appropriate age range to the `Age`. We'll do this using `dplyr::between`. `between` takes three arguments - a value x, a left and a right. If x >= left & x <= right then `between` returns `TRUE`. Otherwise `between` returns `FASLE`. The resulting code is perhaps long, and there are more compact ways to do this, but it's also very readable, approximating written English. Readability is useful in the context of a blog entry and I'll continue to prioritize it throughout.

```
Postal <- Postal %>%
  mutate(
    Age_Group = case_when(
      between(Age, 0, 24) ~ "18-24",
      between(Age, 25, 29) ~ "25-29",
      between(Age, 30, 34) ~ "30-34",
      between(Age, 35, 39) ~ "35-39",
      between(Age, 40, 44) ~ "40-44",
      between(Age, 45, 49) ~ "45-49",
      between(Age, 50, 54) ~ "50-54",
      between(Age, 55, 59) ~ "55-59",
      between(Age, 60, 64) ~ "60-64",
      between(Age, 65, 69) ~ "65-69",
      between(Age, 70, 74) ~ "70-74",
      between(Age, 75, 79) ~ "75-79",
      between(Age, 80, 84) ~ "80-84",
      between(Age, 85, 89) ~ "85-89",
      between(Age, 90, 94) ~ "90-94",
      between(Age, 95, 99)~ "95-99",
      between(Age, 100, 104) ~ "100-104",
      TRUE ~ "NA" # if for some reason Age doesn't match any of the
above this will catch it and write the string 'NA'
    )
  ) %>%
```

```
  mutate(Age_Group = factor(Age_Group, levels = c("18-24", "25-29",
"30-34", "35-39", "40-44", "45-49", "50-54", "55-59", "60-64", "65-69",
"70-74", "75-79", "80-84", "85-89", "90-94", "95-99")))

# demonstration table
Postal %>%
  select(Place, Name, Distance, Year, Age, Age_Group, Gender) %>%
  head(5) %>%
  flextable_style()
```

Place	Name	Distance	Year	Age	Age_Group	Gender
1	Robert Wagner	5450	2021	19	18-24	M
2	Elliott Roman	5215	2021	24	18-24	M
3	William Kemp	4700	2021	22	18-24	M
4	Dylan Ogle	4250	2021	23	18-24	M
5	Gregory Willett	4035	2021	24	18-24	M

Athlete Relative Place

As discussed above the athlete place column will contain a string giving an individual athlete's place within their age and gender category for a given year. The point is to provide a means of comparing two athletes in the Shiny app. If Athlete A and Athlete B both finished 6th, but Athlete A did so in a category with 50 entrants vs. only 10 in Athlete B's category then that's worth knowing when comparing them.

Here we'll just `paste` an athlete's `Place`, the string `" of "` and the `max`imumn place from that age group together.

```
Postal <- Postal %>%
  group_by(Gender, Age_Group, Year) %>% # places are caluclated by
gender, age group and year
  mutate(Relative_Place = paste(Place, max(Place, na.rm = TRUE), sep =
" of ")) # use paste to build string

# demonstration table
Postal %>%
  select(Place, Name, Distance, Year, Age_Group, Gender,
Relative_Place) %>%
  head(5) %>%
  flextable_style()
```

Place	Name	Distance	Year	Age_Group	Gender	Relative_Place

Place	Name	Distance	Year	Age_Group	Gender	Relative_Place
1	Robert Wagner	5450	2021	18-24	M	1 of 5
2	Elliott Roman	5215	2021	18-24	M	2 of 5
3	William Kemp	4700	2021	18-24	M	3 of 5
4	Dylan Ogle	4250	2021	18-24	M	4 of 5
5	Gregory Willett	4035	2021	18-24	M	5 of 5

Average 50 Split

I'm accustomed to looking at 50 splits in swimming, and I think it's an interesting metric by which to evaluate ePostal results as well. An athlete's split can be calculated by converting the time (1 hour), then multiplying that number of seconds by 50 and then multiplying again by reciprocal distance to get a number in units of seconds per 50 yards. We can then `round` and `format` the result to make it pleasant to look at.

```
Postal <- Postal %>%
  mutate(Avg_Split_50 = (1 / Distance) * 60 * 60 * 50) %>% # compute
split
  mutate(Avg_Split_50 = format(round(Avg_Split_50, 2), nsmall = 2)) #
want two decimal places, even if the last one is a zero

# demonstration table
Postal %>%
  select(Place, Name, Distance, Year, Age_Group, Gender, Avg_Split_50)
%>%
  head(5) %>%
  flextable_style()
```

Place	Name	Distance	Year	Age_Group	Gender	Avg_Split_50
1	Robert Wagner	5450	2021	18-24	M	33.03
2	Elliott Roman	5215	2021	18-24	M	34.52
3	William Kemp	4700	2021	18-24	M	38.30
4	Dylan Ogle	4250	2021	18-24	M	42.35
5	Gregory Willett	4035	2021	18-24	M	44.61

USMS_ID

The value in `USMS_ID` has two parts. The first four characters, before the `"-"` vary year to year. The last five characters, after the `"-"` are an athlete's permanent identification string, used to identify athletes without relaying on names. We discuss this records matching problem a lot around here, because athlete names aren't a stable means of identification. Sometimes people get married and change their names. Sometimes people use nicknames. Things happen and the permanant portion of the `USMS_ID` is a good way of handling things. Sadly ePostal results only include `USMS_ID` after 2010, so we need to come up with something for pre-2011 results.

Here's the plan. We'll break off the permanent portion of `USMS_ID` into a new column called `Perm_ID` based on the location of `"-"` using `str_split_fixed`. Rows without a `USMS_ID` will have an empty character string `""` in `Perm_ID`, which we'll convert to `NA` with `na_if`. Then we'll group athletes by name. If any entry for that athlete, using that name, is from post-2010 they'll have a `Perm_ID` which we'll be able to copy to all rows involving that name using the `tidyr::fill` function. It's of course possible to have two athletes with the same name. We could be stricter here and `group_by` name and club for example, but athletes do change clubs. There are other things we could try as well, like matching on age progression, but for right now we're just going to accept that there might be some false matches.

```
Postal <- Postal %>%
  mutate(Perm_ID = str_split_fixed(USMS_ID, "-", n = 2)[, 2], # only
want the second part of the split
         Perm_ID = na_if(Perm_ID, "")) %>%  # turn empty strings ""
into NAs
  group_by(Name) %>%
  tidyr::fill(Perm_ID, .direction = "updown") # all instances of name
will get non-NA value of Perm_ID - assumes there's only one unique
Perm_ID for each name
```

Some athletes still don't have a `Perm_ID` though, because they don't have a `USMS_ID` listed.

```
# demonstration table
Postal %>%
  filter(Year == 1998) %>%
  select(Place, Name, Year, USMS_ID, Perm_ID) %>%
  head(5) %>%
  flextable_style()
```

Place	Name	Year	USMS_ID	Perm_ID
1	Becky Crowe	1998		
2	Johanna Hardin	1998		
3	Sarah Anderson	1998		
4	Sarah Baker	1998		09RB9

Place	Name	Year	USMS_ID	Perm_ID
5	Jane Kelsey	1998		

We're going to make them fake Perm_IDs. Each fake Perm_ID will be a six character string of upper case letters. We'll use this slightly different format (compared to the five character alphanumeric real Perm_IDs) so that it's possible to differentiate the fake from the real.

Each unique name without a real Perm_ID needs a fake Perm_ID. Let's first collect those unique names.

```
Unique_Names <- Postal %>%
  ungroup() %>%
  select(Name, Perm_ID) %>% # don't need all the columns, only these two
  filter(is.na(Perm_ID) == TRUE) %>% # want only rows where there isn't a Perm_ID
  unique() # don't need duplicates

Unique_Names %>%
  head(5) %>%
  flextable_style()
```

Name	Perm_ID
Glen Christiansen	
Lou Hill	
Sue Lyon	
Masao Miyasaka	
Karina Horton	

Now we need a list of random strings, one for each name. Since we're generating something random we'll use set.seed to make it reproducible. Then we'll use the stringi::stri_rand_strings function to generate a list of random strings with length 6. The length of the list will be the number of rows in unique_names.

```
set.seed(1) # to make random strings reproducible

Unique_Names <- Unique_Names %>%
  mutate(Perm_ID = stringi::stri_rand_strings( # make random strings
    n = nrow(Unique_Names), # number of random strings to make
    length = 6, # number of characters in each string
    pattern = "[A-Z]" # what to make the string out of, in this case
```

```
all capital letters
  ))

# demonstration table
Unique_Names %>%
  head(5) %>%
  flextable_style()
```

Name	Perm_ID
Glen Christiansen	GJOXFX
Lou Hill	YRQBFE
Sue Lyon	RJUMSZ
Masao Miyasaka	JUYFQD
Karina Horton	GKAJWI

Now we'll join `Postal` and `Unique_Names` back up by `Name` and use `coalesce` to get non-`NA` values of `Perm_ID` for each row. Each `Name`, which hopefully means each athlete, now has a unique `Perm_ID`.

```
Postal <- Postal %>%
  left_join(Unique_Names, by = "Name") %>% # attach newly made strings
back to original data frame based on name
  mutate(Perm_ID = coalesce(Perm_ID.x, Perm_ID.y)) %>% # use first non-
na value between original data frame (x) and new data frame (y)
  select(-Perm_ID.x, -Perm_ID.y) # don't need these columns any more

# demonstration table
Postal %>%
  filter(Year == 1998) %>%
  select(Place, Name, Year, USMS_ID, Perm_ID) %>%
  head(5) %>%
  flextable_style()
```

Place	Name	Year	USMS_ID	Perm_ID
1	Becky Crowe	1998		XZPOKS
2	Johanna Hardin	1998		EOFXZG
3	Sarah Anderson	1998		YSAWZT

Place	Name	Year	USMS_ID	Perm_ID
4	Sarah Baker	1998		09RB9
5	Jane Kelsey	1998		DHNSNX

Club Sizes

USMS defines categories of club size for the ePostal as small, medium, large and extra large based on the number of athletes representing that club. Here we'll count the number of athletes for each club with `n` and categorize appropriately with `case_when`. It's also interesting to look at participation by gender, so we'll count the male and female athletes for each club using `sum`. We'll get new columns of the form `Club_Count` (number of athletes in a club) and `Club_Size` (a factor with levels S, M, L, XL).

```
# total club size
Postal <- Postal %>%
    group_by(Club, Year) %>% # working with clubs now, by year
    mutate(Club_Count = n()) %>% # number of athletes in each club for
a given year
    mutate(Club_Size_Combined = case_when( # code in club sizes based
on number of athletes
      Club_Count < 26 ~ "S",
      Club_Count < 50 ~ "M",
      Club_Count <= 100 ~ "L",
      TRUE ~ "XL"
    )) %>%
  mutate(Club_Size_Combined = factor(Club_Size_Combined, levels =
c("S", "M", "L", "XL")))

# male club size
Postal <- Postal %>%
    group_by(Club, Year) %>%
    mutate(Club_Count_Male = sum(Gender == "M", na.rm = TRUE)) %>% #
only want to count men this time
    mutate(Club_Size_Male = case_when(
      Club_Count_Male < 26 ~ "S",
      Club_Count_Male < 50 ~ "M",
      Club_Count_Male <= 100 ~ "L",
      TRUE ~ "XL"
    )) %>%
    mutate(Club_Size_Male = factor(Club_Size_Male, levels = c("S", "M",
"L", "XL")))

# female club size
Postal <- Postal %>%
    group_by(Club, Year) %>%
    mutate(Club_Count_Female = sum(Gender == "W", na.rm = TRUE)) %>% #
only want to count women this time
    mutate(Club_Size_Female = case_when(
```

```
      Club_Count_Female < 26 ~ "S",
      Club_Count_Female < 50 ~ "M",
      Club_Count_Female <= 100 ~ "L",
      TRUE ~ "XL"
    )) %>%
    mutate(Club_Size_Female = factor(Club_Size_Female, levels = c("S",
"M", "L", "XL")))

# demonstration table
Postal %>%
  select(Club, Year, Club_Count, Club_Size_Combined, Club_Size_Male)
%>%
  head(5) %>%
  flextable_style()
```

Club	Year	Club_Count	Club_Size_Combined	Club_Size_Male
BSMT	2021	46	M	S
SKY	2021	15	S	S
SKY	2021	15	S	S
GS	2021	3	S	S
SKY	2021	15	S	S

Club Summary Stats

In addition to making comparisons between athletes we can also make comparisons between clubs.

Club Total and Average Distance

Clubs are scored based on the total distance swam by their memberships. Here we can `group_by` club can year, then add up the total distance each club swam with `sum`.

```
# total club stats
Postal <- Postal %>%
  mutate(Distance = na_if(Distance, 0)) %>% # shouldn't be any distance
NA values, but convert to zero if there are
  group_by(Club, Year) %>%
  mutate(Total_Distance_Combined = sum(Distance, na.rm = TRUE)) %>% #
add up distance for each club/year
  mutate(Avg_Distance_Combined = Total_Distance_Combined / Club_Count)
%>% # calculate avg distance per athlete
  mutate(Avg_Distance_Combined = round(Avg_Distance_Combined, 0))#
don't want decimal places
```

```
# male stats
Postal <- Postal %>%
  group_by(Club, Year) %>%
  mutate(Total_Distance_Male = sum(Distance[Gender == "M"], na.rm =
TRUE)) %>%
  mutate(Avg_Distance_Male = Total_Distance_Male / Club_Count_Male) %>%
  mutate(Avg_Distance_Male = round(Avg_Distance_Male, 0))

# female stats
Postal <- Postal %>%
  group_by(Club, Year) %>%
  mutate(Total_Distance_Female = sum(Distance[Gender == "W"], na.rm =
TRUE)) %>%
  mutate(Avg_Distance_Female = Total_Distance_Female /
Club_Count_Female) %>%
  mutate(Avg_Distance_Female = round(Avg_Distance_Female, 0))

# demonstration table
Postal %>%
  filter(Gender == "W") %>%
  select(Club, Year, Total_Distance_Female, Avg_Distance_Female) %>%
  head(5) %>%
  flextable_style()
```

Club	Year	Total_Distance_Female	Avg_Distance_Female
IM	2021	45420	3785
GS	2021	5850	2925
UC08	2021	3400	3400
CRUZ	2021	18475	4619
1776	2021	38340	4260

Club Rank

Clubs can be ranked within their size/gender categories by total distance swam in much the same way we ranked swimmers within their age/gender categories. Since their are only three categories (combined, male, female) I'm not going to bother about including category size like with did with individual athletes although it's certainly possible to do so. Here we'll just `group_by` the appropriate `Club_size` column and the year and then use `dense_rank` to get the ranking for each club. `dense_rank` is one of the the six `dplyr` ranking functions. It ranks values in a vector giving tied values a minimum rank *and* does not skip places as a result of ties. Here's a demonstration, because some of you might not be familiar with `dense_rank`.

Assume four clubs A-D, each of which swam some total distance.

```
distances <- c(10000, 15000, 15000, 20000)
names(distances) <- c("A", "B", "C", "D")
distances
##     A     B     C     D
## 10000 15000 15000 20000
```

What we'd like to say is that club D is first, clubs B and C are tied for second and club A is third. Club B and C both getting second (rather than say, 2.5th, or randomly giving one 2nd and the other 3rd) is what I mean by "giving tied values a minimum rank". Club A getting third, rather than forth (as the forth club on the list) is what I mean by "not skip[ping] places as a result of ties". We also need to use `desc` because we want the clubs with the largest distance values to get the low...