# Prep2S24

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Reminder: Prep assignments are to be completed individually. Upload a final copy of the .Qmd and renamed .pdf to your private repo, and submit the renamed pdf to Gradescope before Sunday, Feb. 11th at midnight (11:59 pm is what Gradescope shows).

# Reading

The associated reading for the week is Chapter 4, Chapter 5, Chapter 6 (skip 6.4) and Sections 8.3 and 8.4. This reading explores major functions in wrangling data, including reshaping data. There are many commands here to learn about - do your best to develop a sense of what they each do, and we will build on that by using them for the rest of the semester. You don't need to memorize them all.

Remember, I recommend you code along with the book examples. You can try out the code yourself - just be sure to load the mdsr package and any other packages referenced. You can get the code in R script files (basically, files of just R code, not like a .Rmd or .Qmd) from the book website.

# 1 - Some basics

Many different data wrangling commands are covered in these chapters. Identify the command you'd use for each of the operations below.

part a - Add the average of 3 variables to the data set as a new variable.

Solution: Use mutate()

part b - Keep only 4 columns of a data frame in a new data set.

Solution: We would use the select() function.

part c - Choose observations that match a particular category of a categorical variable to keep in a new data set.

Solution: group\_by() and summarize()

part d - Combine two data sets based on common variables where all rows from the first are returned, along with any matches in the second.

Solution: Not sure about this

# 2 - NYC Flights

In Section 5.1, the flights and airlines tables within the nycflights13 package are joined together.

part a - Recreate the flights\_joined dataset from Section 5.1, being sure to glimpse the data in the Console (or via the code chunk) to verify the join worked.

```
flights_joined <- flights %>%
  inner_join(airlines, by = c("carrier" = "carrier"))
glimpse(flights_joined)
```

```
Rows: 336,776
Columns: 20
$ year
               <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2~
$ month
               $ day
$ dep_time
               <int> 517, 533, 542, 544, 554, 554, 555, 557, 557, 558, 558, ~
$ sched_dep_time <int> 515, 529, 540, 545, 600, 558, 600, 600, 600, 600, 600, ~
$ dep_delay
               <dbl> 2, 4, 2, -1, -6, -4, -5, -3, -3, -2, -2, -2, -2, -2, -1~
               <int> 830, 850, 923, 1004, 812, 740, 913, 709, 838, 753, 849,~
$ arr_time
$ sched_arr_time <int> 819, 830, 850, 1022, 837, 728, 854, 723, 846, 745, 851,~
               <dbl> 11, 20, 33, -18, -25, 12, 19, -14, -8, 8, -2, -3, 7, -1~
$ arr_delay
$ carrier
               <chr> "UA", "UA", "AA", "B6", "DL", "UA", "B6", "EV", "B6", "~
$ flight
               <int> 1545, 1714, 1141, 725, 461, 1696, 507, 5708, 79, 301, 4~
               <chr> "N14228", "N24211", "N619AA", "N804JB", "N668DN", "N394~
$ tailnum
               <chr> "EWR", "LGA", "JFK", "JFK", "LGA", "EWR", "EWR", "LGA",~
$ origin
               <chr> "IAH", "IAH", "MIA", "BQN", "ATL", "ORD", "FLL", "IAD",~
$ dest
$ air_time
               <dbl> 227, 227, 160, 183, 116, 150, 158, 53, 140, 138, 149, 1~
               <dbl> 1400, 1416, 1089, 1576, 762, 719, 1065, 229, 944, 733, ~
$ distance
$ hour
               <dbl> 5, 5, 5, 5, 6, 5, 6, 6, 6, 6, 6, 6, 6, 6, 6, 5, 6, 6, 6
               <dbl> 15, 29, 40, 45, 0, 58, 0, 0, 0, 0, 0, 0, 0, 0, 0, 59, 0~
$ minute
               <dttm> 2013-01-01 05:00:00, 2013-01-01 05:00:00, 2013-01-01 0~
$ time_hour
               <chr> "United Air Lines Inc.", "United Air Lines Inc.", "Amer~
$ name
```

part b - Now, starting from flights\_joined, create a new dataset flights\_short that does the following:

- creates a new variable, distance\_km, which is distance in kilometers (note that 1 mile is about 1.6 kilometers)
- keeps only the variables: name, flight, arr\_delay, and distance\_km and

• keeps only observations where the distance is less than 480 kilometers (300 miles).

#### Solution:

```
flights_short <- flights_joined %>%
  mutate(distance_km = distance*1.6) %>%
  select(name,flight,arr_delay,distance_km) %>%
  filter(distance_km < 480)

glimpse(flights_short)</pre>
```

part c - Using the functions introduced in Section 4.1.4, compute the number of flights (call this N), the average arrival delay (call this avg\_arr\_delay), and the average distance in kilometers (call this avg\_dist\_km) among these flights with distances less than 480 km (i.e. working off of flights\_short), grouping by the carrier name. Sort the results in descending order based on avg\_arr\_delay. Save the results in a tibble object called delay\_summary, and display the table.

1	SkyWest Airlines Inc.	1	3	366.
2	American Airlines Inc.	1455	NA	299.
3	Delta Air Lines Inc.	1214	NA	325.
4	Endeavor Air Inc.	5779	NA	319.
5	Envoy Air	2924	NA	350.
6	ExpressJet Airlines Inc.	15588	NA	372.
7	JetBlue Airways	10813	NA	360.
8	Mesa Airlines Inc.	319	NA	361.
9	Southwest Airlines Co.	208	NA	272.
10	US Airways Inc.	9633	NA	309.
11	United Air Lines Inc.	3353	NA	320.

part d - Rename the four columns in the delay\_summary data table to Airline, "Total flights under 480 km", "Average arrival delay (mins)" and "Average distance (km)", respectively, then use kable(booktabs = TRUE, digits = 0) to make the final table output in the pdf close to publication quality.

```
Airline <- delay_summary %>%
  rename(
          Airline = name,
          "Total flights under 480 km" = N,
          "Average arrival delay (mins)" = avg_arr_delay,
          "Average distance (km)" = avg_dist_km
    )

kable(delay_summary, booktabs = TRUE, digits = 1)
```

name	N	avg_arr_delay	avg_dist_km
SkyWest Airlines Inc.	1	3	366.4
American Airlines Inc.	1455	NA	299.2
Delta Air Lines Inc.	1214	NA	324.8
Endeavor Air Inc.	5779	NA	318.7
Envoy Air	2924	NA	350.4
ExpressJet Airlines Inc.	15588	NA	372.3
JetBlue Airways	10813	NA	359.6
Mesa Airlines Inc.	319	NA	361.1
Southwest Airlines Co.	208	NA	272.2
US Airways Inc.	9633	NA	308.6
United Air Lines Inc.	3353	NA	319.7

## Airline

## # A tibble: 11 x 4

	Airline	Total	flights	under ·	~1	Average	arrival	dela~2	Average	distance	(km~3
	<chr></chr>			<in< td=""><td>t&gt;</td><td></td><td></td><td><dbl></dbl></td><td></td><td></td><td><dbl></dbl></td></in<>	t>			<dbl></dbl>			<dbl></dbl>
1	SkyWest~				1			3			366.
2	America~			14	55			NA			299.
3	Delta A~			12:	14			NA			325.
4	${\tt Endeavo} \texttt{~}$			57	79			NA			319.
5	Envoy A~			292	24			NA			350.
6	Express~			1558	88			NA			372.
7	${\tt JetBlue"}$			108	13			NA			360.
8	Mesa Ai~			3:	19			NA			361.
9	${\tt Southwe~}$			20	80			NA			272.
10	US Airw~			963	33			NA			309.
11	United $\sim$			33!	53			NA			320.

 $<sup>\</sup>mbox{\tt\#}$  i abbreviated names: 1: `Total flights under 480 km`,

<sup># 2: `</sup>Average arrival delay (mins)`, 3: `Average distance (km)`

# 3 - Baby names - Variant of 6.2.5 example

part a - Working with the babynames data in the babynames package, create a dataset recent\_names that only includes years 2003 to 2017 (giving us the most recent 15 years of data).

#### Solution:

```
recent_names <- babynames %>%
    filter(year >= 2003 & year <= 2017)
glimpse(recent_names)

Rows: 501,324
Columns: 5
$ year <dbl> 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 2003, 20
```

Solution:

```
recentnames_summary <- recent_names %>%
group_by(name, sex) %>%
summarize(total = sum(n))
```

`summarise()` has grouped output by 'name'. You can override using the `.groups` argument.

tory (years 2003 to 2017) with each name, grouped by sex.

part c - Now, following the third and fourth code chunks presented in Section 6.2.5, reshape or *pivot* the summary data from *long* format to *wide* format. Only keep observations where more than 8,000 babies have been named in each sex (M and F), and find the smaller of the two ratios M / F and F / M to identify the top three sex-balanced names (and only the top three!). Save the wide data as recentnames\_balanced\_wide. Display the table.

```
recentnames_summary %>%
     pivot_wider(
      names_from = sex,
      values_from = total
    )
# A tibble: 63,515 x 3
# Groups:
            name [63,515]
  name
                 М
                        F
   <chr>
             <int> <int>
1 Aaban
               107
                       NA
2 Aabha
                NA
                       35
3 Aabid
                10
                       NA
4 Aabir
                 5
                       NA
5 Aabriella
                NA
                       32
6 Aada
                NA
                        5
7 Aadam
               185
                       NA
8 Aadan
               130
                       NA
9 Aadarsh
               177
                       NA
                        5
10 Aaden
              4633
# i 63,505 more rows
```

part d - Finally, use pivot\_longer() to put the dataset back into *long* form. Call this dataset recentnames\_balanced and display the table.

# 4 - Ethics

Each subsection of Section 8.4 discusses an ethical scenario and ends with one or more questions. Consider the subsection 8.4.6 on "Reproducible spreadsheet analysis".

Write two or three sentences reflecting on how using RMarkdown would help avoid some of the issues described in this scenario, or at least make them easier to spot.

Solution: Since Rmarkdown is code based rather than a visual spreadsheet, to spot ethical errors would be easier as the code is more concise and easier to follow. This makes it easier to then spot any biases or cherry picking of data.