MTH 3270 Notes 3

4 Data Wrangling (4)

- ***Data wrangling*** refers to re-organizing, transforming, and re-formatting data to make it more suitable for statistical analysis.

4.1 Introduction: The `"dplyr"` Package

- The `"dplyr"` package (H. Wickham) contains several functions for **data wrangling**. Type:

```
help(package = dplyr)
```

  to see a list of the functions (and data sets) contained in `"dplyr"`.

- Here are five important functions for data wrangling. These are the so-called ***verbs*** of `"dplyr"`:

```
select()       Take a subset of the columns (i.e. variables).
filter()       Take a subset of the rows (i.e. observations).
mutate()       Add columns computed from existing ones.  Use
               transmute() instead if you only want to keep the
               newly computed columns.
arrange()      Sort the rows of a data set according to the values
               in one or more columns.
summarize()    Summarize a data frame or a grouped data frame (as
               created by group_by()), returning one row for each
               group.
```

- Each of these functions takes a *data frame* as its main argument (`.data`), and returns a *data frame*.

  This is important because it means **the output of any one of them can be used as the input of another**, and "chaining" together function calls in this manner is made simple by `"dplyr"`'s so-called ***pipe operator***:

```
%>%           # Pipe operator, for passing the returned value from one
              # function call as the main argument of another function
              # call, e.g. x %>% f() %>% g() is the same as g(f(x)).
```

- Another important function in `"dplyr"` is:

```
rename()      Modify the names of columns in a data set.
```

Data Set: `flights`

The `flights` data set is in the `"nycflights13"` package. It contains all 336,776 flights that departed New York City in 2013. The data set is from the U.S. Bureau of Transportation Statistics,

`https://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236`

It contains 19 variables:

`year, month, day`	Date of departure
`dep_time, arr_time`	Actual departure and arrival times (format HHMM or HMM), local tz.
`sched_dep_time, sched_arr_time`	Scheduled departure and arrival times (format HHMM or HMM), local tz.
`dep_delay, arr_delay`	Departure and arrival delays, in minutes. Negative times represent early departures/arrivals.
`hour, minute`	Time of scheduled departure broken into hour and minutes.
`carrier`	Two letter carrier abbreviation. See `airlines()` to get name
`tailnum`	Plane tail number
`flight`	Flight number
`origin, dest`	Origin and destination. See airports() for additional metadata.
`air_time`	Amount of time spent in the air, in minutes
`distance`	Distance between airports, in miles
`time_hour`	Scheduled date and hour of the flight as a POSIXct date. Along with origin, can be used to join flights data to weather data.

For more information, see the help file (after installing the `"nycflights13"` package):

```
library(nycflights13)
? flights
```

4.2 Extracting Columns with `select()`

- We can extract **columns** (**variables**) from a data frame using `select()`.

  For example, to extract the columns `year`, `month`, and `day` from the `flights` data set (from the `"nycflights13"` package), we can type:

```
library(nycflights13)
select(.data = flights, year, month, day)

## # A tibble: 336,776 x 3
##     year month   day
##    <int> <int> <int>
##  1  2013     1     1
##  2  2013     1     1
##  3  2013     1     1
##  4  2013     1     1
##  5  2013     1     1
##  6  2013     1     1
##  7  2013     1     1
##  8  2013     1     1
##  9  2013     1     1
## 10  2013     1     1
## # ... with 336,766 more rows
```

  Recall that in Class Notes 1 we **selected** columns using the dollar sign `$`, single square brackets `[ ]`, or double square brackets `[[ ]]`. `select()` provides one more way to do it.

- None of `"dplyr"`'s *verb* functions *changes* the data frame passed to it. So in practice, we'd usually *save* the changes as a new data frame, for example (below) as `flights_ymd`:

```
flights_ymd <- select(.data = flights, year, month, day)
```

- Here's an example that uses the **pipe operator** `%>%` to accomplish the *same thing* as the command above:

```
flights_ymd <- flights %>% select(year, month, day)
```

  We'll discuss the **pipe operator** more later.

- We can extract a *range* of columns using the colon operator ':'. For example:

```
select(.data = flights, year:day)

## # A tibble: 336,776 x 3
##     year month   day
##    <int> <int> <int>
##  1  2013     1     1
##  2  2013     1     1
##  3  2013     1     1
##  4  2013     1     1
##  5  2013     1     1
##  6  2013     1     1
##  7  2013     1     1
##  8  2013     1     1
##  9  2013     1     1
## 10  2013     1     1
## # ... with 336,766 more rows
```

- A minus sign '-' can be used to extract all columns *except* a specified set of them. For example:

```
select(.data = flights, -(year:day))
```

- Here are some **"helper"** functions that can be used with `select()`:
  - `starts_with("abc")` matches names that begin with `"abc"`.
  - `ends_with("xyz")` matches names that end with `"xyz"`.
  - `contains("ijk")` matches names that contain `"ijk"`.
  - `num_range("x", 1:3)` matches `x1`, `x2`, `x3`.

  For more information, see the help file for `select()`:

```
? select
```

- `select()` can also be used to *rearrange* columns. For this, the `everything()` function is useful for moving a few columns to the front:

```
select(.data = flights, time_hour, air_time, everything())

## # A tibble: 336,776 x 19
##    time_hour           air_time  year month   day dep_time
##    <dttm>                 <dbl> <int> <int> <int>    <int>
##  1 2013-01-01 05:00:00      227  2013     1     1      517
##  2 2013-01-01 05:00:00      227  2013     1     1      533
##  3 2013-01-01 05:00:00      160  2013     1     1      542
##  4 2013-01-01 05:00:00      183  2013     1     1      544
##  5 2013-01-01 06:00:00      116  2013     1     1      554
##  6 2013-01-01 05:00:00      150  2013     1     1      554
##  7 2013-01-01 06:00:00      158  2013     1     1      555
```

```
##  8 2013-01-01 06:00:00       53  2013     1     1      557
##  9 2013-01-01 06:00:00      140  2013     1     1      557
## 10 2013-01-01 06:00:00      138  2013     1     1      558
## # ... with 336,766 more rows, and 13 more variables:
## #   sched_dep_time <int>, dep_delay <dbl>, arr_time <int>,
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   distance <dbl>, hour <dbl>, minute <dbl>
```

Section 4.2 Exercises

Exercise 1 The `flights` data set is contained in the `"nycflights13"` package. Load the package:

```
library(nycflights13)
```

You can look at the names of the variables in `flights` by typing:

```
names(flights)
```

Guess what each of the following commands returns, then check your answers:

a) `select(.data = flights, year, day)`

b) `select(.data = flights, year:day)`

c) `select(.data = flights, -(year:day))`

Exercise 2 This exercise concerns the **"helper"** functions used with `select()`.

Look again at the names of the variables in `flights`:

```
names(flights)
```

Guess what each of the following commands returns, then check your answers:

a) `select(.data = flights, starts_with("sched"))`

b) `select(.data = flights, contains("arr"))`

c) `select(.data = flights, starts_with("dep_"), starts_with("arr_"))`

4.3 Tibbles

- In `"dplyr"` (and other packages in the so-called ***tidyverse*** suite of packages), a ***tibble*** *is* a **data frame**:

```
is.data.frame(flights)

## [1] TRUE
```

They differ from regular data frames in how they get printed to the console. Dimension and type information is printed, and only ten rows and as many columns as fit in the console appear.

To view the entire data set, use `View()`:

```
View(flights)
```

Tibbles belong to the `"tbl_df"` class of objects, which is a *special case* of the `"data.frame"` class. Actually, they belong to *three* classes:

```
class(flights)

## [1] "tbl_df"     "tbl"        "data.frame"
```

When an object belongs to *more than one class*, each class is a *special case* of the classes that come after it in the list returned by `class()`.

For example, `"tbl_df"` is a *special case* of the `"tbl"` class, which in turn is a *special case* of the `"data.frame"` class.

Because `"tbl_df"` is a *special case* of `"data.frame"`, *any action that can be performed on data frames can also be performed on tibbles.*

- To convert a *tibble* to a standard *data frame*, or a standard *data frame* to a *tibble*, use the following functions. The first is built in to R, the second is in `"dplyr"`.

```
as.data.frame()      Can be used to convert a tibble to a standard data frame.
as_tibble()          Can be used to convert a standard data frame to a tibble.
```

4.4 Filtering Rows with `filter()`

- We can use `filter()` to extract from a data frame the rows that satisfy one or more conditions. For example, to obtain all the `flights` on January 1st, type:

```
filter(.data = flights, month == 1, day == 1)

## # A tibble: 842 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515         2      830
##  2  2013     1     1      533            529         4      850
##  3  2013     1     1      542            540         2      923
##  4  2013     1     1      544            545        -1     1004
##  5  2013     1     1      554            600        -6      812
##  6  2013     1     1      554            558        -4      740
##  7  2013     1     1      555            600        -5      913
##  8  2013     1     1      557            600        -3      709
##  9  2013     1     1      557            600        -3      838
## 10  2013     1     1      558            600        -2      753
## # ... with 832 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dttm>
```

Recall that in Class Notes 1 we **filtered** using single square brackets `[ ]` or `subset()`. `filter()` provides another way to do it.

- The logical operators '`&`', '`|`', and '`!`' ("and", "or", and "not") from Class Notes 1 are useful when specifying the condition(s) to be met by extracted rows.

  For example, to obtain the `flights` that departed in November *or* December, type:

  ```
  # The condition is a "logical" vector:
  filter(.data = flights, month == 11 | month == 12)
  ```

  Note that the specified condition, `month == 11 | month == 12`, is a `"logical"` vector indicating which rows of `flights` should be extracted.

- Another useful operator is the **"in"** operator:

  ```
  %in%        # Tests whether a value is in a set of values. Returns
              # TRUE or FALSE.
  ```

  It returns `TRUE` or `FALSE` depending on whether a given value is among a set of values:

  ```
  7 %in% c(2, 4, 7, 9, 6)

  ## [1] TRUE
  ```

  ```
  3 %in% c(2, 4, 7, 9, 6)

  ## [1] FALSE
  ```

  And it's *vectorized*, operating elementwise on the left-side vector:

  ```
  c(7, 3) %in% c(2, 4, 7, 9, 6)

  ## [1]  TRUE FALSE
  ```

  As an example of its use in `filter()`, here's another way to to obtain the `flights` that departed in November *or* December:

  ```
  filter(.data = flights, month %in% c(11, 12))
  ```

  Note again that the specified condition (`month %in% c(11, 12)`) is a `"logical"` vector.

- When we specify *more than one* condition in `filter()`, they're combined with '`&`'. For example, the following commands do the *same thing*:

  ```
  filter(.data = flights, month == 1, day == 1)
  ```

  ```
  filter(.data = flights, month == 1 & day == 1)
  ```

- We can remove rows for which one or more columns have `NA`s using `filter()` with `!is.na()`. For example, consider this data frame:

  ```
  x <- data.frame(x1 = c(2, 1, NA, 8, 7, 5, 4),
                  x2 = c("a", NA, "c", "d", "c", "a", "d"),
                  stringsAsFactors = FALSE)
  x
  ```

```
##   x1   x2
## 1  2    a
## 2  1 <NA>
## 3 NA    c
## 4  8    d
## 5  7    c
## 6  5    a
## 7  4    d
```

Note that R represents missing `"character"` values as `<NA>` to allow for the possibility that `"NA"` might appear as a data *value* in a `"character"` vector (e.g. the abbreviation for "Narcotics Anonymous").

To remove rows for which `x1` is `NA`, type:

```
filter(x, !is.na(x1))

##   x1   x2
## 1  2    a
## 2  1 <NA>
## 3  8    d
## 4  7    c
## 5  5    a
## 6  4    d
```

To remove rows for which *either* of the variables `x1` or `x2` contains an `NA`, type:

```
filter(x, !is.na(x1), !is.na(x2))   # Could also use filter(x, !(is.na(x1) | is.na(x2)))

##   x1 x2
## 1  2  a
## 2  8  d
## 3  7  c
## 4  5  a
## 5  4  d
```

Above, we could also use `filter(x, !(is.na(x1) | is.na(x2)))`.

Another way to remove rows for which *any* of the variables in a data frame contains an `NA` is using the `complete.cases()` function:

```
filter(x, complete.cases(x))

##   x1 x2
## 1  2  a
## 2  8  d
## 3  7  c
## 4  5  a
## 5  4  d
```

The `complete.cases()` function (which is built in to R) returns a `"logical"` vector whose elements are `TRUE` if the corresponding row of `x` is "complete" (doesn't contain any `NA`s) and `FALSE` otherwise.

- `filter()` *only* returns rows for which the specified condition is `TRUE`. It *doesn't* return rows for which the condition is `NA`. For example:

```
x

##   x1   x2
## 1  2    a
```

```
## 2  1 <NA>
## 3 NA    c
## 4  8    d
## 5  7    c
## 6  5    a
## 7  4    d
```

```
filter(x, x1 < 5)
```

```
##   x1   x2
## 1  2    a
## 2  1 <NA>
## 3  4    d
```

To tell `filter()` to *also* return rows for which the condition is `NA`, type:

```
filter(x, is.na(x1) | x1 < 5)
```

```
##   x1   x2
## 1  2    a
## 2  1 <NA>
## 3 NA    c
## 4  4    d
```

Section 4.4 Exercises

Exercise 3 Report R commands that use `filter()` and the logical operators ('`&`', '`|`', and '`!`') with the `flights` data to find all flights that:

a) Had an arrival delay of two or more hours.

b) Flew to Houston (`IAH` or `HOU`).

c) Were operated by United, American, or Delta.

d) Departed in summer (July, August, or September).

e) Departed between midnight and 6:00 AM (inclusive).

f) Were operated by United, departed in July, and had an arrival delay of two or more hours.

4.5 Arranging Rows with `arrange()`

- We can use `arrange()` sort the rows of a data frame according to the values in one or more columns.

  For example, to sort the rows of `flights` in **ascending** order according to the departure delay, type:

```
arrange(.data = flights, dep_delay)
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013    12     7     2040           2123       -43       40
##  2  2013     2     3     2022           2055       -33     2240
##  3  2013    11    10     1408           1440       -32     1549
##  4  2013     1    11     1900           1930       -30     2233
##  5  2013     1    29     1703           1730       -27     1947
##  6  2013     8     9      729            755       -26     1002
```

```
##  7  2013    10    23     1907           1932       -25     2143
##  8  2013     3    30     2030           2055       -25     2213
##  9  2013     3     2     1431           1455       -24     1601
## 10  2013     5     5      934            958       -24     1225
## # ... with 336,766 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dttm>
```

- To sort in **descending** order, use `desc()`, for example:

```
arrange(.data = flights, desc(dep_delay))
```

Recall that in Class Notes 1 we **arranged** rows using single square brackets `[ ]`. `arrange()` provides another way to do it.

- If you specify more than one column, each additional column will be used to break ties in the previous columns. For example:

```
arrange(.data = flights, year, month, day)

## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515         2      830
##  2  2013     1     1      533            529         4      850
##  3  2013     1     1      542            540         2      923
##  4  2013     1     1      544            545        -1     1004
##  5  2013     1     1      554            600        -6      812
##  6  2013     1     1      554            558        -4      740
##  7  2013     1     1      555            600        -5      913
##  8  2013     1     1      557            600        -3      709
##  9  2013     1     1      557            600        -3      838
## 10  2013     1     1      558            600        -2      753
## # ... with 336,766 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dttm>
```

Section 4.5 Exercises

Exercise 4 Report R commands that use `arrange()` to sort the `flights` data to:

a) Find the `flights` that had the shortest delays.

b) Find the `flights` that had the longest delays.

c) Find the `flights` that had the earliest departure times.

d) Find the `flights` that had the latest departure times.

e) Find the `flights` that traveled the shortest distance.

f) Find the `flights` that traveled the longest distance.

Exercise 5 Occasionally, we want to sort the rows of a data frame so that all of the `NA`s are at the top. Consider the following data frame:

```r
x <- data.frame(x1 = c(2, 1, NA, 8, 7, 5, 4),
                x2 = c("a", NA, "c", "d", "c", "a", "d"),
                stringsAsFactors = FALSE)
x
```

```
##   x1   x2
## 1  2    a
## 2  1 <NA>
## 3 NA    c
## 4  8    d
## 5  7    c
## 6  5    a
## 7  4    d
```

Recall that `is.na()` returns a `"logical"` vector whose `TRUE`s indicate `NA`s. Recall also that `"logical"` values are treated as `0` and `1` in operations that expect a numerical value.

a) Guess what the following command does, then check your answer:

```r
arrange(.data = x, is.na(x1))
```

b) Guess what the following command does, then check your answer:

```r
arrange(.data = x, desc(is.na(x1)))
```

4.6 Creating New Variables (Columns) with `mutate()`

- We can use `mutate()` to add new columns that are computed from existing columns of a data frame.
- `mutate()` always adds the columns to the rightmost end of the data frame.
- For the examples, we'll use a smaller data frame:

```r
flights_small <- select(.data = flights,
                        year:day,
                        ends_with("delay"),
                        distance,
                        air_time)

head(flights_small)
```

```
## # A tibble: 6 x 7
##    year month   day dep_delay arr_delay distance air_time
##   <int> <int> <int>     <dbl>     <dbl>    <dbl>    <dbl>
## 1  2013     1     1         2        11     1400      227
## 2  2013     1     1         4        20     1416      227
## 3  2013     1     1         2        33     1089      160
## 4  2013     1     1        -1       -18     1576      183
## 5  2013     1     1        -6       -25      762      116
## 6  2013     1     1        -4        12      719      150
```

Here's an example:

```r
mutate(.data = flights_small,
       gain = dep_delay - arr_delay,
       speed = distance / air_time * 60)
```

```
## # A tibble: 336,776 x 9
```

```
##     year month   day dep_delay arr_delay distance air_time  gain speed
##    <int> <int> <int>     <dbl>     <dbl>    <dbl>    <dbl> <dbl> <dbl>
##  1  2013     1     1         2        11     1400      227    -9  370.
##  2  2013     1     1         4        20     1416      227   -16  374.
##  3  2013     1     1         2        33     1089      160   -31  408.
##  4  2013     1     1        -1       -18     1576      183    17  517.
##  5  2013     1     1        -6       -25      762      116    19  394.
##  6  2013     1     1        -4        12      719      150   -16  288.
##  7  2013     1     1        -5        19     1065      158   -24  404.
##  8  2013     1     1        -3       -14      229       53    11  259.
##  9  2013     1     1        -3        -8      944      140     5  405.
## 10  2013     1     1        -2         8      733      138   -10  319.
## # ... with 336,766 more rows
```

- If we *only* want to keep the newly computed variables, we use `transmute()`:

```
transmute(.data = flights_small,
       gain = dep_delay - arr_delay,
       speed = distance / air_time * 60)
```

Recall that in Class Notes 1 we **added** new columns using the dollar sign `$` or double square brackets `[[ ]]`. `mutate()` provides one more way to do it.

Section 4.6 Exercises

Exercise 6 Report an R command that uses `mutate()` or `transmute()`, with `flights`, to compute `arr_time - dep_time`, and compare it with `air_time`. Why are they different?

Exercise 7 A newly computed variable (column) can be used *within* `mutate()`.

Execute the following command (using `flights_small` from above):

```
mutate(.data = flights_small,
       gain = dep_delay - arr_delay,
       hours = air_time / 60,
       gain_per_hour = gain / hours)
```

Does the variable `gain_per_hour` get computed?

4.7 Renaming Variables (Columns) with `rename()`

- We use `rename()` to rename variables (columns) in a data frame. For example (using `x` from above):

```
x

##   x1   x2
## 1  2    a
## 2  1 <NA>
## 3 NA    c
## 4  8    d
## 5  7    c
## 6  5    a
## 7  4    d

new_x <- rename(.data = x, new_x1 = x1, new_x2 = x2)
new_x
```

```
##   new_x1 new_x2
## 1      2      a
## 2      1   <NA>
## 3     NA      c
## 4      8      d
## 5      7      c
## 6      5      a
## 7      4      d
```

Recall that in Class Notes 1 we **renamed** variables using `names()`. `rename()` provides another way to do it.

Section 4.7 Exercises

Exercise 8 Here's a small data frame:

```
z <- data.frame(z1 = c(5, 4, 3),
                z2 = c("a", "c", "b"),
                z3 = c(14, 22, 13))
```

Use `rename()` to change the names of the variables in `z` to `new_z1`, `new_z2`, and `new_z3`. Report your R command(s).

4.8 Summarizing Data with `summarize()`

- The function `summarize()` is used to **summarize** one or more variables (columns) of a data frame.

  It "collapses" the data frame into a *single row* containing summary statistics for the variables (columns).

  For example, to compute the mean (average) departure and arrival delays, type:

```
summarize(.data = flights,
          mean_dep_delay = mean(dep_delay, na.rm = TRUE),
          mean_arr_delay = mean(arr_delay, na.rm = TRUE))

## # A tibble: 1 x 2
##   mean_dep_delay mean_arr_delay
##            <dbl>          <dbl>
## 1           12.6           6.90
```

  Note that `summarize()` returned a data frame (*tibble*) with a single row and two columns. Setting `na.rm = TRUE` in `mean()` removes the `NA`s before the means are computed.

- Not all functions have the `na.rm` argument, so sometimes it's better to just remove the rows with `NA`s in the variables you're interested in:

```
not_cancelled <- filter(.data = flights, !is.na(dep_delay), !is.na(arr_delay))
```

```
summarize(.data = not_cancelled,
          mean_dep_delay = mean(dep_delay),
          mean_arr_delay = mean(arr_delay))

## # A tibble: 1 x 2
##   mean_dep_delay mean_arr_delay
##            <dbl>          <dbl>
## 1           12.6           6.90
```

- Here are some functions that compute **statistics** for use with `summarize()`.
  - For summarizing the **center** (typical value) of a variable:

```
mean()     # Mean (average)
median()   # Median (middle value, i.e. 50th percentile)
```

  - For summarizing the **spread** (variation) of a variable:

```
sd()       # Standard deviation (typical deviation away from the
           # mean)
IQR()      # Interquartile range (amount of spread between 25th
           # and 75th percentiles)
mad()      # Median absolute deviation (median of the deviations
           # away from the median of the data)
```

  - For summarizing a **ranked value** (smallest, largest, 25th percentile, etc.) of a variable:

```
min()        # Minimum (smallest) value
max()        # Maximum (largest) value
quantile()   # Percentile (also called quantile), e.g.
             # quantile(x, 0.25) returns the 25th percentile of
             # the data.
```

  - For summarizing the **position** among the (unsorted) values of the variable (these are in the `"dplyr"` package):

```
first()      # First value, equivalent to x[1]
last()       # Last value, equivalent to x[length(x)]
nth()        # nth value, e.g. nth(x, 2) returns the 2nd value in x
```

  - For **counting** values of the variable (this is in the `"dplyr"` package):

```
n()          # The number of values (i.e. number of observations),
             # equivalent to length(), but specifically for use in
             # summarize(), mutate(), and filter().
```

Section 4.8 Exercises

Exercise 9 Create the `not_cancelled` data frame (using `flights`):

```
not_cancelled <- filter(.data = flights, !is.na(dep_delay), !is.na(arr_delay))
```

Using `not_cancelled`, do the following.

a) Use `summarize()` with `median()` to find the median departure delay and the median arrival delay. Report the two values.

b) Use `summarize()` with `max()` to find the longest departure delay and the longest arrival delay. Report the two values.

c) Use `summarize()` with `min()` to find the shortest departure delay and the shortest arrival delay. Report the two values.

Exercise 10 If you don't still have it, re-create the `not_cancelled` data frame from Exercise 9.

We might be interested in *how many* (non-cancelled) flights there were in total, *how many* arrivals were delayed by more than an hour, and what *proportion* of arrivals were delayed by more than an hour.

a) The function `n()` (from `"dplyr"`) is used in `summarize()` to *count* how many values (total) are in a variable. What does the following command do?

```
summarize(.data = not_cancelled,
          total_flights = n())
```

b) Recall that `"logical"` values are converted to `0` and `1` in computations, and we can `sum()` values in a `"logical"` vector to *count* how many `TRUE`'s it contains. What does the following command do?

```
summarize(.data = not_cancelled,
          hour_arr_delay_total = sum(arr_delay > 60))
```

c) What does the following command do?

```
summarize(.data = not_cancelled,
          hour_arr_delay_proportion = sum(arr_delay > 60) / n())
```

4.9 Applying `summarize()` to Groups using `group_by()`

- We can summarize variables separately for each of two or more **groups**, corresponding to values of a *categorical* (or *discrete* numerical) variable, using `summarize()` and `group_by()` (from the `"dplyr"` package).

group_by()	*Group together rows of a data set according to values in one or more categorical columns, for use in summarize(), etc.*

- For example, using the `flights` data, to compute the mean (average) **delay** *by* `month`, type:

```
by_month <- group_by(.data = flights, month)
summarize(.data = by_month, mean_dep_delay = mean(dep_delay, na.rm = TRUE))

## # A tibble: 12 x 2
##    month mean_dep_delay
##    <int>          <dbl>
##  1     1          10.0
##  2     2          10.8
##  3     3          13.2
##  4     4          13.9
##  5     5          13.0
##  6     6          20.8
##  7     7          21.7
##  8     8          12.6
##  9     9           6.72
## 10    10           6.24
## 11    11           5.44
## 12    12          16.6
```

This returns a data frame (*tibble*) with one row for each `month` and a column containing the monthly mean delays.

- `group_by()` returns a data frame (saved as `by_month` above) that belongs to the `"grouped_df"` class of objects, which is a special case of the `"data.frame"` class:

```
class(by_month)

## [1] "grouped_df" "tbl_df"     "tbl"        "data.frame"
```

All of "dplyr"'s *verb* functions (`select()`, `filter()`, etc.) accept `"grouped_df"`s as their `.data` argument.

Passing a `"grouped_df"` to a `"dplyr"` *verb* function changes the scope the function from operating on the entire data set to operating on it **group-by-group**.

- We can **group** by *more than one* grouping variable. For example, here we group by `year`, `month`, and `day` to obtain the daily mean **delay** for each day in 2013:

```
by_day <- group_by(flights, year, month, day)
summarize(by_day, mean_dep_delay = mean(dep_delay, na.rm = TRUE))

## # A tibble: 365 x 4
## # Groups:   year, month [12]
##     year month   day mean_dep_delay
##    <int> <int> <int>          <dbl>
##  1  2013     1     1          11.5
##  2  2013     1     2          13.9
##  3  2013     1     3          11.0
##  4  2013     1     4           8.95
##  5  2013     1     5           5.73
##  6  2013     1     6           7.15
##  7  2013     1     7           5.42
##  8  2013     1     8           2.55
##  9  2013     1     9           2.28
## 10  2013     1    10           2.84
## # ... with 355 more rows
```

This returns a data frame (*tibble*) with one row for each combination of `year`, `month`, and `day`, and a column containing the daily mean delays.

Section 4.9 Exercises

Exercise 11 This problem concerns the `group_by()` and `summarize()` functions. It uses the `flights` data frame.

a) Explain in words what the following commands do (recall that `dest` is the *destination* of the flight):

```
by_dest <- group_by(.data = flights, dest)
delay_by_dest <- summarize(.data = by_dest,
                           mean_arr_delay = mean(arr_delay, na.rm = TRUE))
```

b) `summarize()` can summarize *more than one variable* at a time. Explain in words what the following commands do:

```
by_dest <- group_by(.data = flights, dest)
delay_dist_by_dest <- summarize(.data = by_dest,
                                mean_dist = mean(distance, na.rm = TRUE),
                                mean_arr_delay = mean(arr_delay, na.rm = TRUE))
```

Exercise 12 Here's a data frame `ExpData` containing responses to treatments in an experiment and ages and genders of the subjects who participated in the experiment:

```
resp <- c(23, 11, 14, 16, 19, 26, 24, 29, 31, 28, 34, 25)
trt <- c(rep("Ctrl", 4), rep("TrtA", 4), rep("TrtB", 4))
age <- c(33, 45, 30, 24, 22, 31, 39, 40, 29, 19, 27, 25)
gndr <- c("m", "m", "f", "f", "m", "f", "f", "m", "f", "m", "f", "m")
```

```
ExpData <- data.frame(TrtGrp = trt,
                      SubjectGender = gndr,
                      SubjectAge = age,
                      Response = resp, stringsAsFactors = FALSE)
```

a) The function `n()` (from `"dplyr"`) is used (without any arguments) in `summarize()` to *count* observations. Explain in words what the following commands do:

```
by_TrtGrp <- group_by(.data = ExpData, TrtGrp)
summarize(.data = by_TrtGrp, Count = n())
```

b) Use `group_by()` and `summarize()` to compute the *mean* `Response` by `TrtGrp`. Report the three mean `Response` values.

c) Now use `group_by()` and `summarize()` to compute the *mean* `Response` *and mean* `SubjectAge` by `TrtGrp`. Report the three mean `Response` values *and* the three mean `SubjectAge` values.

Exercise 13 This problem concerns the `group_by()` and `summarize()` functions. It uses the `flights` data frame.

a) Use `group_by()`, `summarize()` with `n()`, and `arrange()` to determine which `tailnum` (i.e. which individual **airplane**) flew the *most* times. Report the `tailnum` value of the airplane.

b) Use `group_by()`, `summarize()` with `n()`, and `arrange()` to determine which `dest` (i.e. which **destination**) was flown to the *most* times. Report the (abbreviated) destination name.

4.10 Chaining Together Actions Using the Pipe Operator %>%

- The **pipe operator** `%>%` comes with `"dplyr"` (but is originally from the `"magrittr"` package). It passes the *output* value from one function call as the *input* (first argument) for the next:
  - `x %>% f()` is equivalent to `f(x)`.
  - `x %>% f(y)` is equivalent to `f(x, y)`.
  - `x %>% f(y) %>% g(z)` is equivalent to `g(f(x, y), z)`.
  - etc.
- We'll use the `flights` data to illustrate.

  Suppose we want to look at the relationship between the `distance` traveled and arrival `delay` for destinations that received more than 20 flights. We could type:

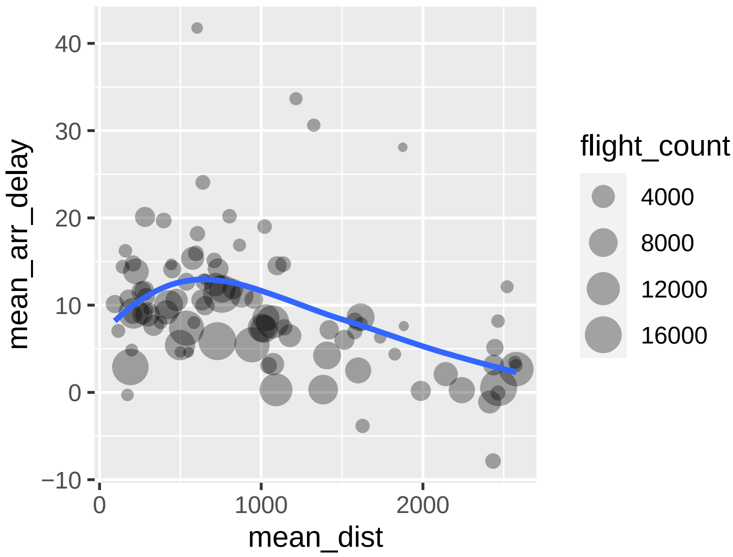
```
# flights is passed to group_by():
by_dest <- group_by(.data = flights, dest)

# by_dest is passed to summarize():
delay_dist_by_dest <- summarize(.data = by_dest,
                                flight_count = n(),
                                mean_dist = mean(distance, na.rm = TRUE),
                                mean_arr_delay = mean(arr_delay, na.rm = TRUE))

# delay_dist_by_dest is passed to filter():
flights_20_plus <- filter(.data = delay_dist_by_dest, flight_count > 20, dest != "HNL")
```

  Here's a plot of the data:

```
ggplot(data = flights_20_plus,
       mapping = aes(x = mean_dist, y = mean_arr_delay)) +
  geom_point(aes(size = flight_count), alpha = 1/3) +
  geom_smooth(se = FALSE)
```



The `alpha` argument to `geom_point()` controls the degree of transparency of points for overplotting.

It looks like arrival delays increase with distance up to a distance of about 600 miles, then decrease. Perhaps with longer flights, there's more ability to make up for lost time.

- Another way to write the above command is to use the **pipe operator** `%>%`, which passes the *output* data frame from one command as the *input* (first argument) for the next command:

```
flights_20_plus <- flights %>%
    group_by(dest) %>%
    summarize(flight_count = n(),
              mean_dist = mean(distance, na.rm = TRUE),
              mean_arr_delay = mean(arr_delay, na.rm = TRUE)) %>%
    filter(flight_count > 20, dest != "HNL")
```

With the **pipe operator**, there's no need to pick names for intermediate data frames (such as `by_dest` and `delay_dist_by_dest` in the earlier set of commands). This can make the code more **readable**.

Section 4.10 Exercises

Exercise 14 The **pipe operator** `%>%` can be applied to *any* type of object (not just data frames). Here's a *vector* `x`:

```
x <- c(2, 5, 4, 3, 7, 9)
```

a) In words, what does the following command do?

```
x %>% mean()
```

b) In words, what does the following command do?

```
x %>% mean() %>% sqrt() %>% round(digits = 2)
```

c) With the **pipe operator**, there's no need to pick names for intermediate values. This can make the code more **readable**. Rewrite the following sequence of commands using the **pipe operator**.

```
mean_x <- mean(x)
sqrt_mean_x <- sqrt(mean_x)
round_sqrt_mean_x <- round(sqrt_mean_x, digits = 2)
```

d) The **pipe operator** %>% can be used instead of *nested* function calls to make your code more **readable**. Rewrite the following command using the **pipe operator**. Report your R command(s).

```
round(sqrt(mean(x)), digits = 2)
```

Exercise 15 This exercise concerns the **pipe operator** %>% and uses the `flights` data.

a) Rewrite the following command using the **pipe operator**.

```
delay <- select(.data = flights, arr_delay)
```

b) Rewrite the following command using the **pipe operator**.

```
dest_delay <- select(.data = flights, dest, arr_delay)
```

c) Rewrite the following pair of commands using the **pipe operator**.

```
dest_delay <- select(.data = flights, dest, arr_delay)
sea_den <- filter(.data = dest_delay,
                  dest == "SEA" | dest == "DEN")
```

d) Rewrite the following sequence of commands using the **pipe operator**.

```
dest_delay <- select(.data = flights, dest, arr_delay)
sea_den <- filter(.data = dest_delay,
                  dest == "SEA" | dest == "DEN")
by_dest <- group_by(sea_den, dest)
delay_by_dest <- summarize(by_dest,
                           mean_arr_delay = mean(arr_delay, na.rm = TRUE))
```

Exercise 16 The **pipe operator** %>% can be used instead of *nested* function calls to make your code more **readable**. Rewrite the following command using the **pipe operator**.

```
den_delays <- summarize(filter(.data = flights,
                               dest == "DEN"),
                        mean_dep_delay = mean(dep_delay, na.rm = TRUE),
                        mean_arr_delay = mean(arr_delay, na.rm = TRUE))
```

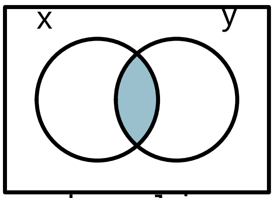
4.11 Combining Multiple Data Frames

- These three functions (from the `"dplyr"` package) are useful for *combining* two data frames:

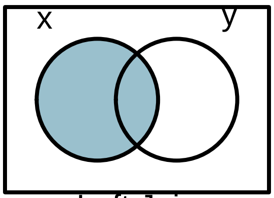
```
inner_join()    # Merge two data frames x and y by matching rows.
                # Returns only rows that have matches in both x and y.
left_join()     # Merge two data frames x and y by matching rows.
                # Returns all rows of x even if they do not have
                # a match in y.
full_join()     # Merge two data frames x and y by matching rows.
```

```
# Returns all rows of x and all rows of y regardless
# of whether they have a match.
```

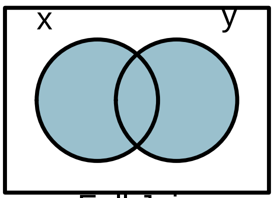
- All three functions append the columns of a data frame `y` to another data frame `x` by matching the rows of the two data frames.



Inner Join



Left Join



Full Join

- Here's a data frame with **names** and **ages** of four people:

```
NamesAndAges

##    Name Age
## 1  John  23
## 2 Karen  27
## 3   Ann  19
```

and here's another with their **names** and **weights**:

```
NamesAndWeights

##    Name Weight
## 1  John    155
## 2 Karen    170
## 3   Ann    157
```

To combine the two data frames using `inner_join()`, matching their rows by the `Name` variable, we type:

```
inner_join(x = NamesAndAges, y = NamesAndWeights, by = "Name")

##    Name Age Weight
## 1  John  23    155
## 2 Karen  27    170
## 3   Ann  19    157
```

To combine them using `left_join()`, we type:

```
left_join(x = NamesAndAges, y = NamesAndWeights, by = "Name")
```

```
##    Name Age Weight
## 1  John  23    155
## 2 Karen  27    170
## 3   Ann  19    157
```

To combine them using `full_join()`, we type:

```
full_join(x = NamesAndAges, y = NamesAndWeights, by = "Name")
```

```
##    Name Age Weight
## 1  John  23    155
## 2 Karen  27    170
## 3   Ann  19    157
```

- Above, `inner_join()`, `left_join()`, and `full_join()` all returned the **same thing** because the rows of the two data frames matched.

  They return **different things** when some rows of `x` and `y` don't match:

  - `inner_join()` returns only the rows that have matches in both `x` and `y`.
  - `left_join()` returns all rows of `x` regardless of whether or not there's a match in `y`. Rows of `x` with no match in `y` will have `NA` values in the new columns.
  - `full_join()` returns all rows of `x` *and* all rows of `y` regardless of whether they have a match in the other data frame. Rows of either data frame that don't have a match in the other will have `NA` values in the new columns.

- For example, consider again the `NamesAndAges` data frame:

```
NamesAndAges
```

```
##    Name Age
## 1  John  23
## 2 Karen  27
## 3   Ann  19
```

  and this other data frame containing three `Names`, *only two of which match* the first data frame, and their `Heights`:

```
NamesAndHeights
```

```
##    Name Height
## 1 Karen     63
## 2   Ann     65
## 3  Karl     36
```

  - Using `inner_join()` gives:

```
inner_join(x = NamesAndAges, y = NamesAndHeights, by = "Name")
```

```
##    Name Age Height
## 1 Karen  27     63
## 2   Ann  19     65
```

    Only the `Names` that are in *both* data frames are returned.

  - Using `left_join()` gives:

```
left_join(x = NamesAndAges, y = NamesAndHeights, by = "Name")
```

```
##    Name Age Height
## 1  John  23     NA
## 2 Karen  27     63
## 3   Ann  19     65
```

All the `Names` that are in the first data frame are returned, and `NA` is inserted for the missing `Height`. Note that the third `Name` in the second data frame isn't returned.

- Using `full_join()` gives:

```
full_join(x = NamesAndAges, y = NamesAndHeights, by = "Name")
```

```
##    Name Age Height
## 1  John  23     NA
## 2 Karen  27     63
## 3   Ann  19     65
## 4  Karl  NA     36
```

All the `Names` from *both* data frames are returned, and `NA`s are inserted for the missing `Height` and the missing `Age`.

- The `Name` variable is common to both data frames, and is used to match rows.

  The variable (such as `Name`) that's common to both data frames and is used to match their rows (via the `by` argument to `*_join()`) is called the ***key***.

- The **key** values don't have to be in the same order in the two data frames (i.e. the rows of the data frames can be ordered differently).

  For example, if the `Names` were in different orders in the two data frames, `inner_join()`, `left_join()`, and `full_join()` would match their orders before combining:

```
NamesAndAges
```

```
##    Name Age
## 1  John  23
## 2 Karen  27
## 3   Ann  19
```

```
## These Names are in a jumbled order:
JumbledNamesAndWts
```

```
##    Name Weight
## 3   Ann    157
## 2 Karen    170
## 1  John    155
```

```
## The rows are put in matching order before combining:
inner_join(NamesAndAges, JumbledNamesAndWts, by = "Name")
```

```
##    Name Age Weight
## 1  John  23    155
## 2 Karen  27    170
## 3   Ann  19    157
```

- Sometimes *two* **key** variables needed to distinguish rows in a data set.

  For example, suppose some `Names` were *duplicated* (e.g. there are *two* `"John"`s and *three* `"Ann"`s below), but we had another column `City` that could be used to distinguish between them:

```
NamesDuplicatedAndAges

##    Name      City Age
## 1  John    Denver  23
## 2  John  Longmont  42
## 3 Karen    Salida  27
## 4   Ann   Boulder  19
## 5   Ann    Denver  29
## 6   Ann Leadville  45
## 7  Karl    Denver  36
```

```
NamesDuplicatedAndWts

##    Name      City Weight
## 1  John    Denver    155
## 2  John  Longmont    203
## 3 Karen    Salida    170
## 4   Ann   Boulder    157
## 5   Ann    Denver    161
## 6   Ann Leadville    164
## 7  Karl    Denver    201
```

In this case, a proper merge of the two data frames would need to be done by the values in *both* columns.

To to do this, we specify both `Name` *and* `City` in a `"character"` vector passed to `inner_join()` via the `by` argument:

```
inner_join(x = NamesDuplicatedAndAges,
           y = NamesDuplicatedAndWts,
           by = c("Name", "City"))

##    Name      City Age Weight
## 1  John    Denver  23    155
## 2  John  Longmont  42    203
## 3 Karen    Salida  27    170
## 4   Ann   Boulder  19    157
## 5   Ann    Denver  29    161
## 6   Ann Leadville  45    164
## 7  Karl    Denver  36    201
```

- In fact, by default `inner_join()`, `left_join()`, and `full_join()` merge data frames by whatever column names the two data frames have in common.

  So in all of the examples above, it actually *wasn't necessary* to specify the **key** variable(s) explicitly via the `by` argument.

Section 4.11 Exercises

Exercise 17 Here are two data frames, `df1` and `df2`, containing responses to two survey questions:

```r
df1 <- data.frame(Respondent_ID = c(1001, 1002, 1003),
                  Q1_Response = c(55, 62, 39))
df1
```

```
##   Respondent_ID Q1_Response
## 1          1001          55
## 2          1002          62
## 3          1003          39
```

```r
df2 <- data.frame(Respondent_ID = c(1002, 1003, 1004),
                  Q2_Response = c("yes", "no", "yes"))
df2
```

```
##   Respondent_ID Q2_Response
## 1          1002         yes
## 2          1003          no
## 3          1004         yes
```

Notice that the `Respondent_ID`s **differ** across two data frames.

a) Guess what the result of the following command will be, then check your answer and report the result.

```r
inner_join(x = df1, y = df2, by = "Respondent_ID")
```

b) Guess what the result of the following command will be, then check your answer and report the result.

```r
left_join(x = df1, y = df2, by = "Respondent_ID")
```

c) Guess what the result of the following command will be, then check your answer and report the result.

```r
full_join(x = df1, y = df2, by = "Respondent_ID")
```

d) If we didn't specify `by = "Respondent_ID"`, by default what **key** variable would each of the `*_join()` functions use to match rows? Try it, for example:

```r
full_join(x = df1, y = df2)
```

e) What would happen if `Q1_Response` and `Q2_Response` were *both* named `Response` in the two data frames, e.g.

```r
df1 <- rename(.data = df1, Response = Q1_Response)
df2 <- rename(.data = df2, Response = Q2_Response)
```

and we typed:

```r
full_join(x = df1, y = df2)
```

Try it, and report the result.

f) What would happen if, as in part *e*, `Q1_Response` and `Q2_Response` were *both* named `Response`, and we typed:

```r
inner_join(x = df1, y = df2)
```

Try it and report the result.

Exercise 18 Here are two data frames containing responses to two survey questions:

```r
df1 <- data.frame(Respondent_ID = c(1000, 1001, 1002, 1003, 1004, 1005, 1006),
                  Q1_Response = c(55, 62, 39, 45, 70, 77, 56))
df1
```

```r
df2 <- data.frame(Respondent_ID = c(1003, 1002, 1000, 1004, 1006, 1001, 1005),
                  Q2_Response = c(12, 17, 23, 24, 19, 30, 20))
df2
```

Note that the `Respondent_ID`s are the same, but in *different orders.*

a) What happens to the ordering of the rows of `df2` when you combine it with `df1` using:

```r
inner_join(x = df1, y = df2, by = "Respondent_ID")
```

b) How would the result differ if you swapped the roles of `df1` and `df2`, e.g.:

```r
inner_join(x = df2, y = df1, by = "Respondent_ID")
```

Exercise 19 Here are two data frames:

```r
dfX <- data.frame(LastName = c("Smith", "Smith", "Jones", "Smith",
                               "Olsen", "Taylor", "Olsen"),
                  FirstName = c("John", "Kim", "John", "Marge", "Bill",
                                "Bill", "Erin"),
                  Gender = c("M", "F", "M", "F", "M", "M", "F"),
                  ExamScore = c(75, 80, 64, 78, 90, 89, 79))
dfX
```

```
##   LastName FirstName Gender ExamScore
## 1    Smith      John      M        75
## 2    Smith       Kim      F        80
## 3    Jones      John      M        64
## 4    Smith     Marge      F        78
## 5    Olsen      Bill      M        90
## 6   Taylor      Bill      M        89
## 7    Olsen      Erin      F        79
```

```r
dfY <- data.frame(LastName = c("Olsen", "Jones", "Taylor", "Smith",
                               "Olsen", "Smith", "Smith"),
                  FirstName = c("Bill", "John", "Bill", "Kim", "Erin",
                               "John", "Marge"),
                  Gender = c("M", "M", "M", "F", "F", "M", "F"),
                  Grade = c("A", "D", "B", "B", "C", "C", "C"))
dfY
```

```
##   LastName FirstName Gender Grade
## 1    Olsen      Bill      M     A
## 2    Jones      John      M     D
## 3   Taylor      Bill      M     B
## 4    Smith       Kim      F     B
## 5    Olsen      Erin      F     C
## 6    Smith      John      M     C
## 7    Smith     Marge      F     C
```

Notice that the two data frames contain the *same* seven people, but in different orders. Notice also that both the `LastName` *and* `FirstName` are needed to uniquely identify the people.

a) Write a command involving, say, `full_join()` that combines the two data frames *by person*. You should end up with this:

```
##   LastName FirstName Gender ExamScore Grade
## 1    Smith      John      M        75     C
## 2    Smith       Kim      F        80     B
## 3    Jones      John      M        64     D
## 4    Smith     Marge      F        78     C
## 5    Olsen      Bill      M        90     A
## 6   Taylor      Bill      M        89     B
## 7    Olsen      Erin      F        79     C
```

b) If you don't specify **key** variables to match by via the `by` argument, matching is done by whatever columns the two data frames have in common (`LastName`, `FirstName`, and `Gender`). For example, the following are equivalent:

```
full_join(x = dfX, y = dfY, by = c("LastName", "FirstName", "Gender"))
```

```
full_join(x = dfX, y = dfY)
```

What happens with the third variable (`Gender`) when you only specify the other two (`LastName` and `FirstName`) as the **key** via the `by` argument? Try it:

```
full_join(x = dfX, y = dfY, by = c("LastName", "FirstName"))
```

c) If values in a **key** variable *don't* uniquely identify rows, i.e. if there are multiple matches between rows of two data frames, **all combinations** of the matches are returned.

What would happen if you tried to combine `dfX` and `dfY` *only* specifying `LastName` as the **key** variable? Try it:

```
full_join(x = dfX, y = dfY, by = "LastName")
```

(Note, this is almost **never** what we want!)

4.12 Acknowledgment

- The above notes (and several examples) on the `"dplyr"` package borrow heavily from the book:

  R for Data Science, by Wickham, H., Grolemund, G., O'Reilly, 2017.