

R4ds Chapter 5 Data Transformation Yuqing Xue

Personal Note

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The following personal code and notes are based on the materials from Hadley Wickham's 'R for Data Science', Chapter 5. <http://r4ds.had.co.nz/transform.html#introduction-2>

- 5.1 Introduction
- 5.2 Filter
- 5.2.4 Exercises
- 5.3 Arrange
- 5.3.1 Exercises
- 5.4 Select
- 5.4.1 Exercises
- 5.5 Mutate
- 5.5.1 Useful Creation Functions
- 5.5.2 Exercises
- 5.6 Summarise
- 5.6.1 Combining multiple operations with the pipe
- 5.6.3 Counts
- 5.6.4 Useful Summary Functions
- 5.6.5 Grouping by multiple variables
- 5.6.6 Ungrouping

5.1 Introduction

nycflights13

```
#####  
##### Dataset: nycflights13::flights  
#####  
library(nycflights13)  
library(tidyverse)  
nycflights13::flights
```

```
## # 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 <dtm>
```

5.2 Filter

Explore, try %in%

```
jan1 <- filter(flights, month == 1, day == 1)
```

```
nov_and_dec = filter(flights, month == 11 | month == 12)
```

A useful short-hand for this problem is x %in% y. This will select every row where x is one of the values in y.

```
nov_dec <- filter(flights, month %in% c(11, 12))
```

```
NYCtoSF <-
  flights %>%
    filter(dest %in% c("SFO", "OAK", "SJC")) %>%
    select(year, month, day, carrier, origin, dest, air_time)
NYCtoSF
```

```
## # A tibble: 13,972 x 7
##   year month   day carrier origin dest air_time
##   <int> <int> <int>   <chr>   <chr> <chr>   <dbl>
## 1 2013     1     1     UA     EWR   SFO     361
## 2 2013     1     1     UA     JFK   SFO     366
## 3 2013     1     1     DL     JFK   SFO     362
## 4 2013     1     1     VX     JFK   SFO     356
## 5 2013     1     1     B6     JFK   SFO     350
## 6 2013     1     1     AA     JFK   SFO     378
## 7 2013     1     1     UA     EWR   SFO     373
## 8 2013     1     1     UA     JFK   SFO     369
## 9 2013     1     1     UA     EWR   SFO     357
## 10 2013     1     1     AA     JFK   SFO     389
## # ... with 13,962 more rows
```

```
NYCtoSF2 <-
  flights %>%
    filter(dest == "SFO" | dest == "OAK" | dest == "SJC") %>%
    select(year, month, day, carrier, origin, dest, air_time)
NYCtoSF2
```

```
## # A tibble: 13,972 x 7
##   year month   day carrier origin dest air_time
##   <int> <int> <int>   <chr>   <chr> <chr>   <dbl>
## 1 2013     1     1     UA     EWR   SFO     361
## 2 2013     1     1     UA     JFK   SFO     366
## 3 2013     1     1     DL     JFK   SFO     362
## 4 2013     1     1     VX     JFK   SFO     356
```

```
## 5 2013 1 1 B6 JFK SFO 350
## 6 2013 1 1 AA JFK SFO 378
## 7 2013 1 1 UA EWR SFO 373
## 8 2013 1 1 UA JFK SFO 369
## 9 2013 1 1 UA EWR SFO 357
## 10 2013 1 1 AA JFK SFO 389
## # ... with 13,962 more rows
```

H.W. As well as & and |, R also has && and ||. Don't use them here! You'll learn when you should use

5.2.4 Exercises

1. Find all flights that

1.1 Had an arrival delay of two or more hours

1.2. Flew to Houston (IAH or HOU)

1.3. Were operated by United, American, or Delta

1.4. Departed in summer (July, August, and September)

1.5. Arrived more than two hours late, but didn't leave late

1.6. Were delayed by at least an hour, but made up over 30 minutes in flight

1.7. Departed between midnight and 6am (inclusive)

```
Ex1.1 <-
  flights %>%
    filter(arr_delay >= 120) %>%
    arrange(desc(arr_delay)) %>%
    select(month, day, carrier, origin, dest, dep_delay, arr_delay)
```

Ex1.1

```
## # A tibble: 10,200 x 7
##   month   day carrier origin dest dep_delay arr_delay
##   <int> <int>   <chr>   <chr> <chr>   <dbl>   <dbl>
## 1     1     9     HA     JFK   HNL     1301    1272
## 2     6    15     MQ     JFK   CMH     1137    1127
## 3     1    10     MQ     EWR   ORD     1126    1109
## 4     9    20     AA     JFK   SFO     1014    1007
## 5     7    22     MQ     JFK   CVG     1005     989
## 6     4    10     DL     JFK   TPA      960     931
## 7     3    17     DL     LGA   MSP      911     915
## 8     7    22     DL     LGA   ATL      898     895
## 9    12     5     AA     EWR   MIA      896     878
## 10    5     3     MQ     EWR   ORD      878     875
## # ... with 10,190 more rows
```

```

Ex1.2 = filter(flights, dest %in% c("IAH", "HOU"))
Ex1.3 = filter(flights, carrier %in% c("UA", "AA", "DL"))
Ex1.4 = filter(flights, month %in% c(7, 8, 9))

Ex1.5 = filter(flights, arr_delay >= 120 & dep_delay <= 0 )
Ex1.6 = filter(flights, dep_delay >= 60 & dep_delay - arr_delay >= 30)
Ex1.7 = filter(flights, dep_time <= 600)

```

2. Another useful dplyr filtering helper is `between()`. What does it do? Can you use it to simplify the code needed to answer the previous challenges?

```

?between
Ex1.4b = filter(flights, between(month, 7, 9))

```

3. How many flights have a missing `dep_time`? What other variables are missing? What might these rows represent?

```

sum(is.na(flights$dep_time)) # 8255

## [1] 8255

flights_missing_dep_time <- flights %>% filter(is.na(dep_time))
flights_missing_dep_time

## # A tibble: 8,255 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     NA             1630         NA       NA
## 2  2013     1     1     NA             1935         NA       NA
## 3  2013     1     1     NA             1500         NA       NA
## 4  2013     1     1     NA              600         NA       NA
## 5  2013     1     2     NA             1540         NA       NA
## 6  2013     1     2     NA             1620         NA       NA
## 7  2013     1     2     NA             1355         NA       NA
## 8  2013     1     2     NA             1420         NA       NA
## 9  2013     1     2     NA             1321         NA       NA
## 10 2013     1     2     NA             1545         NA       NA
## # ... with 8,245 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 <dtm>

flights_cancelled <- flights %>%
  filter(is.na(dep_time) & is.na(dep_delay) & is.na(arr_time) & is.na(arr_delay) & is.na(arr_time))
# same 8255 flights

```

Beside `dep_time`, `dep_delay`, `arr_time`, `arr_delay` and `air_time` are also missing, for all 8255 flights. One possible explanation for it is that those flights were cancelled.

4. Why is `NA ^ 0` not missing? Why is `NA | TRUE` not missing? Why is `FALSE & NA` not missing? Can you figure out the general rule? (`NA * 0` is a tricky counterexample!)

`NA ^ 0` returns 1. Any number to the power of 0 is 1, whether the number is missing or not does not matter.

`NA | TRUE` returns `TRUE`, since the `|` operator returns `TRUE` if either of the terms are `TRUE`. In this case, the right half is `TRUE`, so the whole expression will always return `TRUE`.

`FALSE & NA` returns `FALSE`, because operator `&` returns `TRUE` when both terms are true. The left half is `FALSE`, so the whole expression returns `FALSE` despite the `NA` on the right half.

```
NA * 0
```

```
## [1] NA
```

`NA * 0` returns 0, which may rendered the general rule we discovered from the previous not definite: if `NA` represent a value that is `Inf`, and we know `Inf * 0` should not be a number, i.e., `NaN`.

5.3 Arrange

`arrange()` works similarly to `filter()` except that instead of selecting rows, it changes their order. It takes a data frame and a set of column names (or more complicated expressions) to order by. **If you provide more than one column name, each additional column will be used to break ties in the values of preceding columns:**

```
arrange(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 <dtm>
```

```
arrange(flights, desc(arr_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     1     9     641             900        1301    1242
## 2  2013     6    15    1432            1935        1137    1607
## 3  2013     1    10    1121            1635        1126    1239
## 4  2013     9    20    1139            1845        1014    1457
## 5  2013     7    22     845            1600        1005    1044
## 6  2013     4    10    1100            1900         960    1342
## 7  2013     3    17    2321             810         911     135
## 8  2013     7    22    2257             759         898     121
## 9  2013    12     5     756            1700         896    1058
```

```
## 10 2013      5      3      1133      2055      878      1250
## # ... 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 <dtm>
```

```
df <- tibble(x = c(5, 2, NA))
arrange(df, x)
```

```
## # A tibble: 3 x 1
##       x
##   <dbl>
## 1     2
## 2     5
## 3    NA
```

In this way, `x` then becomes the column name of the tibble `df`.

5.3.1 Exercise

1. How could you use `arrange()` to sort all missing values to the start? (Hint: use `is.na()`).

```
arrange(df, !is.na(x))
```

```
## # A tibble: 3 x 1
##       x
##   <dbl>
## 1    NA
## 2     5
## 3     2
```

It seems that R recognized FALSE as 0 and TRUE as 1, which makes FALSE is less than TRUE, hence can be sorted to the start use `arrange`.

2. Sort flights to find the most delayed flights. Find the flights that left earliest.

```
colnames(flights)
```

```
## [1] "year"      "month"      "day"        "dep_time"
## [5] "sched_dep_time" "dep_delay"  "arr_time"   "sched_arr_time"
## [9] "arr_delay"     "carrier"    "flight"     "tailnum"
## [13] "origin"       "dest"       "air_time"   "distance"
## [17] "hour"        "minute"     "time_hour"
```

```
flights %>%
  arrange(desc(arr_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     1     9     641           900         1301    1242
## 2  2013     6    15    1432          1935         1137    1607
## 3  2013     1    10    1121          1635         1126    1239
## 4  2013     9    20    1139          1845         1014    1457
## 5  2013     7    22     845          1600         1005    1044
## 6  2013     4    10    1100          1900          960    1342
```

```
## 7 2013 3 17 2321 810 911 135
## 8 2013 7 22 2257 759 898 121
## 9 2013 12 5 756 1700 896 1058
## 10 2013 5 3 1133 2055 878 1250
## # ... 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 <dtm>
```

```
flights %>%
  arrange(dep_time)
```

```
## # 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  13      1          2249           72     108
## 2 2013     1  31      1          2100          181     124
## 3 2013    11  13      1          2359           2     442
## 4 2013    12  16      1          2359           2     447
## 5 2013    12  20      1          2359           2     430
## 6 2013    12  26      1          2359           2     437
## 7 2013    12  30      1          2359           2     441
## 8 2013     2  11      1          2100          181     111
## 9 2013     2  24      1          2245           76     121
## 10 2013     3   8      1          2355           6     431
## # ... 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 <dtm>
```

which may lead to an idea to create a function:

idea: do all the common topRanking (smallest/largest, variable) and put it on Shiny

3. Sort flights to find the fastest flights.

time form needs to be clearer, answer not reliable

Idea: create a variable `travelTime` to measure the flight time (`arr_time - dep_time`). Noted that `dep_time` and `arr_time` are coded in a form that is intuitive to read and comprehend, but a little harder to make further calculation with, because they're not continuous. A more convenient representation of number of minutes since midnight are yet to be computed. So `travelTime` are neither real minutes nor hours and minutes like `dep_time` and `arr_time`. More details and discussion can be found in exercise 5.5.2 problem 2. <http://r4ds.had.co.nz/transform.html#exercises-10>).

Tricky: The way how `dep_time` and `arr_time` is coded needs a slightly modification.

```
flights %>%
  mutate(travelTime = ifelse(arr_time - dep_time < 0, arr_time + 2400 - dep_time, arr_time - dep_time))
  select(origin, dest, dep_time, sched_dep_time, arr_time, sched_arr_time, travelTime) %>%
  arrange(travelTime)
```

```
## # A tibble: 336,776 x 7
##   origin dest dep_time sched_dep_time arr_time sched_arr_time travelTime
##   <chr> <chr>   <int>         <int>         <int>         <int>         <dbl>
## 1 EWR   BDL    1323          1325          1358          1421           35
## 2 EWR   BDL    1312          1316          1347          1413           35
```

```
## 3    EWR   BDL    1203          1153    1238          1250          35
## 4    EWR   BDL     722          730    758           830          36
## 5    EWR   BDL     722          729    758           830          36
## 6    EWR   BDL     718          725    754           822          36
## 7    EWR   BDL    1418          1329    1455          1426          37
## 8    EWR   BDL      16          2159     53          2304          37
## 9    EWR   BDL     717          725    754           822          37
## 10   EWR   BDL    1315          1320    1353          1419          38
## # ... with 336,766 more rows

# and the slowest flights
flights %>%
  mutate(travelTime = ifelse(arr_time - dep_time < 0, arr_time + 2400 - dep_time, arr_time - dep_time))
  select(origin, dest, dep_time, sched_dep_time, arr_time, sched_arr_time, travelTime) %>%
  arrange(desc(travelTime))

## # A tibble: 336,776 x 7
##   origin dest dep_time sched_dep_time arr_time sched_arr_time travelTime
##   <chr> <chr>   <int>         <int>    <int>         <int>         <dbl>
## 1    EWR   ORD    1623         1545    1148         1710         1925
## 2    EWR   DFW     959          920    2129         1240         1170
## 3    LGA   ATL    1500         1459     245         1737         1145
## 4    EWR   LAX    1259         1300    2358         1555         1099
## 5    JFK   BOS    2313         2050    1003         2203         1090
## 6    EWR   GSP     653          659    1704          857         1051
## 7    JFK   LAX     625          630    1635          922         1010
## 8    LGA   ATL    1415         1355      18         1617         1003
## 9    LGA   DEN     755          800    1737         1025          982
## 10   JFK   SLC     644          655    1624         1030          980
## # ... with 336,766 more rows

flights_Testimate <- flights %>%
  mutate(travelTime = ifelse(arr_time - dep_time < 0, arr_time + 2400 - dep_time, arr_time - dep_time))
```

The most unexpected flights, like the one from EWR to ORD that took 19 hours 25 minutes, can be spotted and further investigated.

4. Which flights travelled the longest? Which travelled the shortest?

Idea: sort variable distance

```
# The longest flights
flights_Testimate %>%
  select(carrier:distance, travelTime) %>%
  arrange(desc(distance))
```

```
## # A tibble: 336,776 x 8
##   carrier flight tailnum origin dest air_time distance travelTime
##   <chr>   <int>   <chr>   <chr> <chr>    <dbl>    <dbl>         <dbl>
## 1      HA     51  N380HA   JFK   HNL      659     4983          659
## 2      HA     51  N380HA   JFK   HNL      638     4983          616
## 3      HA     51  N380HA   JFK   HNL      616     4983          590
## 4      HA     51  N384HA   JFK   HNL      639     4983          616
## 5      HA     51  N381HA   JFK   HNL      635     4983          661
## 6      HA     51  N385HA   JFK   HNL      611     4983          539
## 7      HA     51  N385HA   JFK   HNL      612     4983          578
```



```
## 8      HA      51 N389HA   JFK   HNL      645      4983      603
## 9      HA      51 N384HA   JFK   HNL      640      4983      601
## 10     HA      51 N388HA   JFK   HNL      633      4983      590
## # ... with 336,766 more rows
```

```
# The longest flight where destination is not HNL
```

```
flights_Testimate %>%
  select(carrier:distance, travelTime) %>%
  filter(dest != 'HNL') %>%
  arrange(desc(distance))
```

```
## # A tibble: 336,069 x 8
```

```
##   carrier flight tailnum origin dest air_time distance travelTime
##   <chr>    <int>    <chr>  <chr> <chr>    <dbl>    <dbl>    <dbl>
## 1      UA      887   N587UA   EWR   ANC      418      3370      325
## 2      UA      887   N572UA   EWR   ANC      404      3370      337
## 3      UA      887   N567UA   EWR   ANC      418      3370      385
## 4      UA      887   N559UA   EWR   ANC      388      3370      289
## 5      UA      887   N572UA   EWR   ANC      434      3370      388
## 6      UA      887   N559UA   EWR   ANC      411      3370      309
## 7      UA      887   N528UA   EWR   ANC      404      3370      302
## 8      UA      887   N534UA   EWR   ANC      428      3370      326
## 9      UA      303   N532UA   JFK   SFO      366      2586      334
## 10     DL     1865   N705TW   JFK   SFO      362      2586      382
## # ... with 336,059 more rows
```

```
# Besides HNL and ANC
```

```
flights_Testimate %>%
  select(carrier:distance, travelTime) %>%
  filter(dest != 'HNL' & dest != "ANC") %>%
  arrange(desc(distance))
```

```
## # A tibble: 336,061 x 8
```

```
##   carrier flight tailnum origin dest air_time distance travelTime
##   <chr>    <int>    <chr>  <chr> <chr>    <dbl>    <dbl>    <dbl>
## 1      UA      303   N532UA   JFK   SFO      366      2586      334
## 2      DL     1865   N705TW   JFK   SFO      362      2586      382
## 3      VX       11   N635VA   JFK   SFO      356      2586      320
## 4      B6      643   N625JB   JFK   SFO      350      2586      313
## 5      AA       59   N336AA   JFK   SFO      378      2586      390
## 6      UA      223   N510UA   JFK   SFO      369      2586      329
## 7      AA      179   N325AA   JFK   SFO      389      2586      398
## 8      VX       23   N625VA   JFK   SFO      363      2586      322
## 9      UA      285   N517UA   JFK   SFO      364      2586      328
## 10     B6      641   N590JB   JFK   SFO      349      2586      311
## # ... with 336,051 more rows
```

```
# Besides HNL, ANC and JFK to SFO
```

```
flights_Testimate %>%
  select(carrier:distance, travelTime) %>%
  filter(dest != 'HNL' & dest != "ANC" & dest != "SFO") %>%
  arrange(desc(distance))
```

```
## # A tibble: 322,730 x 8
```

```
##   carrier flight tailnum origin dest air_time distance travelTime
##   <chr>    <int>    <chr>  <chr> <chr>    <dbl>    <dbl>    <dbl>
```

```
## 1      B6      91 N523JB      JFK      OAK      330      2576      312
## 2      B6      91 N646JB      JFK      OAK      328      2576      317
## 3      B6      91 N636JB      JFK      OAK      319      2576      278
## 4      B6      91 N524JB      JFK      OAK      351      2576      313
## 5      B6      91 N659JB      JFK      OAK      351      2576      320
## 6      B6      91 N784JB      JFK      OAK      341      2576      361
## 7      B6      91 N517JB      JFK      OAK      345      2576      358
## 8      B6      91 N656JB      JFK      OAK      353      2576      313
## 9      B6      91 N563JB      JFK      OAK      364      2576      333
## 10     B6      91 N705JB      JFK      OAK      346      2576      365
## # ... with 322,720 more rows
```

The second longest flight is from EWR to ANC. The third one is JFK to SFO, and the forth longest flight within United States is from JFK to OAK.

```
# The shortest flights
flights_Testimate %>%
  select(carrier:distance, travelTime) %>%
  arrange(distance)
```

```
## # A tibble: 336,776 x 8
##   carrier flight tailnum origin dest air_time distance travelTime
##   <chr>   <int>   <chr>   <chr> <chr>   <dbl>   <dbl>   <dbl>
## 1      US    1632    <NA>     EWR  LGA      NA      17      NA
## 2      EV    3833  N13989    EWR  PHL      30      80      95
## 3      EV    4193  N14972    EWR  PHL      30      80      93
## 4      EV    4502  N15983    EWR  PHL      28      80     108
## 5      EV    4645  N27962    EWR  PHL      32      80      90
## 6      EV    4193  N14902    EWR  PHL      29      80      86
## 7      EV    4619  N22909    EWR  PHL      22      80      99
## 8      EV    4619  N33182    EWR  PHL      25      80      88
## 9      EV    4619  N11194    EWR  PHL      30      80     177
## 10     EV    4619  N17560    EWR  PHL      27      80      91
## # ... with 336,766 more rows
```

```
flights_Testimate %>%
  filter(distance == 17)
```

```
## # A tibble: 1 x 20
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013     7    27      NA             106         NA      NA
## # ... with 13 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 <dtm>, travelTime <dbl>
```

5.4 Select

`select()` can be used to rename variables, but it's rarely useful because it drops all of the variables not explicitly mentioned. Instead, use `rename()`, which is a variant of `select()` that keeps all the variables that aren't explicitly mentioned

```
# change tailnum to tail_num
```

```
flights %>%
  rename(tail_num = tailnum)
```

```
## # 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>, tail_num <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dtm>
```

Nothing changes the original dataset `flights_Testimate`, which still has that variable named `tailnum`.

Another option is to use `select()` in conjunction with the `everything()` helper. This is useful if you have a handful of variables you'd like to move to the start of the data frame.

Move some main information to the start of the dataframe and keep the rest:

```
flights %>%
  select(carrier:dest, everything())
```

```
## # A tibble: 336,776 x 19
##   carrier flight tailnum origin dest year month   day dep_time
##   <chr>   <int>   <chr>   <chr> <chr> <int> <int> <int>   <int>
## 1    UA   1545  N14228   EWR  IAH  2013     1     1     517
## 2    UA   1714  N24211   LGA  IAH  2013     1     1     533
## 3    AA   1141  N619AA   JFK  MIA  2013     1     1     542
## 4    B6    725  N804JB   JFK  BQN  2013     1     1     544
## 5    DL    461  N668DN   LGA  ATL  2013     1     1     554
## 6    UA   1696  N39463   EWR  ORD  2013     1     1     554
## 7    B6    507  N516JB   EWR  FLL  2013     1     1     555
## 8    EV   5708  N829AS   LGA  IAD  2013     1     1     557
## 9    B6     79  N593JB   JFK  MCO  2013     1     1     557
## 10   AA    301  N3ALAA   LGA  ORD  2013     1     1     558
## # ... with 336,766 more rows, and 10 more variables: sched_dep_time <int>,
## #   dep_delay <dbl>, arr_time <int>, sched_arr_time <int>,
## #   arr_delay <dbl>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dtm>
```

5.4.1 Exercise

1. Brainstorm as many ways as possible to select `dep_time`, `dep_delay`, `arr_time`, and `arr_delay` from `flights`.

1.0. Just list all the variables to select

```
flights %>%
  select(dep_time, dep_delay, arr_time, arr_delay)
```

```
## # A tibble: 336,776 x 4
##   dep_time dep_delay arr_time arr_delay
##   <int>    <dbl>    <int>    <dbl>
## 1     517         2      830        11
## 2     533         4      850        20
## 3     542         2      923        33
## 4     544        -1     1004       -18
## 5     554        -6      812       -25
## 6     554        -4      740        12
## 7     555        -5      913        19
## 8     557        -3      709       -14
## 9     557        -3      838        -8
## 10    558        -2      753         8
## # ... with 336,766 more rows
```

1.1. starts_with and ends_with

```
flights %>%
  select(starts_with("dep"), starts_with("arr"))
```

```
## # A tibble: 336,776 x 4
##   dep_time dep_delay arr_time arr_delay
##   <int>    <dbl>    <int>    <dbl>
## 1     517         2      830        11
## 2     533         4      850        20
## 3     542         2      923        33
## 4     544        -1     1004       -18
## 5     554        -6      812       -25
## 6     554        -4      740        12
## 7     555        -5      913        19
## 8     557        -3      709       -14
## 9     557        -3      838        -8
## 10    558        -2      753         8
## # ... with 336,766 more rows
```

```
flights %>%
  select(ends_with("time"), ends_with("delay")) %>%
  select(-c(starts_with("sched"), starts_with("air")))
```

```
## # A tibble: 336,776 x 4
##   dep_time arr_time dep_delay arr_delay
##   <int>    <int>    <dbl>    <dbl>
## 1     517      830         2        11
## 2     533      850         4        20
## 3     542      923         2        33
## 4     544     1004        -1       -18
## 5     554      812        -6       -25
## 6     554      740        -4         12
## 7     555      913        -5         19
## 8     557      709        -3       -14
## 9     557      838        -3         -8
## 10    558      753        -2          8
## # ... with 336,766 more rows
```

1.2. Fancier: contains

```
flights %>% select(dep_time:arr_delay, -c(contains("sched")))
```

```
## # A tibble: 336,776 x 4
##   dep_time dep_delay arr_time arr_delay
##   <int>     <dbl>   <int>     <dbl>
## 1      517         2     830         11
## 2      533         4     850         20
## 3      542         2     923         33
## 4      544        -1    1004        -18
## 5      554        -6     812        -25
## 6      554        -4     740         12
## 7      555        -5     913         19
## 8      557        -3     709        -14
## 9      557        -3     838         -8
## 10     558        -2     753          8
## # ... with 336,766 more rows
```

1.3. Start learning matches syntax

```
flights %>% select(matches("^dep|^arr"))
```

```
## # A tibble: 336,776 x 4
##   dep_time dep_delay arr_time arr_delay
##   <int>     <dbl>   <int>     <dbl>
## 1      517         2     830         11
## 2      533         4     850         20
## 3      542         2     923         33
## 4      544        -1    1004        -18
## 5      554        -6     812        -25
## 6      554        -4     740         12
## 7      555        -5     913         19
## 8      557        -3     709        -14
## 9      557        -3     838         -8
## 10     558        -2     753          8
## # ... with 336,766 more rows
```

2. What happens if you include the name of a variable multiple times in a select() call?

```
flights %>% select(dep_time, dep_time, dep_time)
```

```
## # A tibble: 336,776 x 1
##   dep_time
##   <int>
## 1      517
## 2      533
## 3      542
## 4      544
## 5      554
## 6      554
## 7      555
## 8      557
## 9      557
## 10     558
## # ... with 336,766 more rows
```

Just select the variable once despite multiple select call.

3. What does the `one_of()` function do? Why might it be helpful in conjunction with this vector? `vars <- c("year", "month", "day", "dep_delay", "arr_delay")`

```
vars <- c("year", "month", "day", "dep_delay", "arr_delay")
flights %>% select(one_of(vars))
```

```
## # A tibble: 336,776 x 5
##   year month   day dep_delay arr_delay
##   <int> <int> <int>     <dbl>     <dbl>
## 1  2013     1     1         2         11
## 2  2013     1     1         4         20
## 3  2013     1     1         2         33
## 4  2013     1     1        -1        -18
## 5  2013     1     1        -6        -25
## 6  2013     1     1        -4         12
## 7  2013     1     1        -5         19
## 8  2013     1     1        -3        -14
## 9  2013     1     1        -3         -8
## 10 2013     1     1        -2          8
## # ... with 336,766 more rows
```

4. Does the result of running the following code surprise you? How do the select helpers deal with case by default? How can you change that default?

```
select(flights, contains("TIME"))
```

```
## # A tibble: 336,776 x 6
##   dep_time sched_dep_time arr_time sched_arr_time air_time
##   <int>         <int>     <int>         <int>     <dbl>
## 1     517           515       830           819       227
## 2     533           529       850           830       227
## 3     542           540       923           850       160
## 4     544           545      1004          1022       183
## 5     554           600       812           837       116
## 6     554           558       740           728       150
## 7     555           600       913           854       158
## 8     557           600       709           723         53
## 9     557           600       838           846       140
## 10    558           600       753           745       138
## # ... with 336,766 more rows, and 1 more variables: time_hour <dtm>
```

```
select(flights, contains("TIME", ignore.case = FALSE))
```

```
## # A tibble: 336,776 x 0
```

`contains` does not treat argument with case sensitive by default. Use `ignore.case = FALSE` to change that setting.

5.5 Add new variables with `mutate()`

```
flights_sml <- select(flights,
  year:day,
```

```

ends_with("delay"),
distance,
air_time
)
mutate(flights_sml,
  gain = arr_delay - dep_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     9 370.0441
## 2  2013     1     1         4        20    1416    227    16 374.2731
## 3  2013     1     1         2        33    1089    160    31 408.3750
## 4  2013     1     1        -1       -18    1576    183   -17 516.7213
## 5  2013     1     1        -6       -25     762    116   -19 394.1379
## 6  2013     1     1        -4        12     719    150    16 287.6000
## 7  2013     1     1        -5        19    1065    158    24 404.4304
## 8  2013     1     1        -3       -14     229     53   -11 259.2453
## 9  2013     1     1        -3        -8     944    140    -5 404.5714
## 10 2013     1     1        -2         8     733    138    10 318.6957
## # ... with 336,766 more rows

```

If you only want to keep the new variables, use `transmute()`:

```

transmute(flights,
  gain = arr_delay - dep_delay,
  hours = air_time / 60,
  gain_per_hour = gain / hours # minutes gain per airtime hour
)

```

```

## # A tibble: 336,776 x 3
##   gain  hours gain_per_hour
##   <dbl>  <dbl>      <dbl>
## 1     9 3.7833333      2.378855
## 2    16 3.7833333      4.229075
## 3    31 2.6666667     11.625000
## 4   -17 3.0500000     -5.573770
## 5   -19 1.9333333     -9.827586
## 6    16 2.5000000      6.400000
## 7    24 2.6333333      9.113924
## 8   -11 0.8833333     -12.452830
## 9    -5 2.3333333      -2.142857
## 10   10 2.3000000      4.347826
## # ... with 336,766 more rows

```

5.5.1 Useful creation functions

The key property is that the function `mutate` must be vectorised: it must take a vector of values as input, return a vector with the same number of values as output.

If one parameter is shorter than the other, it will be automatically extended to be the same length. This is most useful when one of the arguments is a single number: `air_time / 60`, `hours * 60 + minute`, etc.

Ranking: The default gives smallest values the small ranks; use `desc(x)` to give the largest values the smallest ranks.

```
y <- c(70, 10, 10, NA, 30, 40)
min_rank(y)
```

```
## [1] 5 1 1 NA 3 4
```

```
min_rank(desc(y)) # order by value, more common
```

```
## [1] 1 4 4 NA 3 2
```

5.5.2 Exercises

1. Currently `dep_time` and `sched_dep_time` are convenient to look at, but hard to compute with because they're not really continuous numbers. Convert them to a more convenient representation of number of minutes since midnight.

Modular arithmetic: `%%` (integer division) and `%%` (remainder), where $x == y * (x \% y) + (x \% y)$

```
flights_5.5.2.1 = flights_Testimate %>%
  mutate(dep_time_totalMinutes = dep_time %% 100 * 60 + dep_time %% 100, sched_dep_time_totalMinutes =
  select(year:dep_delay, dep_time_totalMinutes, sched_dep_time_totalMinutes, arr_time:time_hour )
```

Use `select` to rearrange column orders.

2. Compare `air_time` with `arr_time - dep_time`. What do you expect to see? What do you see? What do you need to do to fix it?

```
flights_Testimate %>%
  mutate(arr_dep = arr_time - dep_time) %>%
  select(carrier:air_time, arr_dep)
```

```
## # A tibble: 336,776 x 7
##   carrier flight tailnum origin dest air_time arr_dep
##   <chr>   <int>   <chr>   <chr> <chr>   <dbl>   <int>
## 1      UA    1545   N14228   EWR   IAH     227     313
## 2      UA    1714   N24211   LGA   IAH     227     317
## 3      AA    1141   N619AA   JFK   MIA     160     381
## 4      B6     725   N804JB   JFK   BQN     183     460
## 5      DL     461   N668DN   LGA   ATL     116     258
## 6      UA    1696   N39463   EWR   ORD     150     186
## 7      B6     507   N516JB   EWR   FLL     158     358
## 8      EV    5708   N829AS   LGA   IAD      53     152
## 9      B6      79   N593JB   JFK   MCO     140     281
## 10     AA     301   N3ALAA   LGA   ORD     138     195
## # ... with 336,766 more rows
```

We expect to see `air_time` equals `arr_time - dep_time`, however they are not remotely equal, and they shouldn't be, because as mentioned in problem 1, `dep_time` and `arr_time` (and their corresponding scheduled version) are not recorded in a manner that easy to add or subtract. So a more convenient version of representation is preferred.

```
flights_Testimate = flights_Testimate %>%
  mutate(dep_time_totalMinutes = dep_time %% 100 * 60 + dep_time %% 100,
         sched_dep_time_totalMinutes = sched_dep_time %% 100 * 60 + sched_dep_time %% 100,
         arr_time_totalMinutes = arr_time %% 100 * 60 + arr_time %% 100,
         sched_arr_time_totalMinutes = sched_arr_time %% 100 * 60 + sched_arr_time %% 100) %>%
```



```
select(year:arr_delay,dep_time_totalMinutes, sched_dep_time_totalMinutes, arr_time_totalMinutes,
       sched_arr_time_totalMinutes, air_time, carrier:travelTime)
```

```
flights_Testimate %>%
```

```
mutate(air_time_minutes = arr_time_totalMinutes - dep_time_totalMinutes) %>%
```

```
select(carrier:distance, sched_dep_time_totalMinutes, sched_arr_time_totalMinutes, dep_time_totalMinutes)
```

```
## # A tibble: 336,776 x 12
```

```
##   carrier flight tailnum origin dest distance
```

```
##   <chr>    <int>    <chr> <chr> <chr>    <dbl>
```

```
## 1      UA    1545  N14228   EWR  IAH    1400
```

```
## 2      UA    1714  N24211   LGA  IAH    1416
```

```
## 3      AA    1141  N619AA   JFK  MIA    1089
```

```
## 4      B6     725  N804JB   JFK  BQN    1576
```

```
## 5      DL     461  N668DN   LGA  ATL     762
```

```
## 6      UA    1696  N39463   EWR  ORD     719
```

```
## 7      B6     507  N516JB   EWR  FLL    1065
```

```
## 8      EV    5708  N829AS   LGA  IAD     229
```

```
## 9      B6      79  N593JB   JFK  MCO     944
```

```
## 10     AA     301  N3ALAA   LGA  ORD     733
```

```
## # ... with 336,766 more rows, and 6 more variables:
```

```
## #   sched_dep_time_totalMinutes <dbl>, sched_arr_time_totalMinutes <dbl>,
```

```
## #   dep_time_totalMinutes <dbl>, arr_time_totalMinutes <dbl>,
```

```
## #   air_time_minutes <dbl>, air_time <dbl>
```

3. Compare dep_time, sched_dep_time, and dep_delay. How would you expect those three numbers to be related?

```
flights_Testimate %>%
```

```
mutate(dep_delay_copy = dep_time - sched_dep_time) %>%
```

```
select(dep_time, sched_dep_time, dep_delay_copy, dep_delay)
```

```
## # A tibble: 336,776 x 4
```

```
##   dep_time sched_dep_time dep_delay_copy dep_delay
```

```
##   <int>         <int>         <int>    <dbl>
```

```
## 1      517           515             2         2
```

```
## 2      533           529             4         4
```

```
## 3      542           540             2         2
```

```
## 4      544           545            -1        -1
```

```
## 5      554           600           -46        -6
```

```
## 6      554           558            -4        -4
```

```
## 7      555           600           -45        -5
```

```
## 8      557           600           -43        -3
```

```
## 9      557           600           -43        -3
```

```
## 10     558           600           -42        -2
```

```
## # ... with 336,766 more rows
```

```
flights_Testimate %>%
```

```
mutate(dep_delay_copy = dep_time_totalMinutes - sched_dep_time_totalMinutes) %>%
```

```
select(dep_time, sched_dep_time, dep_delay_copy, dep_delay)
```

```
## # A tibble: 336,776 x 4
```

```
##   dep_time sched_dep_time dep_delay_copy dep_delay
```

```
##   <int>         <int>         <dbl>    <dbl>
```

```
## 1      517           515             2         2
```

```
## 2      533           529             4         4
```

```
## 3      542      540      2      2
## 4      544      545     -1     -1
## 5      554      600     -6     -6
## 6      554      558     -4     -4
## 7      555      600     -5     -5
## 8      557      600     -3     -3
## 9      557      600     -3     -3
## 10     558      600     -2     -2
## # ... with 336,766 more rows
```

4. Find the 10 most delayed flights using a ranking function. How do you want to handle ties? Carefully read the documentation for `min_rank()`.

My first answer: `arr_delay`

```
flights_Testimate %>%
  mutate(delay_rank = min_rank(desc(arr_delay))) %>%
  select(carrier:dest, arr_delay, delay_rank) %>%
  arrange(delay_rank)

## # A tibble: 336,776 x 7
##   carrier flight tailnum origin dest arr_delay delay_rank
##   <chr>   <int>   <chr>   <chr> <chr>   <dbl>     <int>
## 1      HA      51  N384HA    JFK  HNL    1272         1
## 2      MQ    3535  N504MQ    JFK  CMH    1127         2
## 3      MQ    3695  N517MQ    EWR  ORD    1109         3
## 4      AA     177  N338AA    JFK  SFO    1007         4
## 5      MQ    3075  N665MQ    JFK  CVG     989         5
## 6      DL    2391  N959DL    JFK  TPA     931         6
## 7      DL    2119  N927DA    LGA  MSP     915         7
## 8      DL    2047  N6716C    LGA  ATL     895         8
## 9      AA     172  N5DMAA    EWR  MIA     878         9
## 10     MQ    3744  N523MQ    EWR  ORD     875        10
## # ... with 336,766 more rows
```

Improved version (without having to create a new variable)

```
flights_Testimate %>%
  filter(min_rank(desc(arr_delay)) <= 10) %>%
  select(carrier:dest, arr_delay) %>%
  arrange(desc(arr_delay))

## # A tibble: 10 x 6
##   carrier flight tailnum origin dest arr_delay
##   <chr>   <int>   <chr>   <chr> <chr>   <dbl>
## 1      HA      51  N384HA    JFK  HNL    1272
## 2      MQ    3535  N504MQ    JFK  CMH    1127
## 3      MQ    3695  N517MQ    EWR  ORD    1109
## 4      AA     177  N338AA    JFK  SFO    1007
## 5      MQ    3075  N665MQ    JFK  CVG     989
## 6      DL    2391  N959DL    JFK  TPA     931
## 7      DL    2119  N927DA    LGA  MSP     915
## 8      DL    2047  N6716C    LGA  ATL     895
## 9      AA     172  N5DMAA    EWR  MIA     878
## 10     MQ    3744  N523MQ    EWR  ORD     875
```

5. What does `1:3 + 1:10` return? Why?

```
1:3 + 1:10
```

```
## Warning in 1:3 + 1:10: longer object length is not a multiple of shorter
## object length
```

```
## [1] 2 4 6 5 7 9 8 10 12 11
```

It returns a 10 dimensional vector along with a warning message. Looks like the shorter vector 1:3 is repeated out to the length of the longer 1:10 one.

5.6 Grouped summaries with summarise

It collapses a data frame to a single row.

summarise() is not terribly useful unless we pair it with group_by()

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

```
## Source: local data frame [365 x 4]
```

```
## Groups: year, month [?]
```

```
##
```

```
##   year month   day   delay
##   <int> <int> <int>   <dbl>
```

```
## 1  2013     1     1 11.548926
```

```
## 2  2013     1     2 13.858824
```

```
## 3  2013     1     3 10.987832
```

```
## 4  2013     1     4  8.951595
```

```
## 5  2013     1     5  5.732218
```

```
## 6  2013     1     6  7.148014
```

```
## 7  2013     1     7  5.417204
```

```
## 8  2013     1     8  2.553073
```

```
## 9  2013     1     9  2.276477
```

```
## 10 2013     1    10  2.844995
```

```
## # ... with 355 more rows
```

5.6.1 Combining multiple operations with the pipe

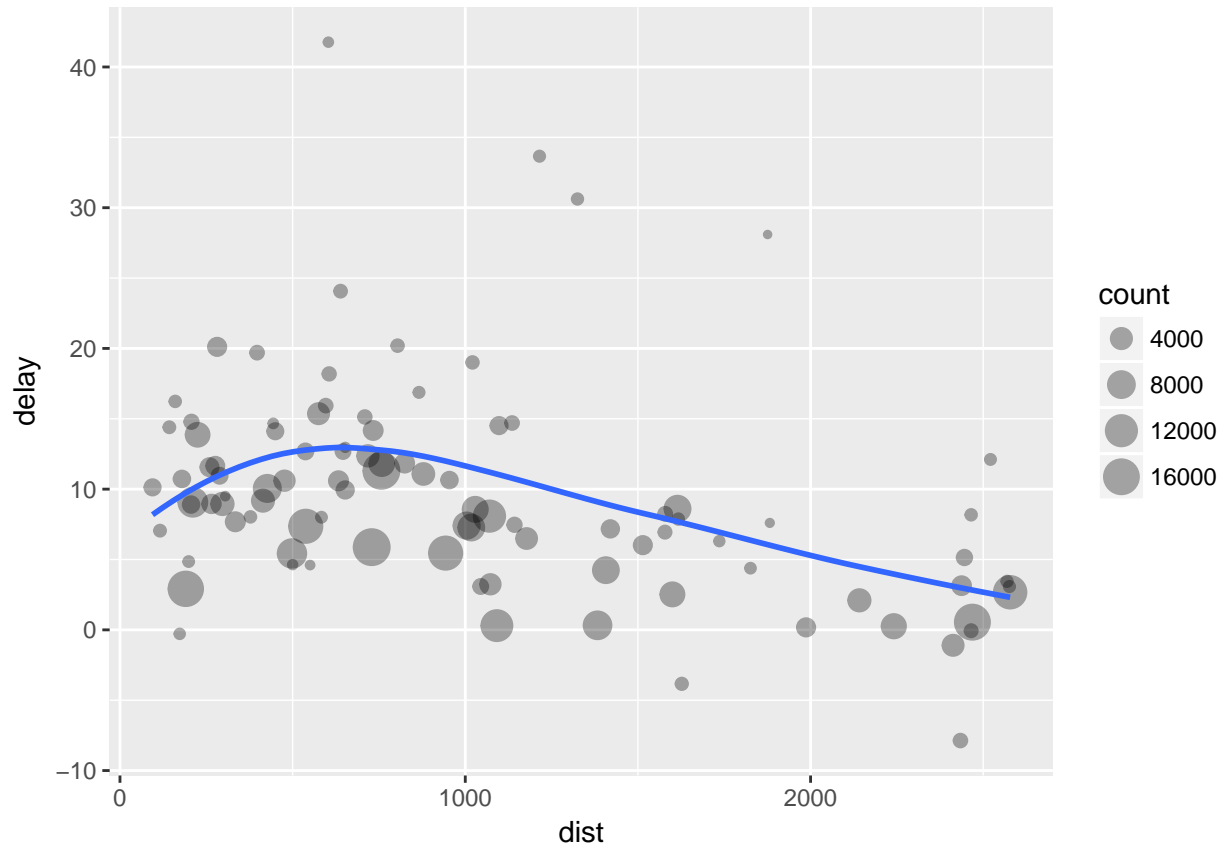
Imagine that we want to explore the relationship between the distance and average delay for each location. Using what you know about dplyr, you might write code like this:

```
delays <- flights %>%
  group_by(dest) %>%
  summarise(
    count = n(),
    dist = mean(distance, na.rm = TRUE),
    delay = mean(arr_delay, na.rm = TRUE)
  ) %>%
  filter(count > 20, dest != "HNL")
```

```
# It looks like delays increase with distance up to ~750 miles and then decrease. Maybe as flights get
ggplot(data = delays, mapping = aes(x = dist, y = delay)) +
```

```
geom_point(aes(size = count), alpha = 1/3) +  
geom_smooth(se = FALSE)
```

```
## `geom_smooth()` using method = 'loess'
```



```
#> `geom_smooth()` using method = 'loess'
```

There are three steps to prepare this data:

Group flights by destination.

Summarise to compute distance, average delay, and number of flights.

Filter to remove noisy points and Honolulu airport, which is almost twice as far away as the next closest airport.

This code is a little frustrating to write because we have to give each intermediate data frame a name, even though we don't care about it. Naming things is hard, so this slows down our analysis.

5.6.2 Missing Values

Naive failure try:

```
flights %>%  
  group_by(year, month, day) %>%  
  summarise(mean = mean(dep_delay))
```

```
## Source: local data frame [365 x 4]  
## Groups: year, month [?]  
##
```

```
##      year month   day mean
##      <int> <int> <int> <dbl>
## 1    2013     1     1    NA
## 2    2013     1     2    NA
## 3    2013     1     3    NA
## 4    2013     1     4    NA
## 5    2013     1     5    NA
## 6    2013     1     6    NA
## 7    2013     1     7    NA
## 8    2013     1     8    NA
## 9    2013     1     9    NA
## 10   2013     1    10    NA
## # ... with 355 more rows
```

All aggregation functions have an `na.rm` argument which removes the missing values prior to computation:

```
flights %>%
  group_by(year, month, day) %>%
  summarise(mean = mean(dep_delay, na.rm = TRUE))
```

```
## Source: local data frame [365 x 4]
## Groups: year, month [?]
##
##      year month   day      mean
##      <int> <int> <int>    <dbl>
## 1    2013     1     1 11.548926
## 2    2013     1     2 13.858824
## 3    2013     1     3 10.987832
## 4    2013     1     4  8.951595
## 5    2013     1     5  5.732218
## 6    2013     1     6  7.148014
## 7    2013     1     7  5.417204
## 8    2013     1     8  2.553073
## 9    2013     1     9  2.276477
## 10   2013     1    10  2.844995
## # ... with 355 more rows
```

Departure delay by day:

```
not_cancelled <- flights %>%
  filter(!is.na(dep_delay), !is.na(arr_delay))

not_cancelled %>%
  group_by(year, month, day) %>%
  summarise(mean = mean(dep_delay))
```

```
## Source: local data frame [365 x 4]
## Groups: year, month [?]
##
##      year month   day      mean
##      <int> <int> <int>    <dbl>
## 1    2013     1     1 11.435620
## 2    2013     1     2 13.677802
## 3    2013     1     3 10.907778
## 4    2013     1     4  8.965859
## 5    2013     1     5  5.732218
```

```
## 6    2013    1    6  7.145959
## 7    2013    1    7  5.417204
## 8    2013    1    8  2.558296
## 9    2013    1    9  2.301232
## 10   2013    1   10  2.844995
## # ... with 355 more rows
```

Useful tool alert!

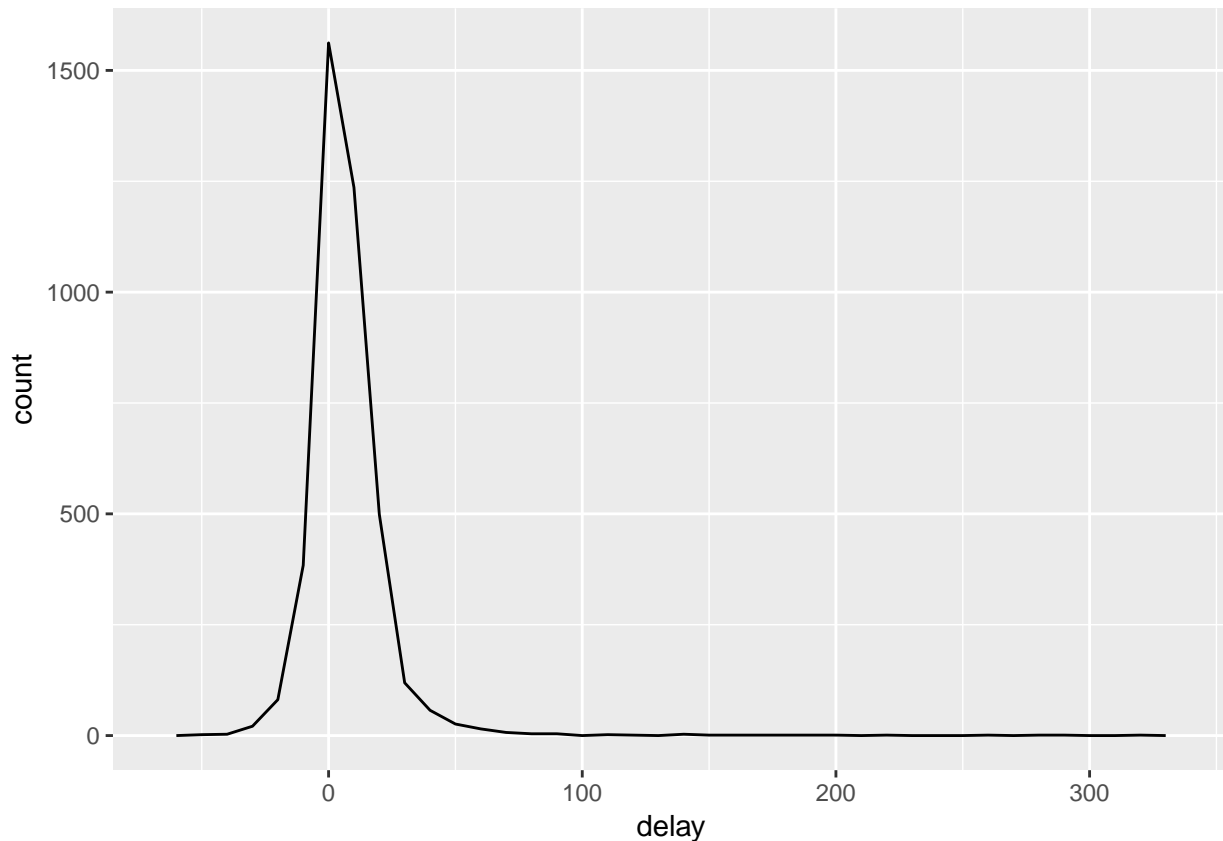
5.6.3 Counts

Whenever you do any aggregation, it's always a good idea to include either a count `n()`, or a count of non-missing values (`sum(!is.na(x))`). That way you can check that you're not drawing conclusions based on very small amounts of data. For example, let's look at the planes (identified by their tail number) that have the highest average delays:

planes identified by their tail number

```
# look at the planes (identified by their tail number) that have the highest average delays
delays <- not_cancelled %>%
  group_by(tailnum) %>%
  summarise(
    delay = mean(arr_delay)
  )

ggplot(data = delays, mapping = aes(x = delay)) +
  geom_freqpoly(binwidth = 10)
```



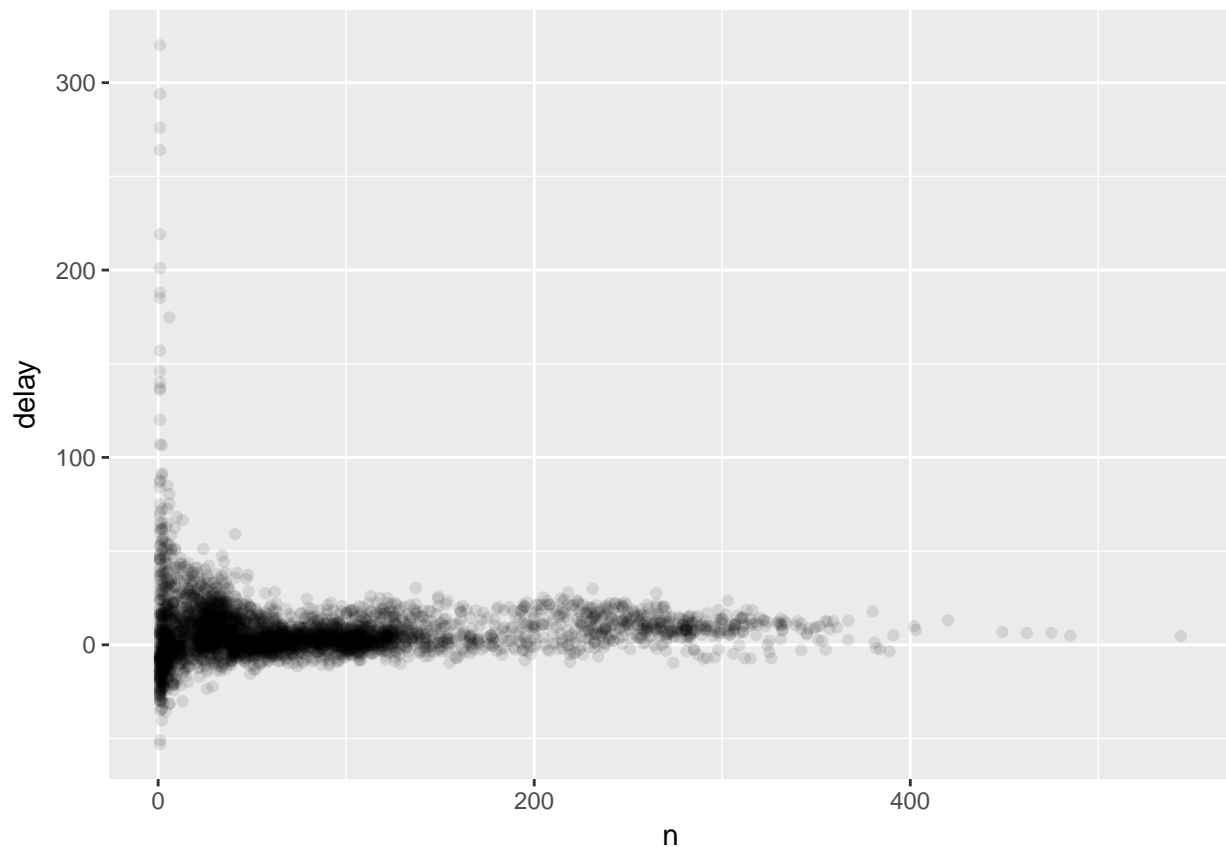
There are some planes that have an average delay of 5 hours (300 minutes), but the story is actually a little more nuanced. We can get more insight if we draw a scatterplot of number of flights vs. average delay:

Use of `n = n()`

Testimate: Displays number of cases within each group you defined by `group_by()`. In this case, if we are interested in delay performance for each plane, which is identified by their tail number (`group_by(tailnum)`), then under column of `n` shows the number of flights each plane took.

```
# draw a scatterplot of number of flights vs. average delay
delays <- not_cancelled %>%
  group_by(tailnum) %>%
  summarise(
    delay = mean(arr_delay, na.rm = TRUE),
    n = n()
  )

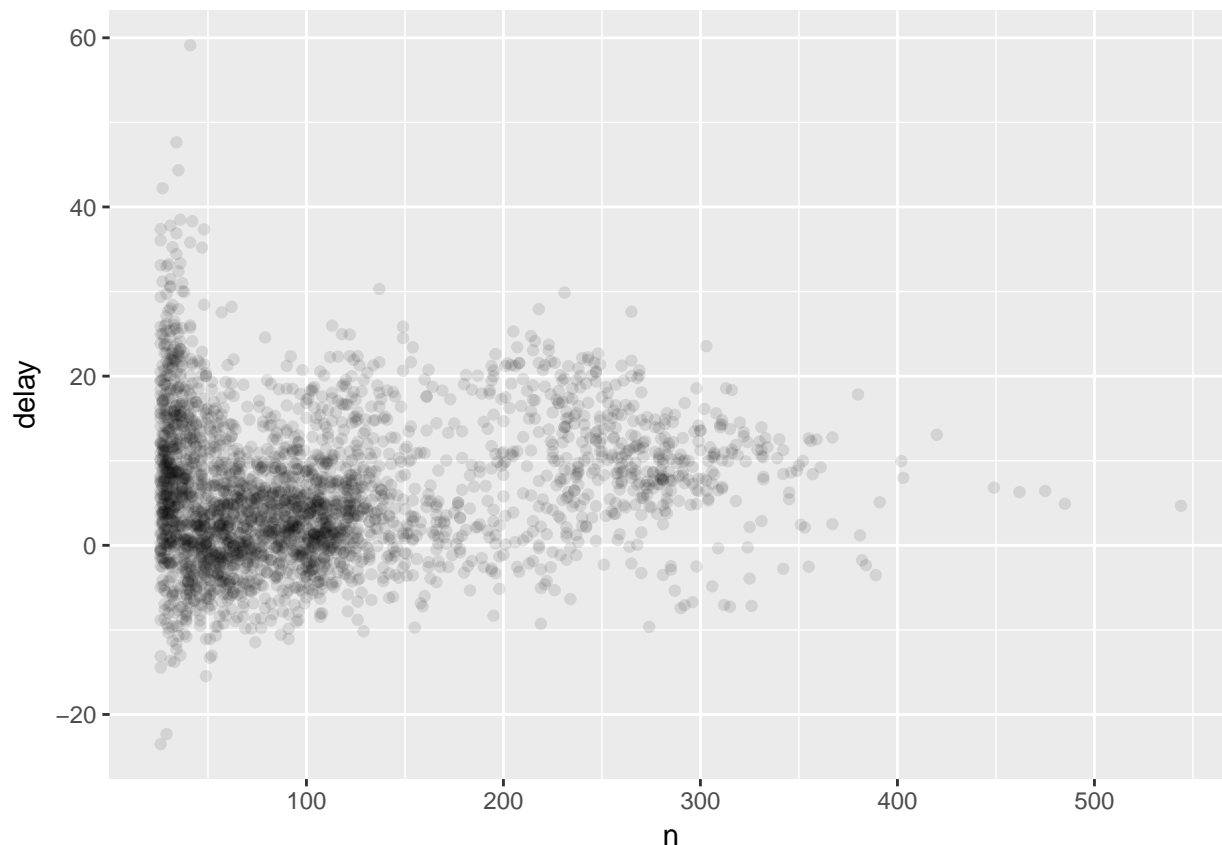
ggplot(data = delays, mapping = aes(x = n, y = delay)) +
  geom_point(alpha = 1/10)
```



Not surprisingly, there is much greater variation in the average delay when there are few flights. The shape of this plot is very characteristic: whenever you plot a mean (or other summary) vs. group size, you'll see that the variation decreases as the sample size increases.

When looking at this sort of plot, it's often useful to filter out the groups with the smallest numbers of observations, so you can see more of the pattern and less of the extreme variation in the smallest groups.

```
# filter out the groups with the smallest numbers of observations to see more of the pattern and less o
delays %>%
  filter(n > 25) %>%
  ggplot(mapping = aes(x = n, y = delay)) +
    geom_point(alpha = 1/10)
```

RStudio tip: a useful keyboard shortcut is Cmd/Ctrl + Shift + P. This resends the previously sent chunk from the editor to the console. This is very convenient when you're (e.g.) exploring the value of `n` in the example above. You send the whole block once with Cmd/Ctrl + Enter, then you modify the value of `n` and press Cmd/Ctrl + Shift + P to resend the complete block.

Baseball performance

Here I use data from the Lahman package to compute the batting average (number of hits / number of attempts) of every major league baseball player.

```
# Convert to a tibble so it prints nicely
library(Lahman)

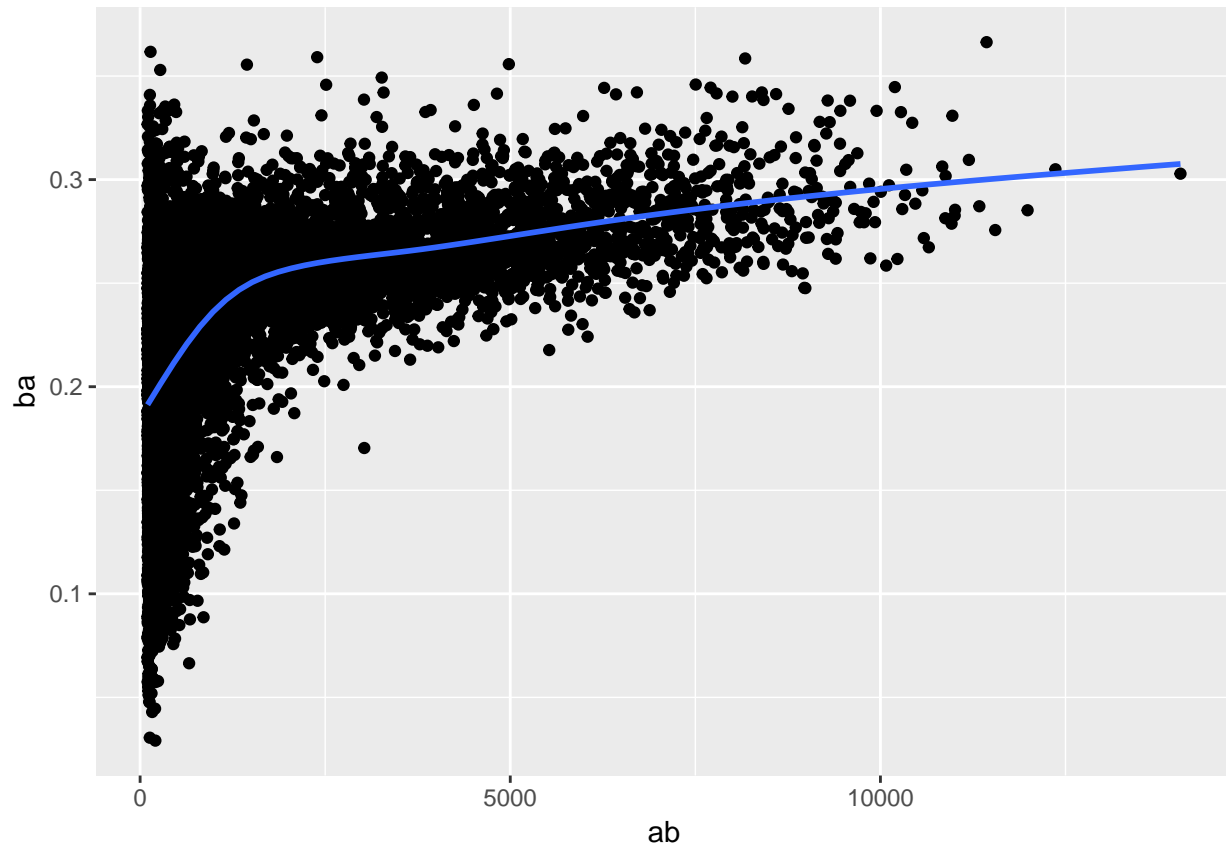
## Warning: package 'Lahman' was built under R version 3.3.2
batting <- as_tibble(Lahman::Batting)

batters <- batting %>%
  group_by(playerID) %>%
  summarise(
    ba = sum(H, na.rm = TRUE) / sum(AB, na.rm = TRUE),
    ab = sum(AB, na.rm = TRUE)
  )

batters %>%
  filter(ab > 100) %>%
  ggplot(mapping = aes(x = ab, y = ba)) +
```

```
geom_point() +  
geom_smooth(se = FALSE)
```

```
## `geom_smooth()` using method = 'gam'
```



```
#> `geom_smooth()` using method = 'gam'
```

you see two patterns:

1. As above, the variation in our aggregate decreases as we get more data points.
2. There's a positive correlation between skill (**ba**) and opportunities to hit the ball (**ab**). This is because teams control who gets to play, and obviously they'll pick their best players.

5.6.4 Useful Summary Functions

It's sometimes useful to combine aggregation with logical subsetting.

Question: Calculate the average positive delay (by day).

```
# Calculate the average positive delay (by day)  
not_cancelled %>%  
  group_by(year, month, day) %>%  
  summarise(  
    avg_delay1 = mean(arr_delay),  
    avg_delay2 = mean(arr_delay[arr_delay > 0]) # the average positive delay  
  )
```

```
## Source: local data frame [365 x 5]
```

```
## Groups: year, month [?]
```

```
##
##   year month   day avg_delay1 avg_delay2
##   <int> <int> <int>      <dbl>      <dbl>
## 1  2013     1     1 12.6510229   32.48156
## 2  2013     1     2 12.6928879   32.02991
## 3  2013     1     3  5.7333333   27.66087
## 4  2013     1     4 -1.9328194   28.30976
## 5  2013     1     5 -1.5258020   22.55882
## 6  2013     1     6  4.2364294   24.37270
## 7  2013     1     7 -4.9473118   27.76132
## 8  2013     1     8 -3.2275785   20.78909
## 9  2013     1     9 -0.2642777   25.63415
## 10 2013     1    10 -5.8988159   27.34545
## # ... with 355 more rows
```

Measures of Position

`first(x)`, `nth(x, 2)`, `last(x)`. These work similarly to `x[1]`, `x[2]`, and `x[length(x)]` but let you set a default value if that position does not exist (i.e. you're trying to get the 3rd element from a group that only has two elements). For example, we can find the first and last departure for each day:

```
not_cancelled %>%
  group_by(year, month, day) %>%
  summarise(
    first_dep = first(dep_time), # smallest number
    last_dep = last(dep_time)
  )
```

```
## Source: local data frame [365 x 5]
## Groups: year, month [?]
##
##   year month   day first_dep last_dep
##   <int> <int> <int>      <int>      <int>
## 1  2013     1     1        517       2356
## 2  2013     1     2         42       2354
## 3  2013     1     3         32       2349
## 4  2013     1     4         25       2358
## 5  2013     1     5         14       2357
## 6  2013     1     6         16       2355
## 7  2013     1     7         49       2359
## 8  2013     1     8        454       2351
## 9  2013     1     9          2       2252
## 10 2013     1    10          3       2320
## # ... with 355 more rows
```

These functions are complementary to filtering on ranks. Filtering gives you all variables, with each observation in a separate row

Question: Find the first and last flight of each day.

Testimate trick: display the first and last (earliest and latest) flight of the day (2 rows for each day): `mutate(r = min_rank(dep_time)) %>% filter(r %in% range(r))`

```
# Find the first and last flight of each day
not_cancelled %>%
  group_by(year, month, day) %>%
```

```
mutate(r = min_rank((dep_time))) %>%
filter(r %in% range(r))
```

```
## Source: local data frame [770 x 20]
```

```
## Groups: year, month, day [365]
```

```
##
```

```
##   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    2356           2359          -3      425
```

```
## 3  2013     1     2     42           2359          43      518
```

```
## 4  2013     1     2    2354           2359          -5      413
```

```
## 5  2013     1     3     32           2359          33      504
```

```
## 6  2013     1     3    2349           2359         -10      434
```

```
## 7  2013     1     4     25           2359          26      505
```

```
## 8  2013     1     4    2358           2359          -1      429
```

```
## 9  2013     1     4    2358           2359          -1      436
```

```
## 10 2013     1     5     14           2359          15      503
```

```
## # ... with 760 more rows, and 13 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 <dtm>, r <int>
```

___ Shiny Idea: The upper bound of r is the number of flights that day (600 ~ 1000) ___

___ n_distinct(): To count the number of non-missing values, use `sum(!is.na(x))`. To count the number of distinct (unique) values, use `n_distinct(x)`.___

Question: Which destinations (`group_by(dest)`) have the most carriers?

```
# Which destinations have the most carriers?
```

```
not_cancelled %>%
```

```
  group_by(dest) %>%
```

```
  summarise(carriers = n_distinct(carrier)) %>%
```

```
  arrange(desc(carriers))
```

```
## # A tibble: 104 x 2
```

```
##   dest carriers
```

```
##   <chr>    <int>
```

```
## 1   ATL         7
```

```
## 2   BOS         7
```

```
## 3   CLT         7
```

```
## 4   ORD         7
```

```
## 5   TPA         7
```

```
## 6   AUS         6
```

```
## 7   DCA         6
```

```
## 8   DTW         6
```

```
## 9   IAD         6
```

```
## 10  MSP         6
```

```
## # ... with 94 more rows
```

```
count
```

```
not_cancelled %>%
```

```
  count(dest)
```

```
## # A tibble: 104 x 2
```

```
##      dest      n
##      <chr> <int>
## 1     ABQ    254
## 2     ACK    264
## 3     ALB    418
## 4     ANC      8
## 5     ATL 16837
## 6     AUS   2411
## 7     AVL    261
## 8     BDL    412
## 9     BGR    358
## 10    BHM    269
## # ... with 94 more rows
```

Testimate: similar to `table()`, with even straightforward command.

You can optionally provide a weight variable. For example, you could use this to “count” (sum) the total number of miles a plane flew:

```
not_cancelled %>%
  count(tailnum, wt = distance) # wt
```

```
## # A tibble: 4,037 x 2
##   tailnum      n
##   <chr>   <dbl>
## 1  D942DN   3418
## 2  NOEGMQ 239143
## 3  N10156 109664
## 4  N102UW  25722
## 5  N103US  24619
## 6  N104UW  24616
## 7  N10575 139903
## 8  N105UW  23618
## 9  N107US  21677
## 10 N108UW  32070
## # ... with 4,027 more rows
```

To verify, we may simply calculate / observe like this:

```
not_cancelled %>%
  filter(tailnum == "D942DN") %>%
  select(tailnum, distance)
```

```
## # A tibble: 4 x 2
##   tailnum distance
##   <chr>   <dbl>
## 1  D942DN      762
## 2  D942DN      950
## 3  D942DN      944
## 4  D942DN      762
```

Counts and proportions of logical values: `sum(x)` gives the number of TRUEs in `x`, and `mean(x)` gives the proportion.

Question: *How many flights left before 5am? (these usually indicate delayed flights from the previous day)*

How many flights left before 5am? (these usually indicate delayed flights from the previous day)

```
not_cancelled %>%
  group_by(year, month, day) %>%
  summarize(n_early = sum(dep_time < 500))
```

```
## Source: local data frame [365 x 4]
## Groups: year, month [?]
##
##   year month   day n_early
##   <int> <int> <int>   <int>
## 1  2013     1     1         0
## 2  2013     1     2         3
## 3  2013     1     3         4
## 4  2013     1     4         3
## 5  2013     1     5         3
## 6  2013     1     6         2
## 7  2013     1     7         2
## 8  2013     1     8         1
## 9  2013     1     9         3
## 10 2013     1    10         3
## # ... with 355 more rows
```

Question: *What proportion of flights are delayed by more than an hour?*

What proportion of flights are delayed by more than an hour?

```
not_cancelled %>%
  group_by(year, month, day) %>%
  summarise(hour_perc = round(mean(arr_delay > 60), digit = 3))
```

```
## Source: local data frame [365 x 4]
## Groups: year, month [?]
##
##   year month   day hour_perc
##   <int> <int> <int>     <dbl>
## 1  2013     1     1     0.072
## 2  2013     1     2     0.085
## 3  2013     1     3     0.057
## 4  2013     1     4     0.040
## 5  2013     1     5     0.035
## 6  2013     1     6     0.047
## 7  2013     1     7     0.033
## 8  2013     1     8     0.021
## 9  2013     1     9     0.020
## 10 2013     1    10     0.018
## # ... with 355 more rows
```

5.6.5 Grouping by multiple variables

When you group by multiple variables, each summary peels off one level of the grouping. That makes it easy to progressively roll up a dataset:

```
daily <- group_by(flights, year, month, day)
(per_day <- summarise(daily, flights = n()))
```

```
## Source: local data frame [365 x 4]
```

```
## Groups: year, month [?]
##
##   year month   day flights
##   <int> <int> <int>   <int>
## 1  2013     1     1     842
## 2  2013     1     2     943
## 3  2013     1     3     914
## 4  2013     1     4     915
## 5  2013     1     5     720
## 6  2013     1     6     832
## 7  2013     1     7     933
## 8  2013     1     8     899
## 9  2013     1     9     902
## 10 2013     1    10     932
## # ... with 355 more rows

(per_month <- summarise(per_day, flights = sum(flights)))
```

```
## Source: local data frame [12 x 3]
## Groups: year [?]
##
##   year month flights
##   <int> <int>   <int>
## 1  2013     1  27004
## 2  2013     2  24951
## 3  2013     3  28834
## 4  2013     4  28330
## 5  2013     5  28796
## 6  2013     6  28243
## 7  2013     7  29425
## 8  2013     8  29327
## 9  2013     9  27574
## 10 2013    10  28889
## 11 2013    11  27268
## 12 2013    12  28135

(per_year <- summarise(per_month, flights = sum(flights)))
```

```
## # A tibble: 1 x 2
##   year flights
##   <int>   <int>
## 1  2013  336776
```

Be careful when progressively rolling up summaries: it's OK for sums and counts, but you need to think about weighting means and variances, and it's not possible to do it exactly for rank-based statistics like the median. In other words, the sum of groupwise sums is the overall sum, but the median of groupwise medians is not the overall median.

5.6.6 Ungrouping

```
daily %>%
  ungroup() %>%           # no longer grouped by date
  summarise(flights = n())

## # A tibble: 1 x 1
##   flights
```

```
##      <int>  
## 1  336776
```