Introduction to the tidyverse: data manipulation with `dplyr`

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dplyr: data manipulation

dplyr is the main workhorse of the tidyverse

This lesson draws on Chapter 5 of R for Data Science. For a condensed version, check out the Introduction to dplyr vignette.

Example data: nycflights13

```r
#install.packages(c('nycflights13', 'tidyverse'))
library(nycflights13)
library(tidyverse)
```

```
## ── Attaching packages ─────────────────────────── tidyverse 1.2.1 ──
```

```
## ✔ ggplot2 2.2.1     ✔ purrr   0.2.5
## ✔ tibble  1.4.2     ✔ dplyr   0.7.5
## ✔ tidyr   0.8.1     ✔ stringr 1.3.1
## ✔ readr   1.1.1     ✔ forcats 0.3.0
```

```
## ── Conflicts ────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
```

Note conflicts when you load the tidyverse

Take careful note of the conflicts message that's printed when you load the tidyverse. It tells you that dplyr overwrites some functions in base R. If you want to use the base version of these functions after loading dplyr, you'll need to use their full names: `stats::filter()` and `stats::lag()`.

nycflights13

Example data: `nycflights13::flights`. This data frame contains all 336,776 flights that departed from New York City in 2013.

```
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 <i
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dl
## #   minute <dbl>, time_hour <dttm>
```

It prints as a tibble

You might also have noticed the row of three (or four) letter abbreviations under the column names. These describe the type of each variable:

- `int` stands for integers.
- `dbl` stands for doubles, or real numbers.
- `chr` stands for character vectors, or strings.
- `dttm` stands for date-times (a date + a time).

Other kinds of variables you may see in a tibble

- `lgl` stands for logical, vectors that contain only `TRUE` or `FALSE`.
- `fctr` stands for factors, which R uses to represent categorical variables with fixed possible values.
- `date` stands for dates.

dplyr verbs

- Pick observations by their values (`filter()`).
- Reorder the rows (`arrange()`).
- Pick variables by their names (`select()`).
- Create new variables with functions of existing variables (`mutate()`).
- Collapse many values down to a single summary (`summarise()`).

We will frequently used these on grouped data

These can all be used in conjunction with `group_by()` which changes the scope of each function from operating on the entire dataset to operating on it group-by-group. These six functions provide the verbs for a language of data manipulation.

How dplyr verbs work

All verbs work similarly:

1. The first argument is a data frame.
2. The subsequent arguments describe what to do with the data frame, using the variable names (without quotes).
3. The result is a new data frame.

Together these properties make it easy to chain together multiple simple steps to achieve a complex result. Let’s dive in and see how these verbs work.

Choose rows with `filter()`

For example, we can select all flights on January 1st with:

```
filter(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 <dl
## #   minute <dbl>, time_hour <dttm>
```

Choose rows with `filter()`

When you run that line of code, dplyr executes the filtering operation and returns a new data frame. dplyr functions never modify their inputs, so if you want to save the result, you'll need to use the assignment operator, `<-`:

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

Comparisons

To use filtering effectively, you have to know how to select the observations that you want using the comparison operators. R provides the standard suite: >, >=, <, <=, != (not equal), and == (equal).

Remember to use = instead of == when testing for equality. When this happens you'll get an informative error:

```
filter(flights, month = 1)
```

```
## Error: `month` (`month = 1`) must not be named, do you need `==`?
```

Issues with floating point numbers

There's another common problem you might encounter when using ==: floating point numbers. These results might surprise you!

```r
sqrt(2) ^ 2 == 2
```

```
## [1] FALSE
```

```r
1/49 * 49 == 1
```

```
## [1] FALSE
```

Use `near()` instead

Computers use finite precision arithmetic (they obviously can't store an infinite number of digits!) so remember that every number you see is an approximation. Instead of relying on ==, use `near()`:

```
near(sqrt(2) ^ 2,  2)
```

```
## [1] TRUE
```

```
near(1 / 49 * 49, 1)
```

```
## [1] TRUE
```

Logical operators

Multiple arguments to `filter()` are combined with "and": every expression must be true in order for a row to be included in the output. For other types of combinations, you'll need to use Boolean operators yourself: `&` is "and", `|` is "or", and `!` is "not".

Find all flights that departed in November or December:

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

Another way to write it using `%in%`

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

Sometimes you can simplify complicated subsetting by remembering De Morgan's law: `!(x & y)` is the same as `!x | !y`, and `!(x | y)` is the same as `!x & !y`. For example, if you wanted to find flights that weren't delayed (on arrival or departure) by more than two hours, you could use either of the following two filters:

```
filter(flights, !(arr_delay > 120 | dep_delay > 120))
filter(flights, arr_delay <= 120, dep_delay <= 120)
```

Missing values

If you want to determine if a value is missing, use `is.na()`:

```
is.na(x)
```

`filter()` only includes rows where the condition is `TRUE`; it excludes both `FALSE` and `NA` values. If you want to preserve missing values, ask for them explicitly:

```
df <- tibble(x = c(1, NA, 3))
filter(df, x > 1)
```

```
## # A tibble: 1 x 1
##         x
##     <dbl>
## 1       3
```

```
filter(df, is.na(x) | x > 1)
```

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

Arrange rows with `arrange()`

`arrange()` changes the order of rows 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:

```r
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 <i
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <db
## #   minute <dbl>, time_hour <dttm>
```

Arrange rows with `arrange()`

Use `desc()` to re-order by a column in descending order:

```
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 <i
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dl
## #   minute <dbl>, time_hour <dttm>
```

Arrange rows with `arrange()`

Missing values are always sorted at the end:

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

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

```
arrange(df, desc(x))
```

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

Exercise

1. Sort `flights` to find the fastest flights.

Solution

```r
flights %>%
  arrange(air_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    16     1355           1315        40     1442
##  2  2013     4    13      537            527        10      622
##  3  2013    12     6      922            851        31     1021
##  4  2013     2     3     2153           2129        24     2247
##  5  2013     2     5     1303           1315       -12     1342
##  6  2013     2    12     2123           2130        -7     2211
##  7  2013     3     2     1450           1500       -10     1547
##  8  2013     3     8     2026           1935        51     2131
##  9  2013     3    18     1456           1329        87     1533
## 10  2013     3    19     2226           2145        41     2305
## # ... with 336,766 more rows, and 12 more variables: sched_arr_time <i
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dl
## #   minute <dbl>, time_hour <dttm>
```

Select columns with `select()`

`select()` chooses the columns you want out of the whole set of columns

```
# Select columns by name
select(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
```

Select columns with `select()`

```r
# Select all columns between year and day (inclusive)
select(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
```

Select columns with `select()`

```
# Select all columns except those from year to day (inclusive)
select(flights, -(year:day))
```

```
## # A tibble: 336,776 x 16
##    dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay
##       <int>          <int>     <dbl>    <int>          <int>     <dbl>
##  1      517            515         2      830            819        1
##  2      533            529         4      850            830        2
##  3      542            540         2      923            850        3
##  4      544            545        -1     1004           1022       -1
##  5      554            600        -6      812            837       -2
##  6      554            558        -4      740            728        1
##  7      555            600        -5      913            854        1
##  8      557            600        -3      709            723       -1
##  9      557            600        -3      838            846        -
## 10      558            600        -2      753            745
## # ... with 336,766 more rows, and 10 more variables: carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <
## #   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

Helpers for `select()`

There are a number of helper functions you can use within `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".
- `matches("(.)\\1")`: selects variables that match a regular expression. This one matches any variables that contain repeated characters. You'll learn more about regular expressions in [strings].
- `num_range("x", 1:3)` matches `x1`, `x2` and `x3`.

Use `rename()` to rename variables

`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:

Use `rename()` to rename variables

```r
rename(flights, 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 <i
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tail_num <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dl
## #   minute <dbl>, time_hour <dttm>
```

Note that it's new_name = old_name. This always throws me off.

Add new variables with `mutate()`

Besides selecting sets of existing columns, it's often useful to add new columns that are functions of existing columns. That's the job of `mutate()`.

Make a smaller version of the dataset so we can see our work

```
flights_sml <- select(flights,
  year:day,
  ends_with("delay"),
  distance,
  air_time
)
```

Add new variables with `mutate()`

```
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
##  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
```

Add new variables with `mutate()`

Note that you can refer to columns that you've just created:

```
mutate(flights_sml,
  gain = arr_delay - dep_delay,
  hours = air_time / 60,
  gain_per_hour = gain / hours
)
```

```
## # A tibble: 336,776 x 10
##     year month   day dep_delay arr_delay distance air_time  gain hours
##    <int> <int> <int>     <dbl>     <dbl>    <dbl>    <dbl> <dbl> <dbl>
##  1  2013     1     1         2        11     1400      227     9 3.78
##  2  2013     1     1         4        20     1416      227    16 3.78
##  3  2013     1     1         2        33     1089      160    31 2.67
##  4  2013     1     1        -1       -18     1576      183   -17 3.05
##  5  2013     1     1        -6       -25      762      116   -19 1.93
##  6  2013     1     1        -4        12      719      150    16 2.5
##  7  2013     1     1        -5        19     1065      158    24 2.63
##  8  2013     1     1        -3       -14      229       53   -11 0.88
##  9  2013     1     1        -3        -8      944      140    -5 2.33
## 10  2013     1     1        -2         8      733      138    10 2.3
## # ... with 336,766 more rows, and 1 more variable: gain_per_hour <dbl>
```

Add new variables with `mutate()`

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
)
```

```
## # A tibble: 336,776 x 3
##      gain hours gain_per_hour
##     <dbl> <dbl>         <dbl>
##  1      9 3.78           2.38
##  2     16 3.78           4.23
##  3     31 2.67          11.6
##  4    -17 3.05          -5.57
##  5    -19 1.93          -9.83
##  6     16 2.5            6.4
##  7     24 2.63           9.11
##  8    -11 0.883        -12.5
##  9     -5 2.33          -2.14
## 10     10 2.3            4.35
## # ... with 336,766 more rows
```

There are many functions for creating new variables that you can use with `mutate()`. The key property is that the function must be vectorised: it must take a vector of values as input, return a vector with the same number of values as output. There's no way to list every possible function that you might use, but here's a selection of functions that are frequently useful:

- Logical comparisons, <, <=, >, >=, `!`=, which you learned about earlier. If you're doing a complex sequence of logical operations it's often a good idea to store the interim values in new variables so you can check that each step is working as expected.

Useful helpers for `mutate()`

- Ranking: there are a number of ranking functions, but you should start with `min_rank()`. It does the most usual type of ranking (e.g. 1st, 2nd, 2nd, 4th). The default gives smallest values the small ranks; use `desc(x)` to give the largest values the smallest ranks.

```
y <- c(1, 2, 2, NA, 3, 4)
min_rank(y)
```

```
## [1]  1  2  2 NA  4  5
```

```
min_rank(desc(y))
```

```
## [1]  5  3  3 NA  2  1
```

Useful helpers for **`mutate()`**

If `min_rank()` doesn't do what you need, look at the variants `row_number()`, `dense_rank()`, `percent_rank()`, `cume_dist()`, `ntile()`. See their help pages for more details.

~~~~
```r
row_number(y)
```

```
## [1]  1  2  3 NA  4  5
```

```r
dense_rank(y)
```

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

```r
percent_rank(y)
~~~~

Grouped summaries with `summarise()`

The last key verb is `summarise()`. It collapses a data frame to a single row:

```
summarise(flights, delay = mean(dep_delay, na.rm = TRUE))
```

```
## # A tibble: 1 x 1
##   delay
##   <dbl>
## 1  12.6
```

Grouped summaries with `summarise()`

`summarise()` is not terribly useful unless we pair it with `group_by()`. This changes the unit of analysis from the complete dataset to individual groups. Then, when you use the dplyr verbs on a grouped data frame they'll be automatically applied "by group". For example, if we applied exactly the same code to a data frame grouped by date, we get the average delay per date:

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

```
## # A tibble: 365 x 4
## # Groups:   year, month [?]
##     year month   day 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
```

```
## 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
```

Missing values

You may have wondered about the `na.rm` argument we used above. What happens if we don't set it?

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

```
## # A tibble: 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
```

```
##  7  2013     1     7    NA

##  8  2013     1     8    NA
##  9  2013     1     9    NA
## 10  2013     1    10    NA
## # ... with 355 more rows
```

Missing values

We get a lot of missing values! That's because aggregation functions obey the usual rule of missing values: if there's any missing value in the input, the output will be a missing value. Fortunately, 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))
```

```
## # A tibble: 365 x 4
## # Groups:   year, month [?]
##     year month   day  mean
##    <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
```

Missing values

In this case, where missing values represent cancelled flights, we could also tackle the problem by first removing the cancelled flights. We'll save this dataset so we can reuse in the next few examples.

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

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

```
## # A tibble: 365 x 4
## # Groups:   year, month [?]
##      year month   day  mean
##     <int> <int> <int> <dbl>
##   1  2013     1     1 11.4
##   2  2013     1     2 13.7
##   3  2013     1     3 10.9
##   4  2013     1     4  8.97
##   5  2013     1     5  5.73
##   6  2013     1     6  7.15
```

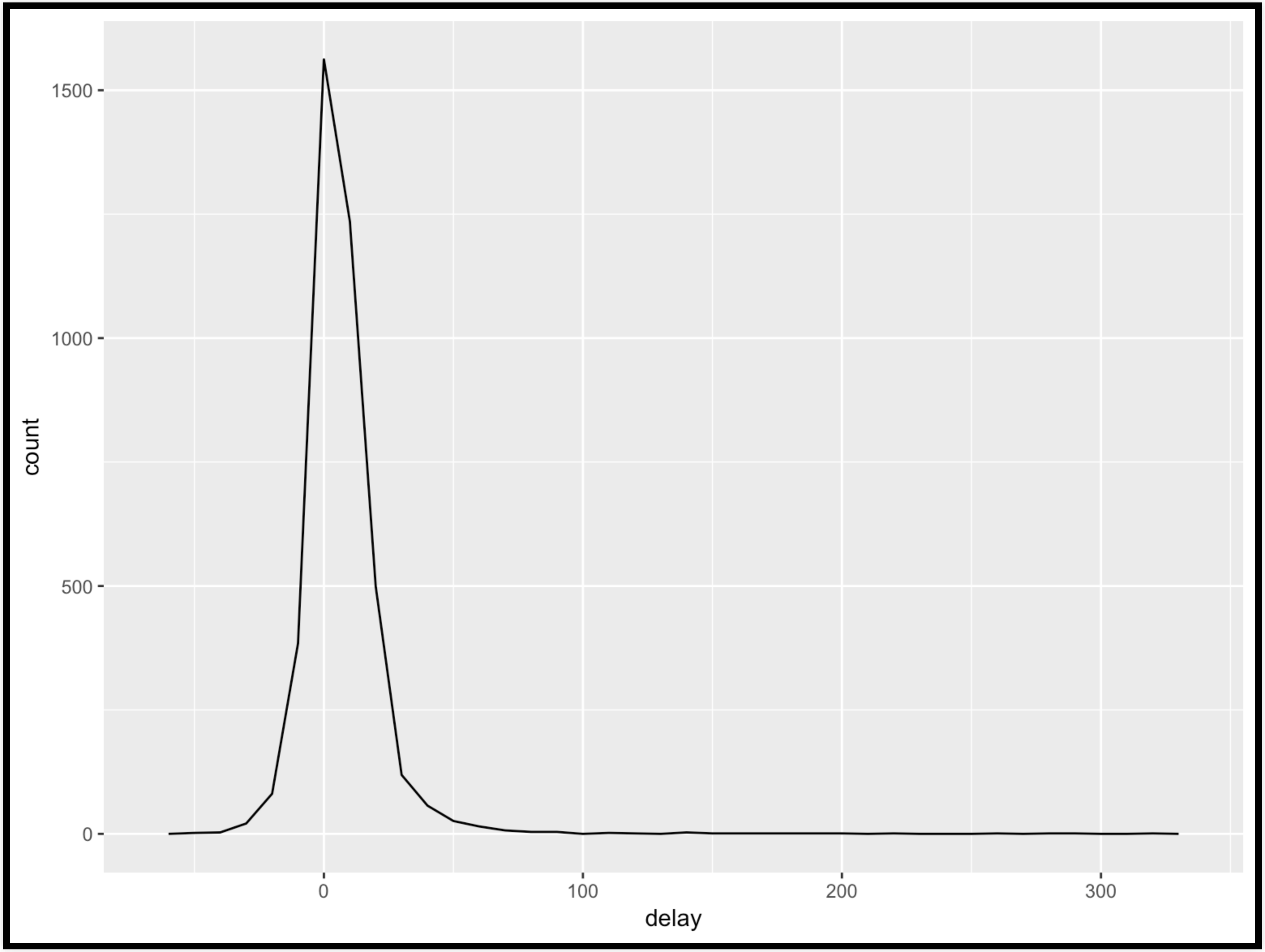
```
##   7  2013     1     7  5.42
##   8  2013     1     8  2.56
##   9  2013     1     9  2.30
## 10  2013     1    10  2.84
## # ... with 355 more rows
```

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:

```
delays <- not_cancelled %>%
  group_by(tailnum) %>%
  summarise(
    delay = mean(arr_delay)
  )

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



1500
1000
500
0
count
0
100
200
300
delay

Exercise

1. Find all flights that
    1. Had an arrival delay of two or more hours
    2. Flew to Houston (`IAH` or `HOU`)
    3. Were operated by United, American, or Delta
    4. Departed in summer (July, August, and September)

Grouped summaries

Counts

You've seen `n()`, which takes no arguments, and returns the size of the current group. 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)`.

```
# 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
```

Counts

Counts are so useful that dplyr provides a simple helper if all you want is a 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
```

Counts

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)
```

```
## # A tibble: 4,037 x 2
##    tailnum       n
##    <chr>     <dbl>
##  1 D942DN     3418
##  2 N0EGMQ   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
```

Counts

Counts and proportions of logical values: `sum(x > 10)`, `mean(y == 0)`. When used with numeric functions, `TRUE` is converted to 1 and `FALSE` to 0. This makes `sum()` and `mean()` very useful: `sum(x)` gives the number of `TRUE`s in `x`, and `mean(x)` gives the proportion.

```
# How many flights left before 5am? (these usually indicate delayed
# flights from the previous day)
not_cancelled %>%
  group_by(year, month, day) %>%
  summarise(n_early = sum(dep_time < 500))
```

```
## # A tibble: 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
```

```
## 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
```

```
# What proportion of flights are delayed by more than an hour?
not_cancelled %>%
  group_by(year, month, day) %>%
  summarise(hour_perc = mean(arr_delay > 60))
```

```
## # A tibble: 365 x 4
## # Groups:   year, month [?]
##     year month   day hour_perc
##    <int> <int> <int>     <dbl>
##  1  2013     1     1    0.0722
##  2  2013     1     2    0.0851
##  3  2013     1     3    0.0567
##  4  2013     1     4    0.0396
##  5  2013     1     5    0.0349
##  6  2013     1     6    0.0470
##  7  2013     1     7    0.0333
##  8  2013     1     8    0.0213
##  9  2013     1     9    0.0202
## 10  2013     1    10    0.0183
## # ... with 355 more rows
```

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()))
```

```
## # A tibble: 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
```

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

```
## # A tibble: 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
```

```r
(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.

Ungrouping

If you need to remove grouping, and return to operations on ungrouped data, use `ungroup()`.

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

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

Grouped mutates (and filters)

Grouping is most useful in conjunction with `summarise()`, but you can also do convenient operations with `mutate()` and `filter()`:

Find the worst members of each group:

```
```r
flights_sml %>%
  group_by(year, month, day) %>%
  filter(rank(desc(arr_delay)) < 10)
```


```
## # A tibble: 3,306 x 7
## # Groups:   year, month, day [365]
##     year month   day dep_delay arr_delay distance air_time
##    <int> <int> <int>     <dbl>     <dbl>    <dbl>    <dbl>
##  1  2013     1     1       853       851      184       41
##  2  2013     1     1       290       338     1134      213
##  3  2013     1     1       260       263      266       46
##  4  2013     1     1       157       174      213       60
##  5  2013     1     1       216       222      708      121
##  6  2013     1     1       255       250      589      115
##  7  2013     1     1       285       246     1085      146
```
```

# Find all groups bigger than a threshold:

````
```r
popular_dests <- flights %>%
  group_by(dest) %>%
  filter(n() > 365)
popular_dests
```


```
## # A tibble: 332,577 x 19
## # Groups:   dest [77]
##      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
````
````

# Standardise to compute per group metrics:

````
```r
popular_dests %>%
  filter(arr_delay > 0) %>%
  mutate(prop_delay = arr_delay / sum(arr_delay)) %>%
  select(year:day, dest, arr_delay, prop_delay)
```


```
## # A tibble: 131,106 x 6
## # Groups:   dest [77]
##      year month   day dest  arr_delay prop_delay
##     <int> <int> <int> <chr>     <dbl>      <dbl>
##  1  2013     1     1 IAH          11  0.000111
##  2  2013     1     1 IAH          20  0.000201
##  3  2013     1     1 MIA          33  0.000235
##  4  2013     1     1 ORD          12  0.0000424
##  5  2013     1     1 FLL          19  0.0000938
##  6  2013     1     1 ORD           8  0.0000283
````
````

# Exercise

1. Come up with another approach that will give you the same output as `not_cancelled %>% count(dest)` and `not_cancelled %>% count(tailnum, wt = distance)` (without using `count()`).

2. Which carrier has the worst delays?

# Advanced verbs: `summarize_all()`, `summarize_at()`, `summarize_if()`

The `_all`, `_at` and `_if` suffixes work on `mutate`, `summarize`, and `transmute`. (British English speakers, you can use `summarise` too.)

- `_all` applies the operation to all columns
- `_at` applies the operation only to named columns
- `_if` applies the operation if some condition is true

# summarize_all()

````
```r
iris %>%
  group_by(Species) %>%
  summarise_all(mean)
```


```
## # A tibble: 3 x 5
##   Species    Sepal.Length Sepal.Width Petal.Length Petal.Width
##   <fct>             <dbl>       <dbl>        <dbl>       <dbl>
## 1 setosa             5.01        3.43         1.46       0.246
## 2 versicolor         5.94        2.77         4.26       1.33
## 3 virginica          6.59        2.97         5.55       2.03
```
````

# summarize_at()

```
starwars %>%
summarise_at(c("height", "mass"), mean, na.rm = TRUE)
```

```
## # A tibble: 1 x 2
##   height  mass
##    <dbl> <dbl>
## 1   174.  97.3
```

# `mutate_at()` with a helper to choose columns

```r
iris %>%
  mutate_at(vars(matches("Sepal")), log)
```

```
##     Sepal.Length Sepal.Width Petal.Length Petal.Width    Species
## 1       1.629241   1.2527630          1.4         0.2     setosa
## 2       1.589235   1.0986123          1.4         0.2     setosa
## 3       1.547563   1.1631508          1.3         0.2     setosa
## 4       1.526056   1.1314021          1.5         0.2     setosa
## 5       1.609438   1.2809338          1.4         0.2     setosa
## 6       1.686399   1.3609766          1.7         0.4     setosa
## 7       1.526056   1.2237754          1.4         0.3     setosa
## 8       1.609438   1.2237754          1.5         0.2     setosa
## 9       1.481605   1.0647107          1.4         0.2     setosa
## 10      1.589235   1.1314021          1.5         0.1     setosa
## 11      1.686399   1.3083328          1.5         0.2     setosa
## 12      1.568616   1.2237754          1.6         0.2     setosa
## 13      1.568616   1.0986123          1.4         0.1     setosa
## 14      1.458615   1.0986123          1.1         0.1     setosa
## 15      1.757858   1.3862944          1.2         0.2     setosa
## 16      1.740466   1.4816045          1.5         0.4     setosa
## 17      1.686399   1.3609766          1.3         0.4     setosa
```

# summarise_if

```r
# The _if() variants apply a predicate function (a function that
# returns TRUE or FALSE) to determine the relevant subset of
# columns. Here we apply mean() to the numeric columns:
starwars %>% summarise_if(is.numeric, mean, na.rm = TRUE)
```

```
## # A tibble: 1 x 3
##   height  mass birth_year
##    <dbl> <dbl>      <dbl>
## 1   174.  97.3       87.6
```

```
#> # A tibble: 1 x 3
#>   height  mass birth_year
#>    <dbl> <dbl>      <dbl>
#> 1   174.  97.3       87.6
```

# Multiple grouped transformations

```
# If you want to apply multiple transformations, use funs()
by_species <- iris %>% group_by(Species)

by_species %>% summarise_all(funs(min, max))
```

```
## # A tibble: 3 x 9
##   Species    Sepal.Length_min Sepal.Width_min Petal.Length_min
##   <fct>                 <dbl>           <dbl>            <dbl>
## 1 setosa                  4.3             2.3              1
## 2 versicolor              4.9             2                3
## 3 virginica               4.9             2.2              4.5
## # ... with 5 more variables: Petal.Width_min <dbl>,
## #   Sepal.Length_max <dbl>, Sepal.Width_max <dbl>, Petal.Length_max <d
## #   Petal.Width_max <dbl>
```

# More complex transformations

```
# You can express more complex inline transformations using .
by_species %>% mutate_all(funs(. / 2.54))
```

```
## # A tibble: 150 x 5
## # Groups:   Species [3]
##    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##           <dbl>       <dbl>        <dbl>       <dbl> <fct>
##  1         2.01        1.38        0.551      0.0787 setosa
##  2         1.93        1.18        0.551      0.0787 setosa
##  3         1.85        1.26        0.512      0.0787 setosa
##  4         1.81        1.22        0.591      0.0787 setosa
##  5         1.97        1.42        0.551      0.0787 setosa
##  6         2.13        1.54        0.669      0.157  setosa
##  7         1.81        1.34        0.551      0.118  setosa
##  8         1.97        1.34        0.591      0.0787 setosa
##  9         1.73        1.14        0.551      0.0787 setosa
## 10         1.93        1.22        0.591      0.0394 setosa
## # ... with 140 more rows
```