CH1-5

2024-03-09

1: The penguins data frame

You can see all variables and the first few observations of each variable by using `glimpse()`.

```
penguins <- palmerpenguins::penguins

glimpse(penguins)
```

```
## Rows: 344
## Columns: 8
## $ species           <fct> Adelie, Adelie, Adelie, Adelie, Adelie, Adelie, Adel~
## $ island            <fct> Torgersen, Torgersen, Torgersen, Torgersen, Torgerse~
## $ bill_length_mm    <dbl> 39.1, 39.5, 40.3, NA, 36.7, 39.3, 38.9, 39.2, 34.1, ~
## $ bill_depth_mm     <dbl> 18.7, 17.4, 18.0, NA, 19.3, 20.6, 17.8, 19.6, 18.1, ~
## $ flipper_length_mm <int> 181, 186, 195, NA, 193, 190, 181, 195, 193, 190, 186~
## $ body_mass_g       <int> 3750, 3800, 3250, NA, 3450, 3650, 3625, 4675, 3475, ~
## $ sex               <fct> male, female, female, NA, female, male, female, male~
## $ year              <int> 2007, 2007, 2007, 2007, 2007, 2007, 2007, 2007, 2007~
```

2: Creating a ggplot

The `mapping` argument of the `ggplot()` function defines how variables in your dataset are mapped to visual properties (*aesthetics*) of your plot. The `mapping` argument is always defined in the `aes()` function, and the `x` and `y` arguments of `aes()` specify which variables to map to the x and y axes.

geom: The geometrical object that a plot uses to represent data. These geometric objects are made available in ggplot2 with functions that start with `geom_`.

People often describe plots by the type of geom that the plot uses. For example, bar charts use bar geoms (`geom_bar()`), line charts use line geoms (`geom_line()`), boxplots use boxplot geoms (`geom_boxplot()`), scatterplots use point geoms (`geom_point()`), and so on.

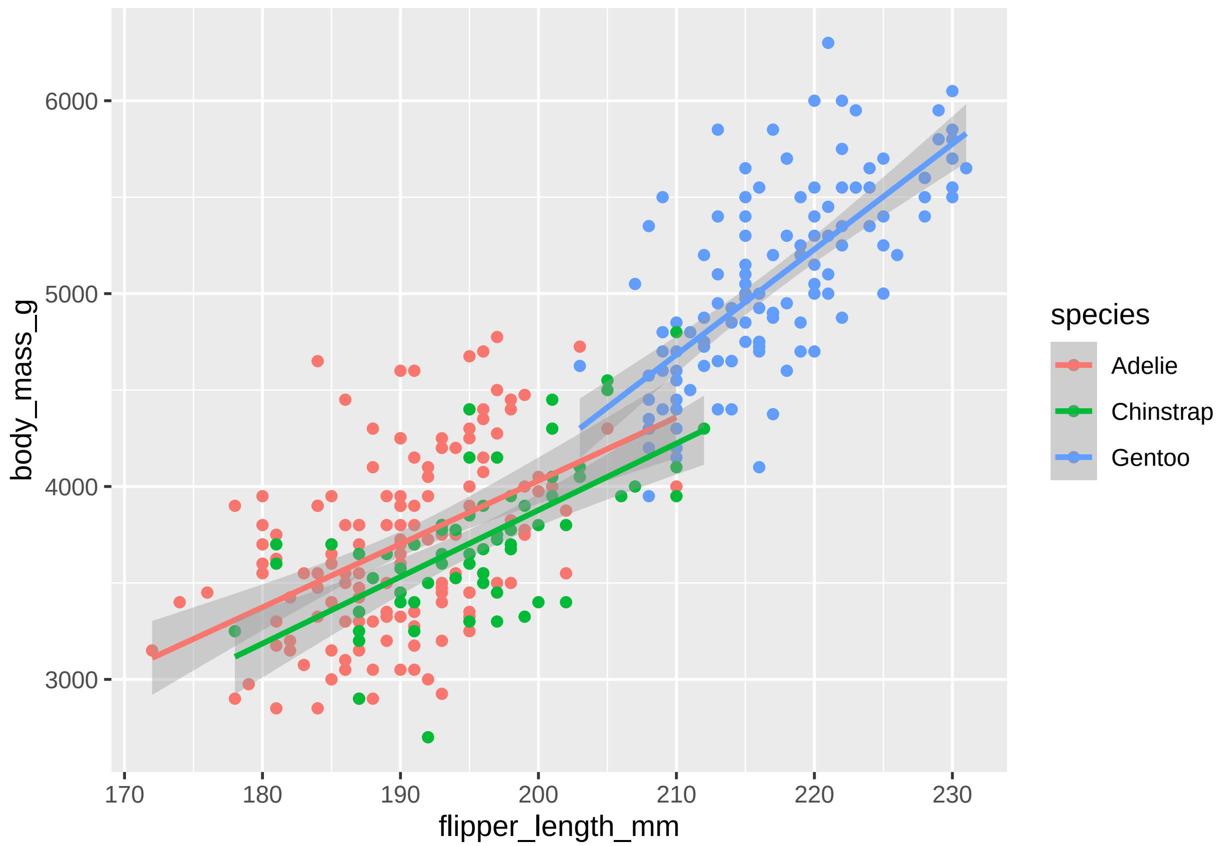
The function `geom_point()` adds a layer of points to your plot, which creates a scatterplot.

When a categorical variable is mapped to an aesthetic, ggplot2 will automatically assign a unique value of the aesthetic (here a unique color) to each unique level of the variable (each of the three species), a process known as *scaling*. ggplot2 will also add a legend that explains which values correspond to which levels.

Now let's add one more layer: a smooth curve displaying the relationship between body mass and flipper length.Since this is a new geometric object representing our data, we will add a new geom as a layer on top of our point geom: `geom_smooth()`. And we will specify that we want to draw the line of best fit based on a linear model with `method = "lm"`.

```
ggplot(penguins,
       mapping = aes(x = flipper_length_mm,
                     y = body_mass_g,
                     color = species)) +
  geom_point() +
  geom_smooth(method = "lm")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



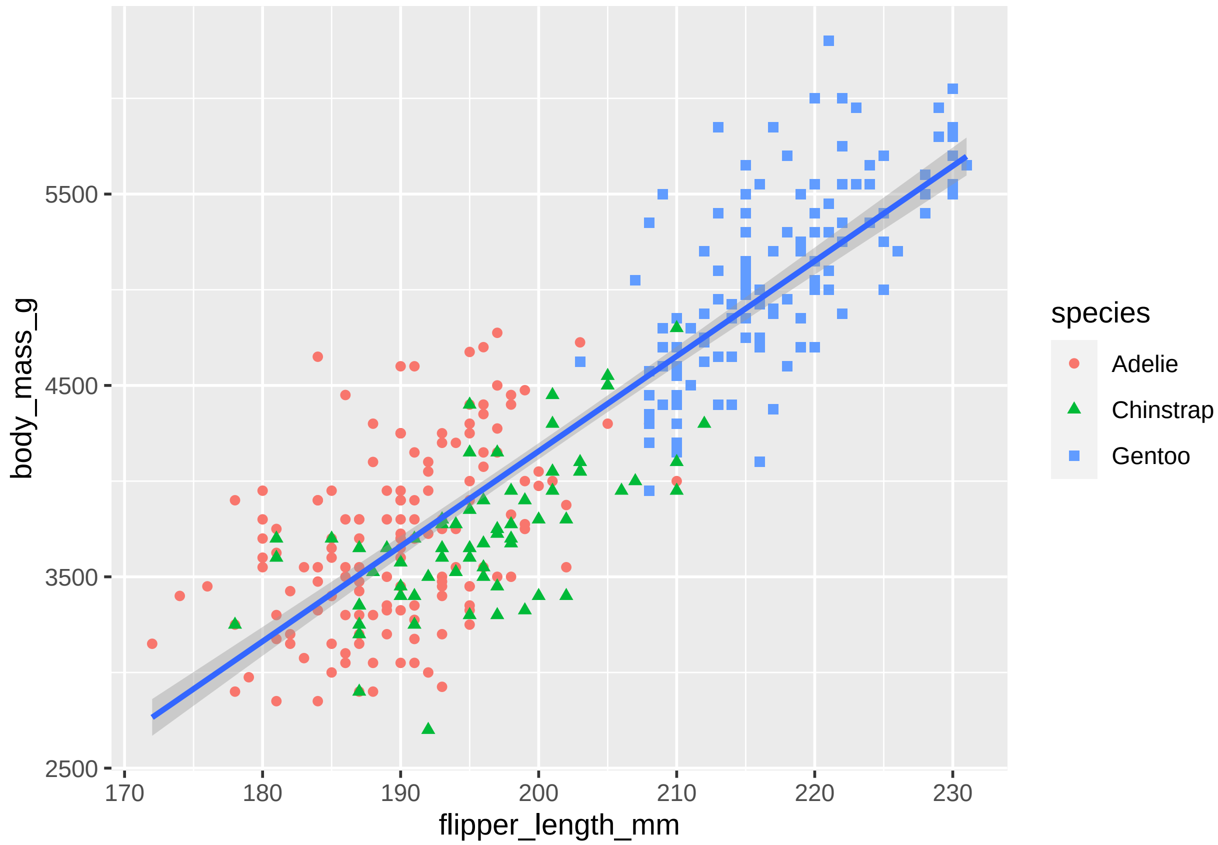
When aesthetic mappings are defined in `ggplot()`, at the global level, they're passed down to each of the subsequent geom layers of the plot. However, each geom function in ggplot2 can also take a `mapping` argument, which allows for aesthetic mappings at the local level that are added to those inherited from the global level.

Since we want points to be colored based on species but don't want the lines to be separated out for them, we should specify `color = species` for `geom_point()` only.

It's generally not a good idea to represent information using only colors on a plot, as people perceive colors differently due to color blindness or other color vision differences. Therefore, in addition to color, we can also map `species` to the `shape` aesthetic.

```
ggplot(penguins,
       mapping = aes(x = flipper_length_mm,
                     y = body_mass_g)) +
  geom_point(mapping = aes(color = species, shape = species)) +
  geom_smooth(method = "lm")
```

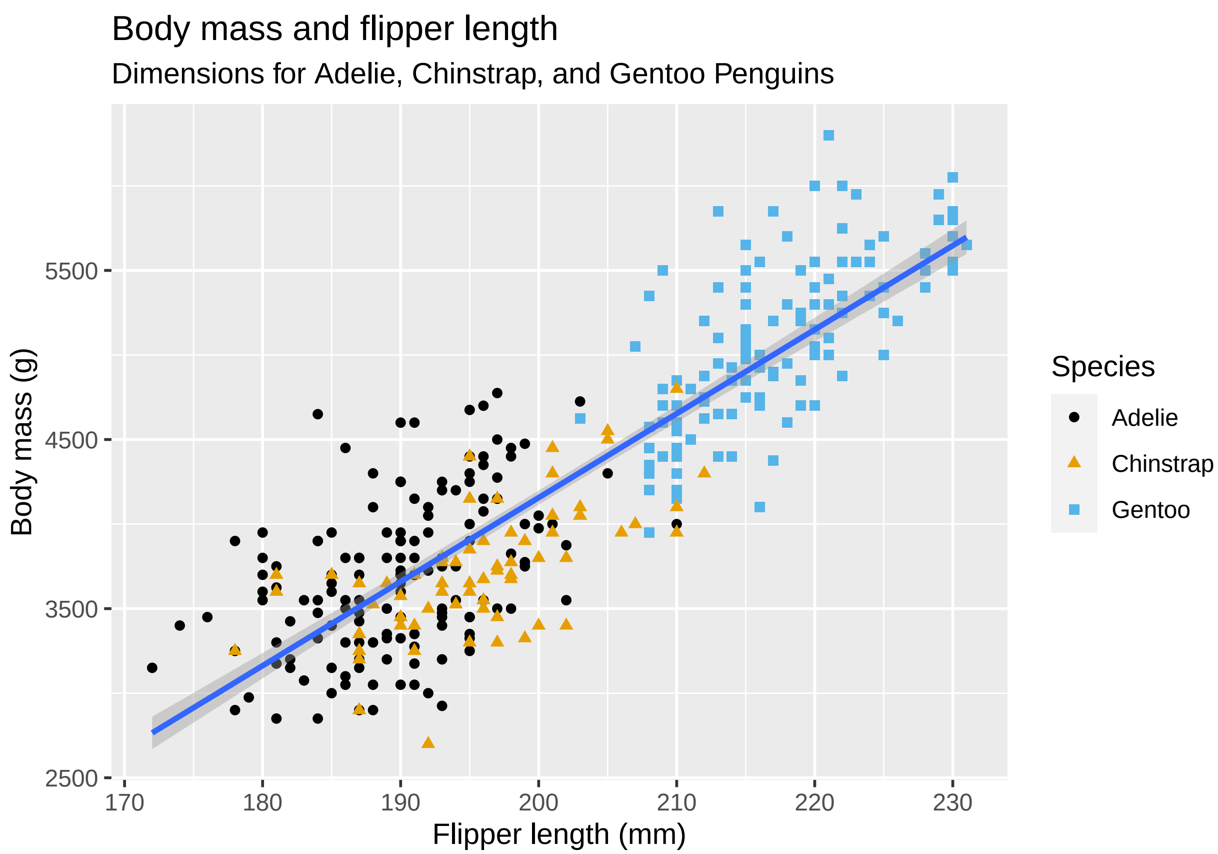
```
## `geom_smooth()` using formula = 'y ~ x'
```



We can improve the labels of our plot using the `labs()` function in a new layer. Some of the arguments to `labs()` might be self explanatory: title adds a `title` and subtitle adds a `subtitle` to the plot. Other arguments match the aesthetic mappings, `x` is the x-axis label, `y` is the y-axis label, and `color` and `shape` define the label for the legend. In addition, we can improve the color palette to be colorblind safe with the `scale_color_colorblind()` function from the `ggthemes` package.

```r
ggplot(penguins,
       mapping = aes(x = flipper_length_mm,
                     y = body_mass_g)) +
  geom_point(mapping = aes(color = species, shape = species)) +
  geom_smooth(method = "lm") +
  labs(title = "Body mass and flipper length",
       subtitle = "Dimensions for Adelie, Chinstrap, and Gentoo Penguins",
       x = "Flipper length (mm)",
       y = "Body mass (g)",
       color = "Species",
       shape = "Species") +
  scale_color_colorblind()
```

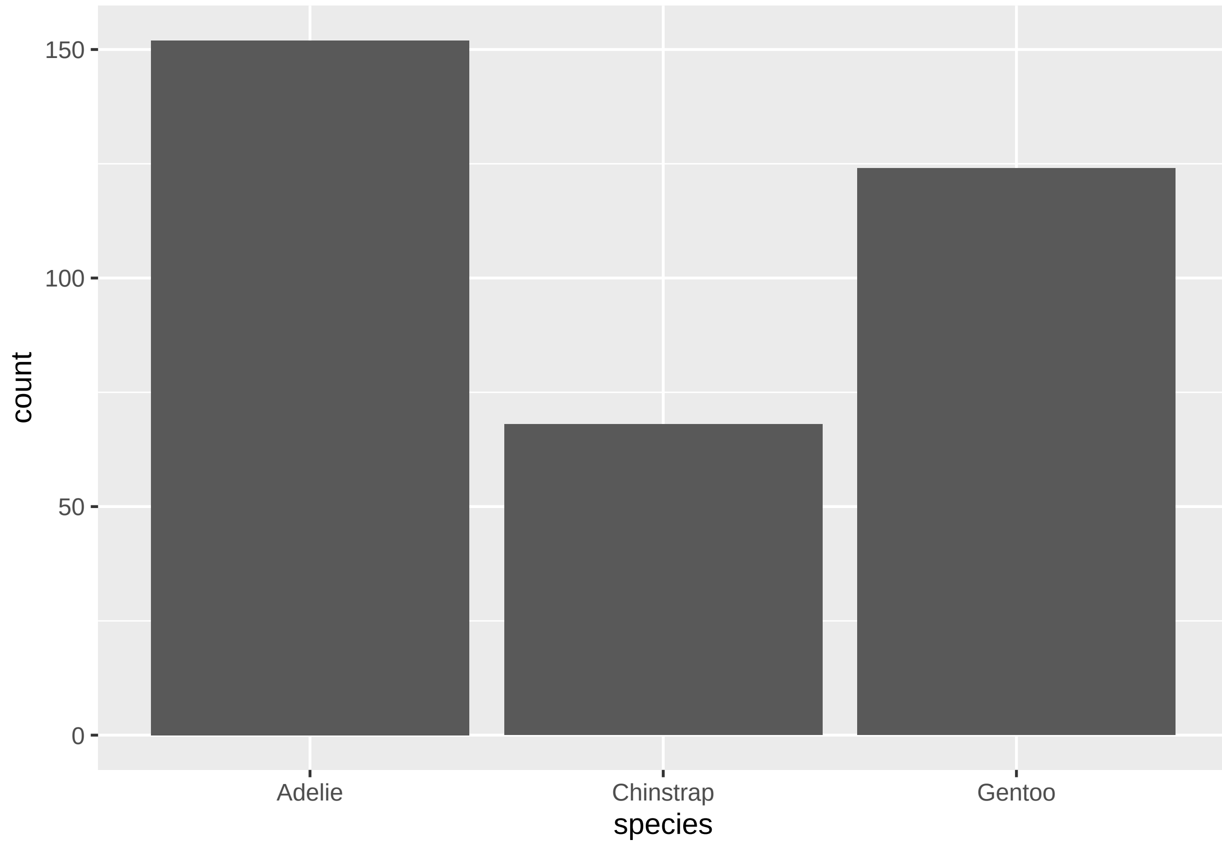
```
## `geom_smooth()` using formula = 'y ~ x'
```



3. Visualizing distributions

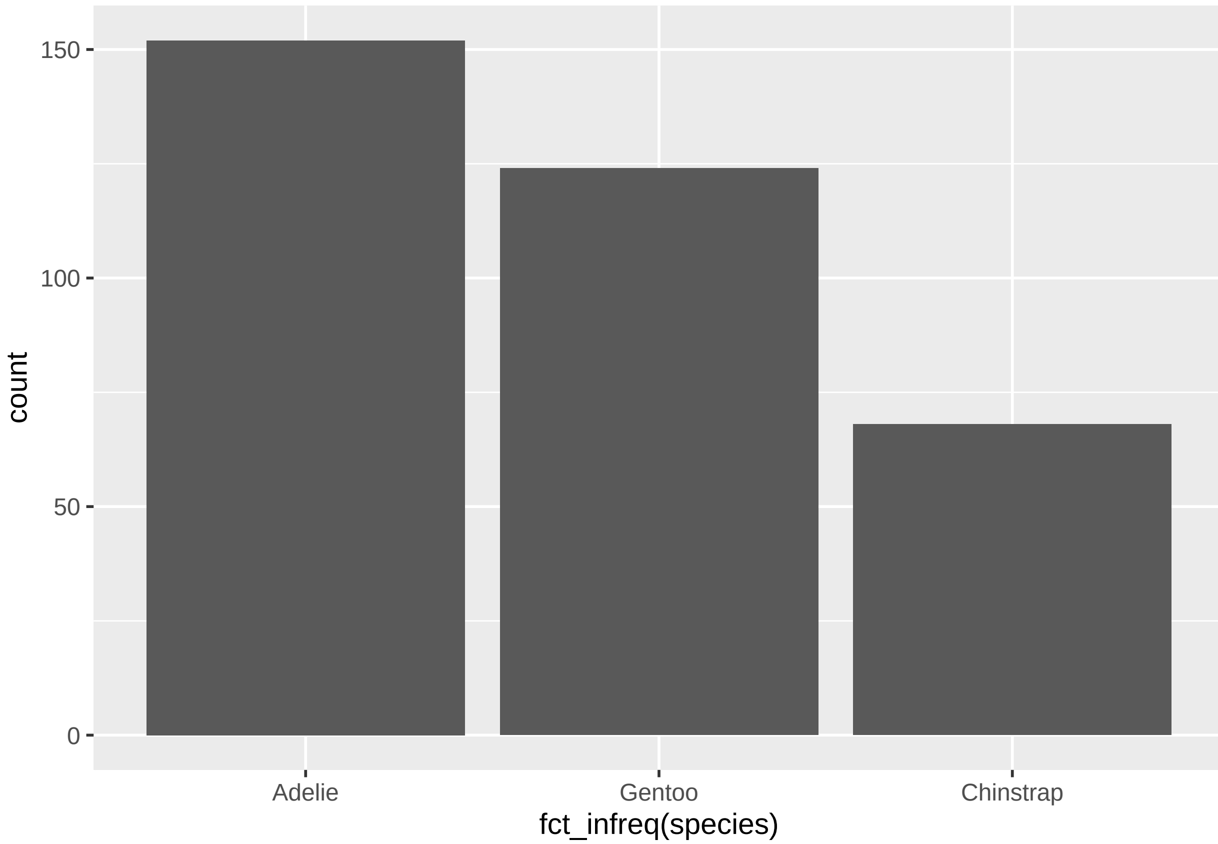
A variable is *categorical* if it can only take one of a small set of values. To examine the distribution of a categorical variable, you can use a bar chart. The height of the bars displays how many observations occurred with each x value.

```
ggplot(penguins,
       aes(x = species)) +
  geom_bar()
```



In bar plots of categorical variables with non-ordered levels, like the penguin species above, it's often preferable to reorder the bars based on their frequencies. Doing so requires transforming the variable to a factor (how R handles categorical data) and then reordering the levels of that factor. So, you can use `fct_infreq()`.

```
ggplot(penguins,
       aes(x = fct_infreq(species))) +
  geom_bar()
```

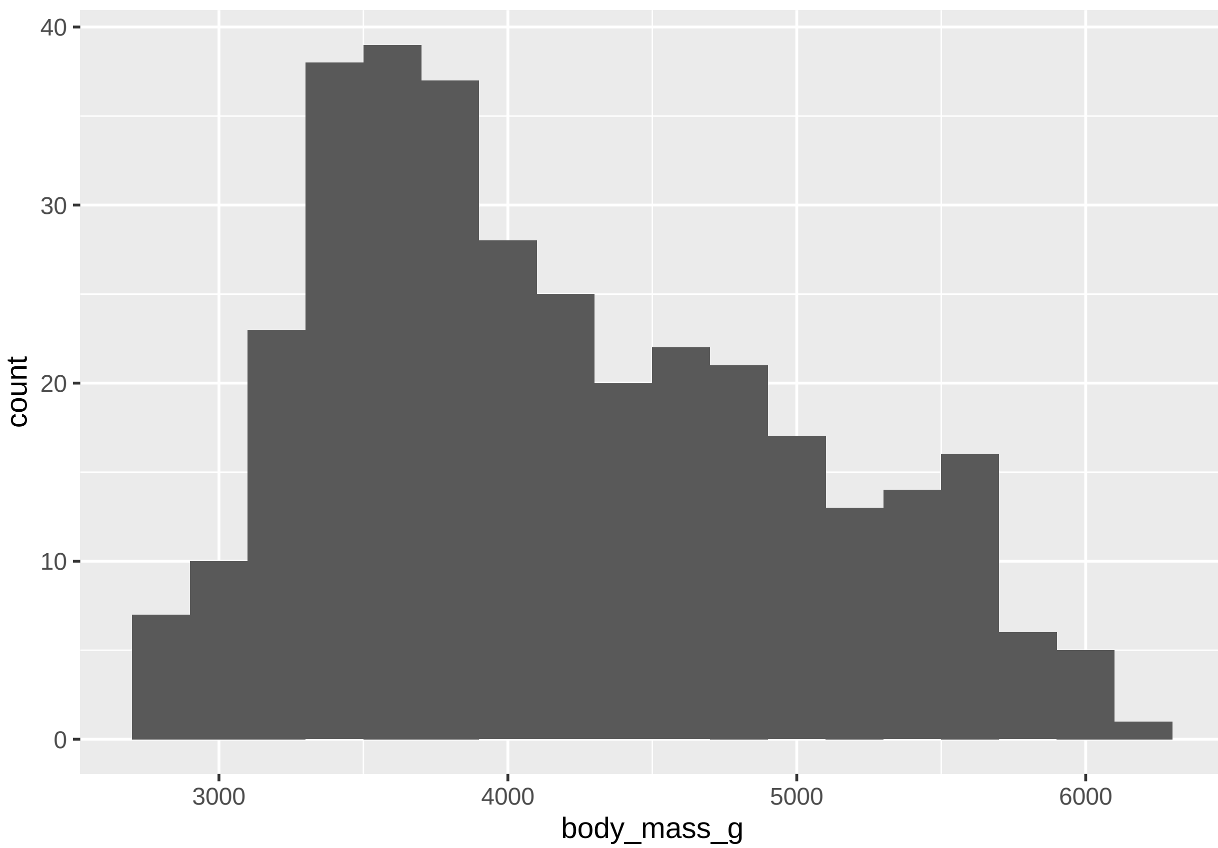


A variable is *numerical* (or quantitative) if it can take on a wide range of numerical values, and it is sensible to add, subtract, or take averages with those values. Numerical variables can be continuous or discrete.

One commonly used visualization for distributions of continuous variables is a *histogram*. A histogram divides the x-axis into equally spaced bins and then uses the height of a bar to display the number of observations that fall in each bin.

You can set the width of the intervals in a histogram with the binwidth argument, which is measured in the units of the x variable.

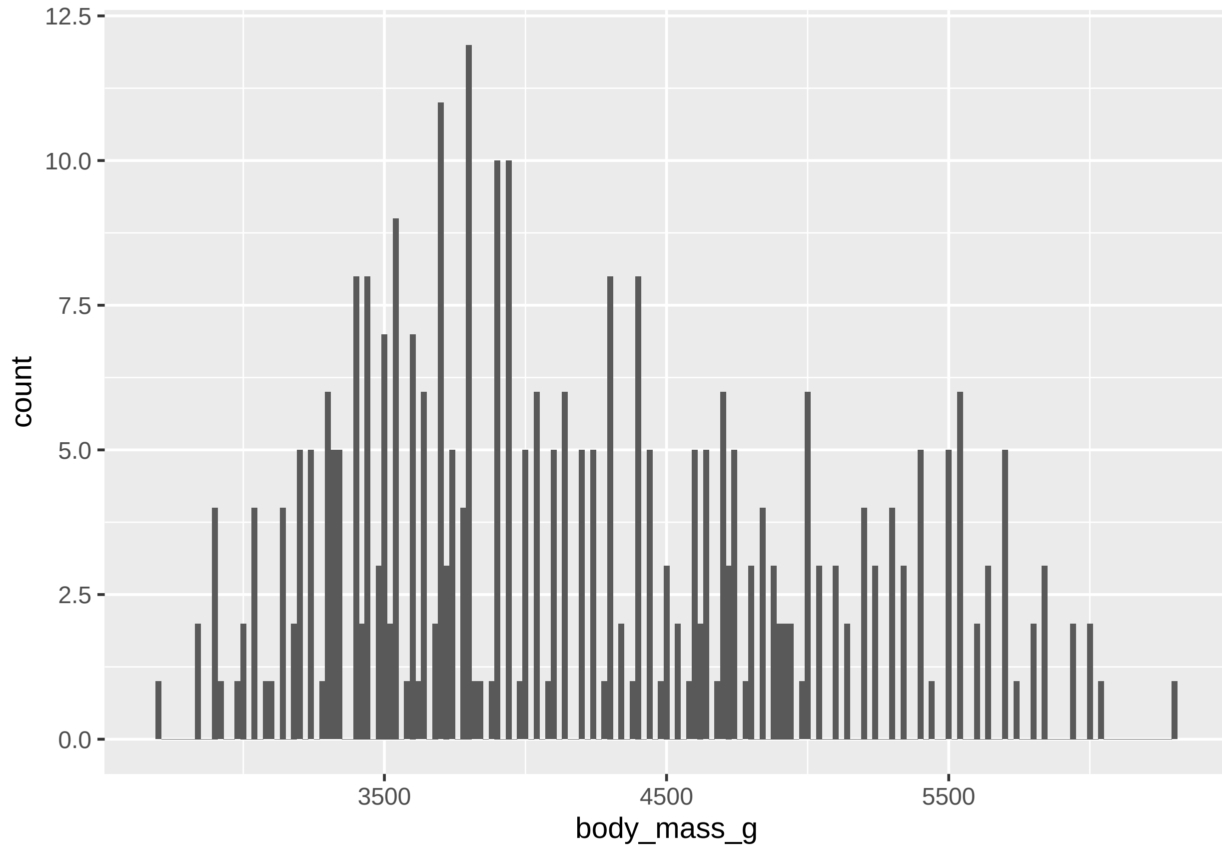
```
ggplot(penguins,
       aes(x = body_mass_g)) +
  geom_histogram(binwidth = 200)
```



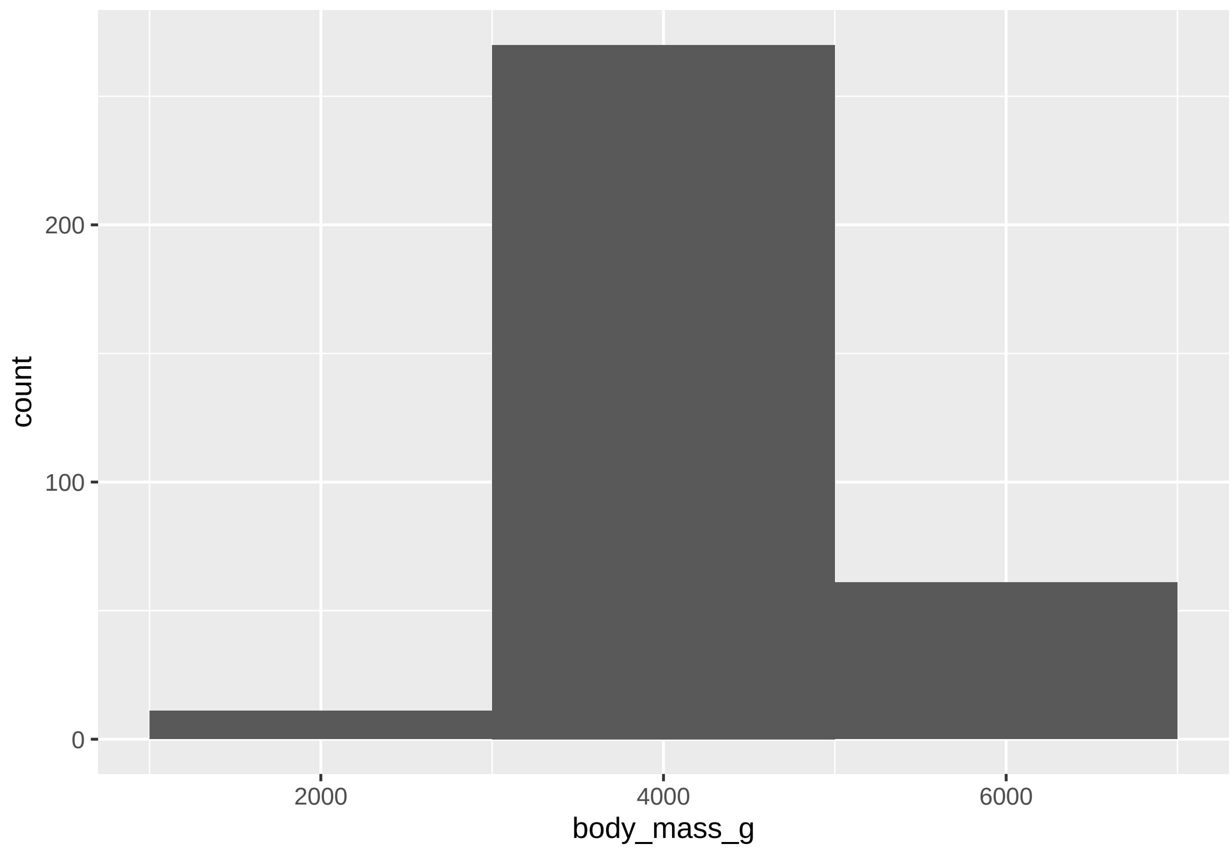
You should always explore a variety of binwidths when working with histograms, as different binwidths can reveal different patterns.

In the plots below a binwidth of 20 is too narrow, resulting in too many bars, making it difficult to determine the shape of the distribution. Similarly, a binwidth of 2,000 is too high, resulting in all data being binned into only three bars, and also making it difficult to determine the shape of the distribution.

```
ggplot(penguins,
       aes(x = body_mass_g)) +
  geom_histogram(binwidth = 20)
```

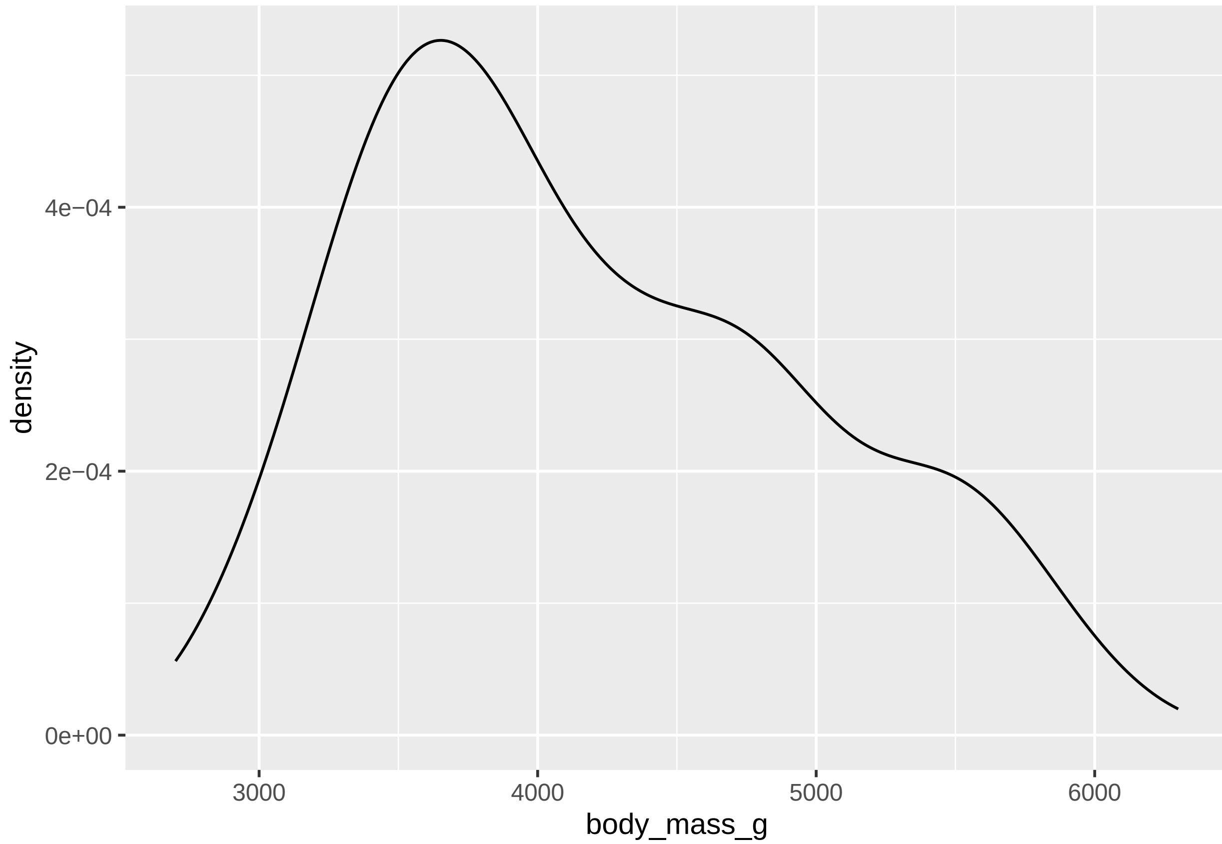



```r
ggplot(penguins,
       aes(x = body_mass_g)) +
  geom_histogram(binwidth = 2000)
```



A *density* plot is a smoothed-out version of a histogram and a practical alternative, particularly for continuous data that comes from an underlying smooth distribution.

```
ggplot(penguins,
       aes(x = body_mass_g)) +
  geom_density()
```



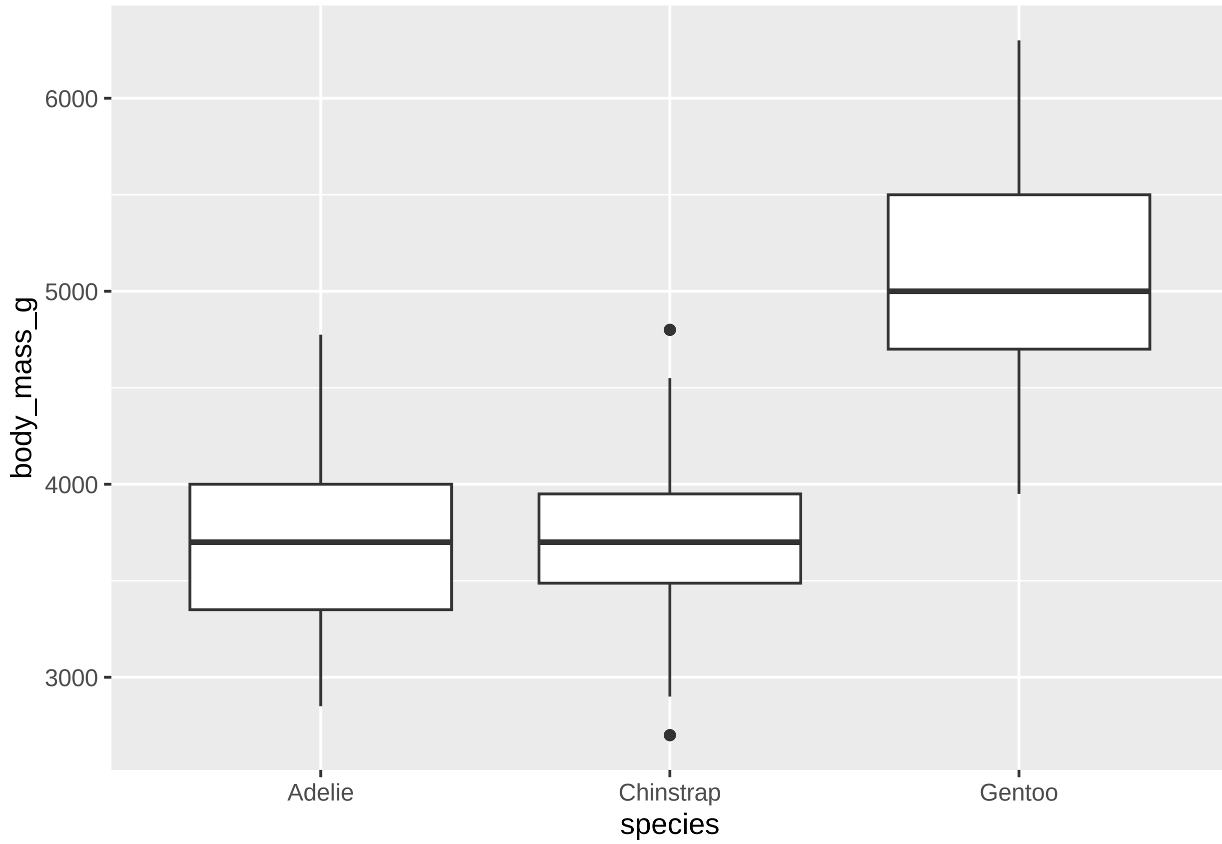
4. Visualizing relationships

To visualize the relationship between a *numerical* and a *categorical* variable we can use side-by-side box plots.

A *boxplot* is a type of visual shorthand for measures of position (percentiles) that describe a distribution. It is also useful for identifying potential outliers.

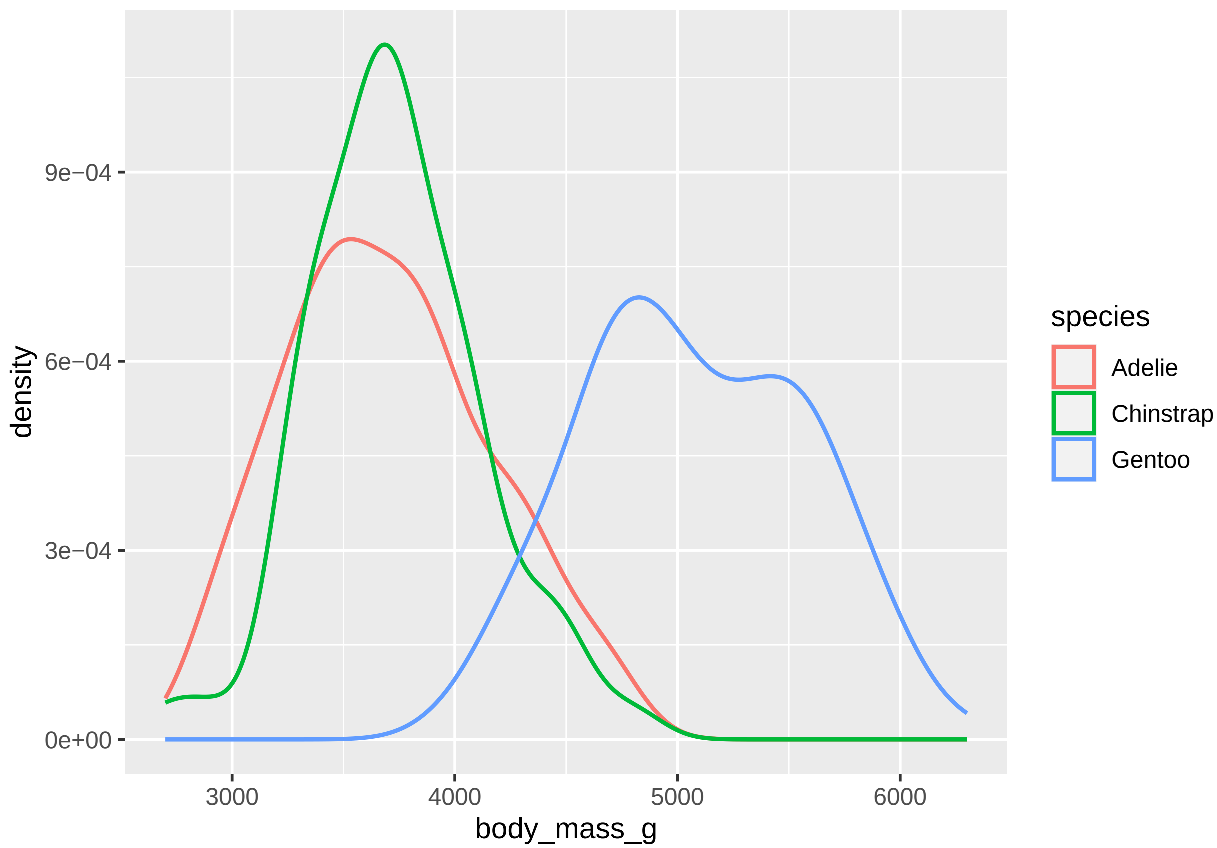
- A box that indicates the range of the middle half of the data, a distance known as the interquartile range (IQR). The 25th, 75th, and the median lines give you a sense of the spread of the distribution and whether or not the distribution is symmetric about the median or skewed to one side.
- A line (or whisker) that extends from each end of the box and goes to the farthest non-outlier point in the distribution.

```
ggplot(penguins,
       aes(x = species,
           y = body_mass_g)) +
  geom_boxplot()
```



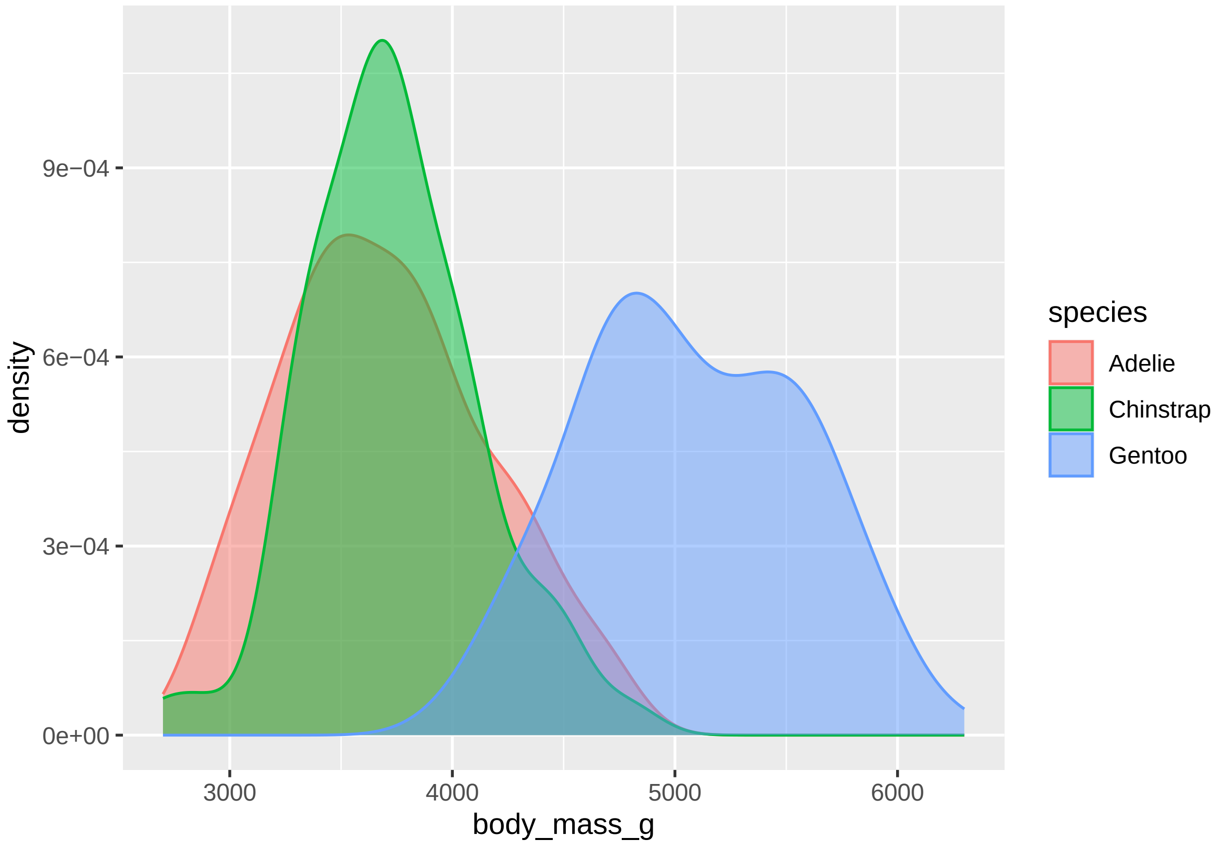
Alternatively, we can make density plots with `geom_density()`. You can customize the thickness of the lines using the `linewidth` argument in order to make them stand out a bit more against the background.

```
ggplot(penguins,
       aes(x = body_mass_g,
           color = species)) +
  geom_density(linewidth = 0.75)
```



Additionally, we can map species to both `color` and `fill` aesthetics and use the `alpha` aesthetic to add transparency to the filled density curves. This aesthetic takes values between 0 (completely transparent) and 1 (completely opaque).

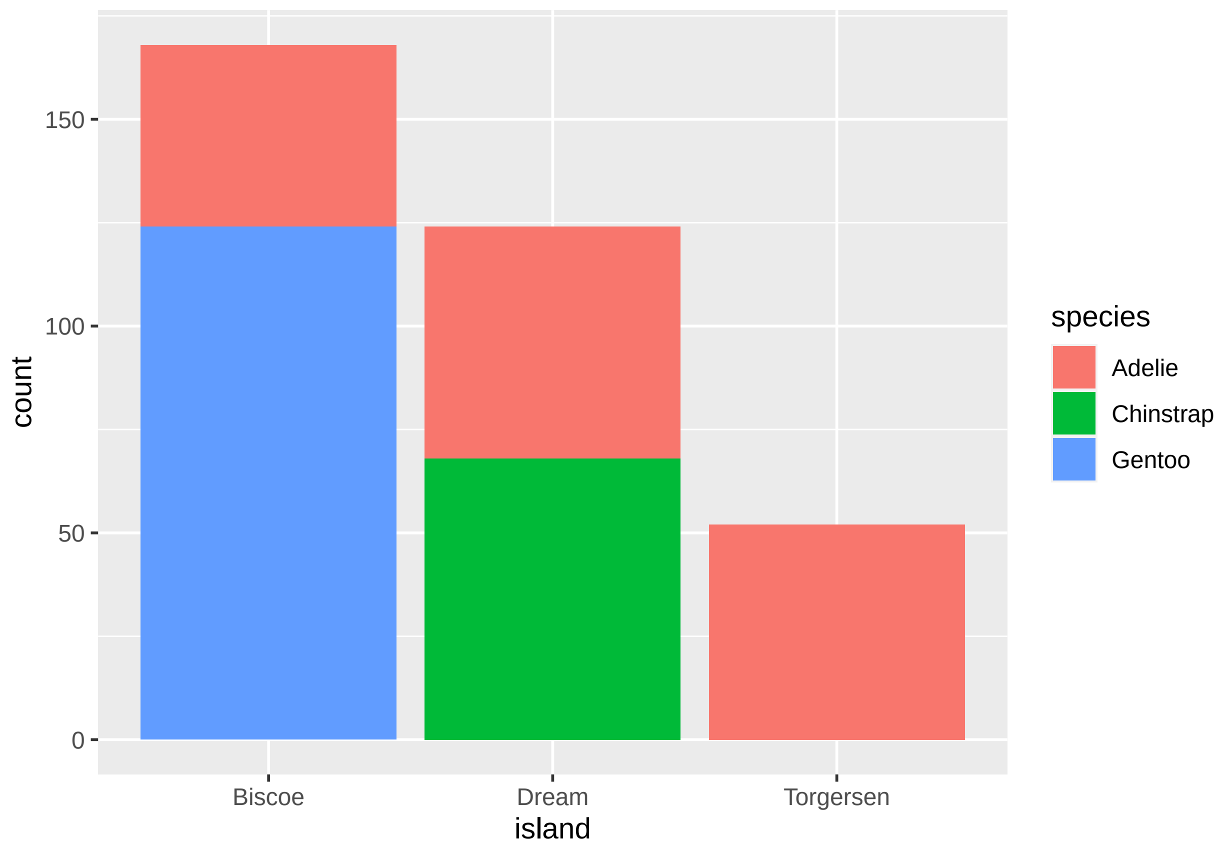
```
ggplot(penguins,
       aes(x = body_mass_g,
           color = species,
           fill = species)) +
  geom_density(alpha = 0.5)
```



We can use `stacked bar plots` to visualize the relationship between two categorical variables.

The first plot shows the frequencies of each species of penguins on each island. The plot of frequencies shows that there are equal numbers of Adelies on each island. But we don't have a good sense of the percentage balance within each island.

```
ggplot(penguins,
       aes(x = island,
           fill = species)) +
  geom_bar()
```

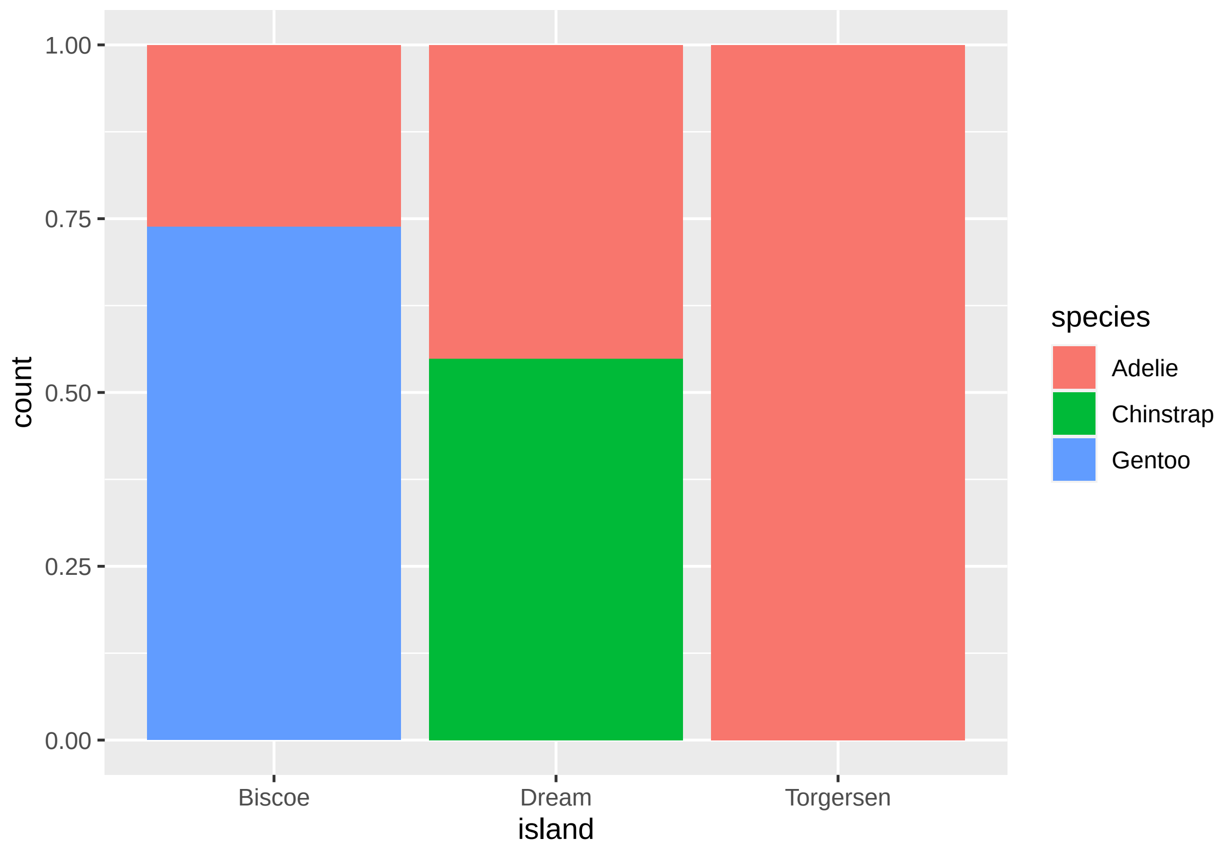


The second plot, a relative frequency plot created by setting `position = "fill"` in the geom, is more useful for comparing species distributions across islands since it's not affected by the unequal numbers of penguins across the islands.

Using this plot we can see that Gentoo penguins all live on Biscoe island and make up roughly 75% of the penguins on that island, Chinstrap all live on Dream island and make up roughly 50% of the penguins on that island, and Adelie live on all three islands and make up all of the penguins on Torgersen.

In creating these bar charts, we map the variable that will be separated into bars to the `x` aesthetic, and the variable that will change the colors inside the bars to the `fill` aesthetic.

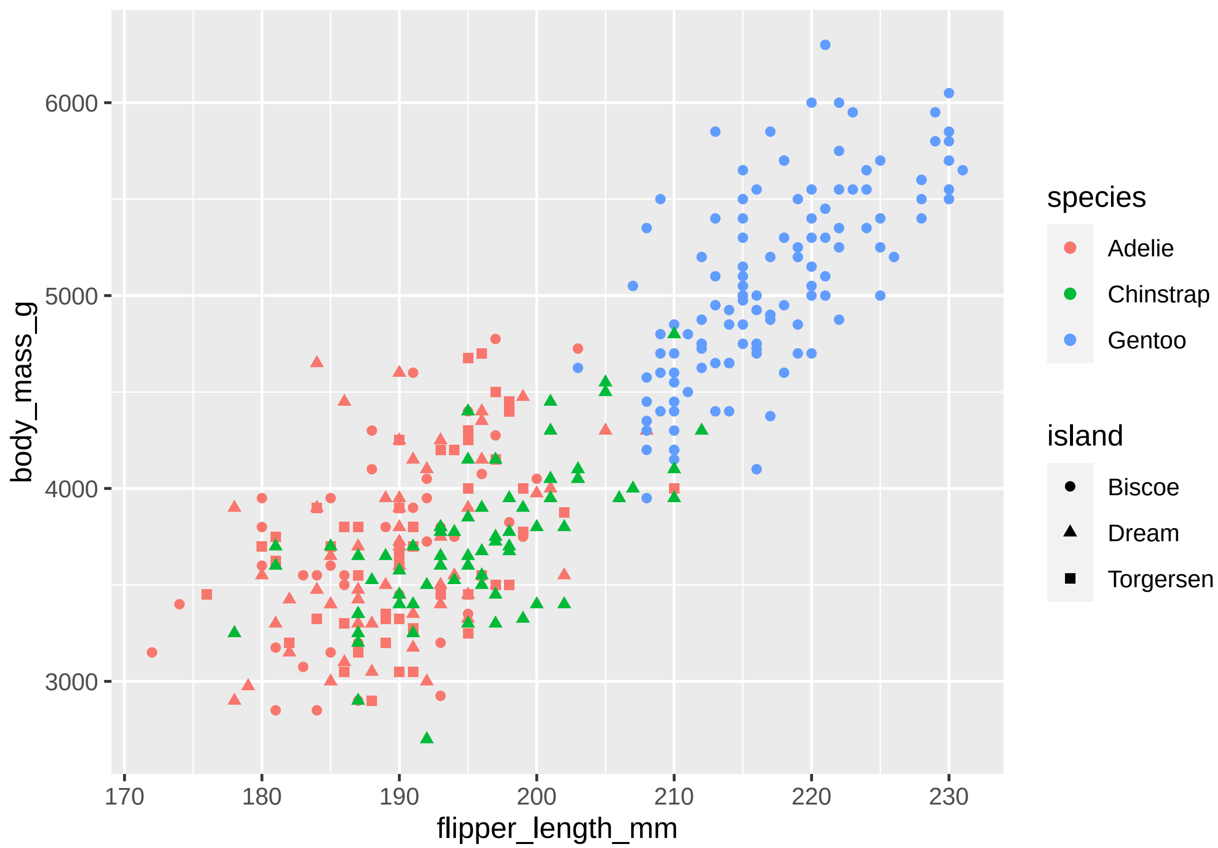
```
ggplot(penguins,
       aes(x = island,
           fill = species)) +
  geom_bar(position = "fill")
```



5. Three or more variables

We can incorporate more variables into a plot by mapping them to additional aesthetics. For example, in the following scatterplot the colors of points represent species and the shapes of points represent islands.

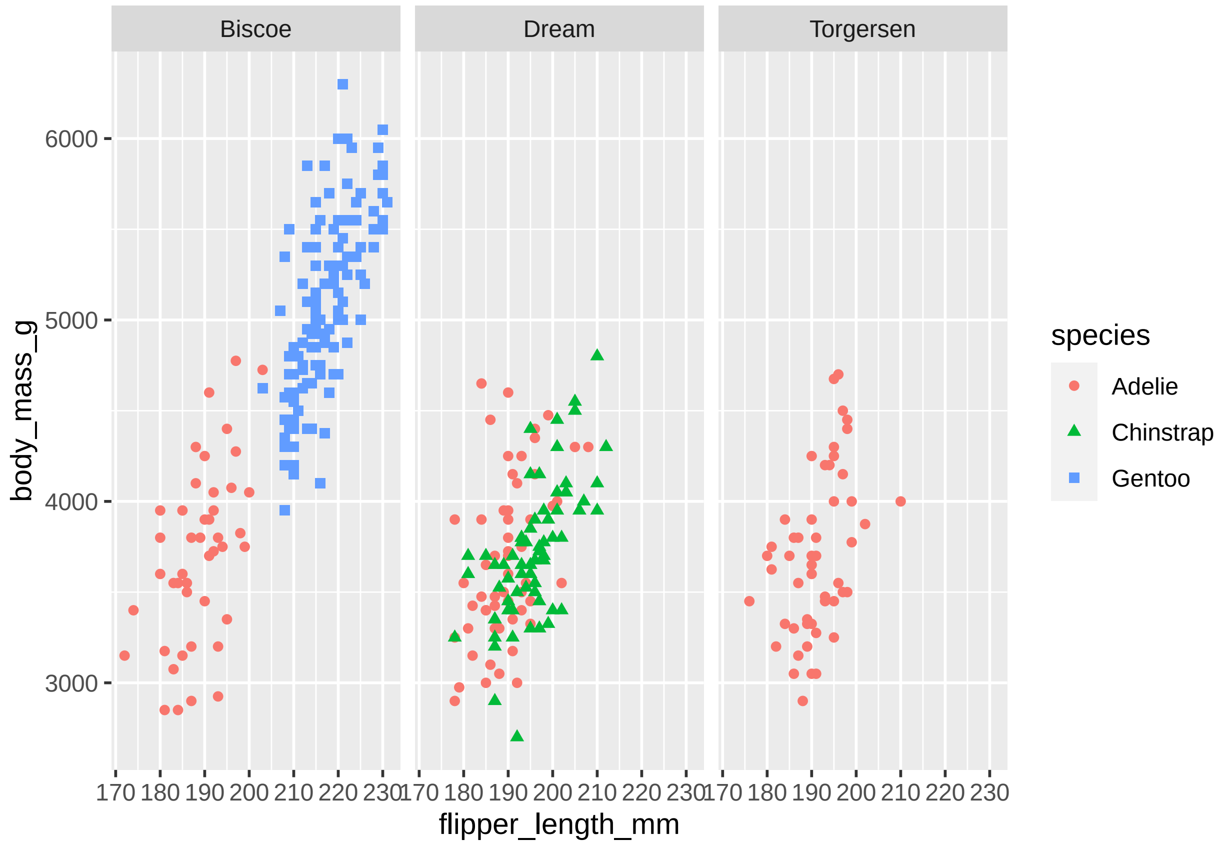
```
ggplot(penguins,
       aes(x = flipper_length_mm,
           y = body_mass_g)) +
  geom_point(aes(color = species,
                 shape = island))
```



However adding too many aesthetic mappings to a plot makes it cluttered and difficult to make sense of. Another way, which is particularly useful for categorical variables, is to split your plot into *facets*, subplots that each display one subset of the data.

To facet your plot by a single variable, use `facet_wrap()`. The first argument of `facet_wrap()` is a formula, which you create with ~ followed by a variable name. The variable that you pass to `facet_wrap()` should be *categorical*.

```
ggplot(penguins,
       aes(x = flipper_length_mm,
           y = body_mass_g)) +
  geom_point(aes(color = species, shape = species)) +
  facet_wrap(~island)
```



6. Data Transformation

The primary dplyr verbs (functions) have in common:

1. The first argument is always a data frame.
2. The subsequent arguments typically describe which columns to operate on, using the variable names (without quotes).
3. The output is always a new data frame.

Because each verb does one thing well, solving complex problems will usually require combining multiple verbs, and we'll do so with the pipe, `|>`.

The pipe takes the thing on its left and passes it along to the function on its right so that `x |> f(y)` is equivalent to `f(x, y)`, and `x |> f(y) |> g(z)` is equivalent to `g(f(x, y), z)`. The easiest way to pronounce the pipe is "then".

```
flights |>
  filter(dest == "IAH") |>
  group_by(year, month, day) |>
  summarize(
    arr_delay = mean(arr_delay, na.rm = TRUE)
  )
```

```
## # A tibble: 365 x 4
```

```
## # Groups:   year, month [12]
##     year month   day arr_delay
##    <int> <int> <int>     <dbl>
##  1  2013     1     1     17.8
##  2  2013     1     2      7
##  3  2013     1     3     18.3
##  4  2013     1     4     -3.2
##  5  2013     1     5     20.2
##  6  2013     1     6      9.28
##  7  2013     1     7     -7.74
##  8  2013     1     8      7.79
##  9  2013     1     9     18.1
## 10  2013     1    10      6.68
## # i 355 more rows
```

dplyr's verbs are organized into four groups based on what they operate on: *rows*, *columns*, *groups*, or *tables.*

6.1. Rows

The most important verbs that operate on rows of a dataset are `filter()`, which changes which rows are present without changing their order, and `arrange()`, which changes the order of the rows without changing which are present. `distinct()` which finds rows with unique values but unlike `arrange()` and `filter()` it can also optionally modify the columns.

6.1.1 filter()

`filter()` allows you to keep rows based on the values of the columns. The first argument is the data frame. The second and subsequent arguments are the conditions that must be true to keep the row.

```
flights |>
  filter(dep_delay > 120)
```

```
## # A tibble: 9,723 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      848           1835       853     1001           1950
##  2  2013     1     1      957            733       144     1056            853
##  3  2013     1     1     1114            900       134     1447           1222
##  4  2013     1     1     1540           1338       122     2020           1825
##  5  2013     1     1     1815           1325       290     2120           1542
##  6  2013     1     1     1842           1422       260     1958           1535
##  7  2013     1     1     1856           1645       131     2212           2005
##  8  2013     1     1     1934           1725       129     2126           1855
##  9  2013     1     1     1938           1703       155     2109           1823
## 10  2013     1     1     1942           1705       157     2124           1830
## # i 9,713 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

As well as `>` (greater than), you can use `>=` (greater than or equal to), `<` (less than), `<=` (less than or equal to), `==` (equal to), and `!=` (not equal to). You can also combine conditions with`&` or `,` to indicate "and" (check for both conditions) or with `|` to indicate "or" (check for either condition):

```r
# Flights that departed on January 1
flights |>
  filter(month == 1 & day == 1)
```

```
## # A tibble: 842 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 832 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

```r
# Flights that departed in January or February
flights |>
  filter(month == 1 | month == 2)
```

```
## # A tibble: 51,955 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 51,945 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

There's a useful shortcut when you're combining `|` and `==`: `%in%`. It keeps rows where the variable equals one of the values on the right.

```r
# A shorter way to select flights that departed in January or February
flights |>
  filter(month %in% c(1, 2))
```

```
## # A tibble: 51,955 x 19
```

```
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 51,945 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

6.1.2 `arrange()`

`arrange()` changes the order of the rows based on the value of the columns. 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. For example, the following code sorts by the departure time, which is spread over four columns. We get the earliest years first, then within a year the earliest months, etc.

```r
flights |>
  arrange(year, month, day, dep_time)
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 336,766 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

You can use `desc()` on a column inside of arrange() to re-order the data frame based on that column in descending (big-to-small) order.

```r
flights |>
  arrange(desc(dep_delay))
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     9      641            900      1301     1242           1530
##  2  2013     6    15     1432           1935      1137     1607           2120
##  3  2013     1    10     1121           1635      1126     1239           1810
##  4  2013     9    20     1139           1845      1014     1457           2210
##  5  2013     7    22      845           1600      1005     1044           1815
##  6  2013     4    10     1100           1900       960     1342           2211
##  7  2013     3    17     2321            810       911      135           1020
##  8  2013     6    27      959           1900       899     1236           2226
##  9  2013     7    22     2257            759       898      121           1026
## 10  2013    12     5      756           1700       896     1058           2020
## # i 336,766 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

6.1.3 distinct()

distinct() finds all the unique rows in a dataset, so in a technical sense, it primarily operates on the rows. Most of the time, however, you'll want the distinct combination of some variables, so you can also optionally supply column names:

```r
# Remove duplicate rows, if any
flights |>
  distinct()
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 336,766 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

```r
# Find all unique origin and destination pairs
flights |>
  distinct(origin, dest)
```

```
## # A tibble: 224 x 2
##    origin dest
```

```
##    <chr>  <chr>
##  1 EWR    IAH
##  2 LGA    IAH
##  3 JFK    MIA
##  4 JFK    BQN
##  5 LGA    ATL
##  6 EWR    ORD
##  7 EWR    FLL
##  8 LGA    IAD
##  9 JFK    MCO
## 10 LGA    ORD
## # i 214 more rows
```

Alternatively, if you want to the keep other columns when filtering for unique rows, you can use the `.keep_all = TRUE` option.

```r
flights |>
  distinct(origin, dest, .keep_all = TRUE)
```

```
## # A tibble: 224 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 214 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

It's not a coincidence that all of these distinct flights are on January 1: `distinct()` will find the first occurrence of a unique row in the dataset and discard the rest.

If you want to find the number of occurrences instead, you're better off swapping `distinct()` for `count()`, and with the `sort = TRUE` argument you can arrange them in *descending* order of number of occurrences.

```r
flights |>
  count(origin, dest, sort = TRUE)
```

```
## # A tibble: 224 x 3
##    origin dest      n
##    <chr>  <chr> <int>
##  1 JFK    LAX   11262
##  2 LGA    ATL   10263
##  3 LGA    ORD    8857
##  4 JFK    SFO    8204
```

```
##   5 LGA    CLT    6168
##   6 EWR    ORD    6100
##   7 JFK    BOS    5898
##   8 LGA    MIA    5781
##   9 JFK    MCO    5464
##  10 EWR    BOS    5327
## # i 214 more rows
```

6.2 Columns

There are four important verbs that affect the columns without changing the rows: `mutate()` creates new columns that are derived from the existing columns, `select()` changes which columns are present, `rename()` changes the names of the columns, and `relocate()` changes the positions of the columns.

6.2.1 `mutate()`

The job of `mutate()` is to add new columns that are calculated from the existing columns.

```
flights |>
  mutate(
    gain = dep_delay - arr_delay,
    speed = distance / air_time * 60
  )
```

```
## # A tibble: 336,776 x 21
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 336,766 more rows
## # i 13 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>, gain <dbl>, speed <dbl>
```

By default, `mutate()` adds new columns on the right hand side of your dataset, which makes it difficult to see what's happening here. We can use the `.before` argument to instead add the variables to the left hand side.

```
flights |>
  mutate(
    gain = dep_delay - arr_delay,
    speed = distance / air_time * 60,
    .before = 1
  )
```

```
## # A tibble: 336,776 x 21
##     gain speed  year month   day dep_time sched_dep_time dep_delay arr_time
##    <dbl> <dbl> <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1    -9  370.  2013     1     1      517            515         2      830
##  2   -16  374.  2013     1     1      533            529         4      850
##  3   -31  408.  2013     1     1      542            540         2      923
##  4    17  517.  2013     1     1      544            545        -1     1004
##  5    19  394.  2013     1     1      554            600        -6      812
##  6   -16  288.  2013     1     1      554            558        -4      740
##  7   -24  404.  2013     1     1      555            600        -5      913
##  8    11  259.  2013     1     1      557            600        -3      709
##  9     5  405.  2013     1     1      557            600        -3      838
## 10   -10  319.  2013     1     1      558            600        -2      753
## # i 336,766 more rows
## # i 12 more variables: sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
## #   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

The `.` is a sign that `.before` is an argument to the function, not the name of a third new variable we are creating. You can also use `.after` to add after a variable, and in both `.before` and `.after` you can use the variable name instead of a position.

```
flights |>
  mutate(
    gain = dep_delay - arr_delay,
    speed = distance / air_time * 60,
    .after = day
  )
```

```
## # A tibble: 336,776 x 21
##     year month   day  gain speed dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int> <dbl> <dbl>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1    -9  370.      517            515         2      830
##  2  2013     1     1   -16  374.      533            529         4      850
##  3  2013     1     1   -31  408.      542            540         2      923
##  4  2013     1     1    17  517.      544            545        -1     1004
##  5  2013     1     1    19  394.      554            600        -6      812
##  6  2013     1     1   -16  288.      554            558        -4      740
##  7  2013     1     1   -24  404.      555            600        -5      913
##  8  2013     1     1    11  259.      557            600        -3      709
##  9  2013     1     1     5  405.      557            600        -3      838
## 10  2013     1     1   -10  319.      558            600        -2      753
## # i 336,766 more rows
## # i 12 more variables: sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
## #   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

Alternatively, you can control which variables are kept with the `.keep` argument. A particularly useful argument is `"used"` which specifies that we only keep the columns that were involved or created in the `mutate()` step. For example, the following output will contain only the variables `dep_delay`, `arr_delay`, `air_time`, `gain`, `hours`, and `gain_per_hour`.

```
flights |>
  mutate(
    gain = dep_delay - arr_delay,
    hours = air_time / 60,
    gain_per_hour = gain / hours,
    .keep = "used"
  )
```

```
## # A tibble: 336,776 x 6
##    dep_delay arr_delay air_time  gain hours gain_per_hour
##        <dbl>     <dbl>    <dbl> <dbl> <dbl>         <dbl>
##  1         2        11      227    -9 3.78          -2.38
##  2         4        20      227   -16 3.78          -4.23
##  3         2        33      160   -31 2.67         -11.6 
##  4        -1       -18      183    17 3.05           5.57
##  5        -6       -25      116    19 1.93           9.83
##  6        -4        12      150   -16 2.5           -6.4 
##  7        -5        19      158   -24 2.63          -9.11
##  8        -3       -14       53    11 0.883         12.5 
##  9        -3        -8      140     5 2.33           2.14
## 10        -2         8      138   -10 2.3           -4.35
## # i 336,766 more rows
```

6.2.2 select()

It's not uncommon to get datasets with hundreds or even thousands of variables. In this situation, the first challenge is often just focusing on the variables you're interested in. `select()` allows you to rapidly zoom in on a useful subset using operations based on the names of the variables.

```
# Select columns by name:
flights |>
  select(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
## # i 336,766 more rows
```

```
# Select all columns between year and day (inclusive):
flights |>
  select(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
## # i 336,766 more rows
```

```
# Select all columns except those from year to day (inclusive):
flights |>
  select(!year:day)
```

```
## # A tibble: 336,776 x 16
##    dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay carrier
##       <int>          <int>     <dbl>    <int>          <int>     <dbl> <chr>
##  1      517            515         2      830            819        11 UA
##  2      533            529         4      850            830        20 UA
##  3      542            540         2      923            850        33 AA
##  4      544            545        -1     1004           1022       -18 B6
##  5      554            600        -6      812            837       -25 DL
##  6      554            558        -4      740            728        12 UA
##  7      555            600        -5      913            854        19 B6
##  8      557            600        -3      709            723       -14 EV
##  9      557            600        -3      838            846        -8 B6
## 10      558            600        -2      753            745         8 AA
## # i 336,766 more rows
## # i 9 more variables: flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

```
# Select all columns that are characters
flights |>
  select(where(is.character))
```

```
## # A tibble: 336,776 x 4
##    carrier tailnum origin dest
##    <chr>   <chr>   <chr>  <chr>
##  1 UA      N14228  EWR    IAH
##  2 UA      N24211  LGA    IAH
##  3 AA      N619AA  JFK    MIA
##  4 B6      N804JB  JFK    BQN
##  5 DL      N668DN  LGA    ATL
##  6 UA      N39463  EWR    ORD
##  7 B6      N516JB  EWR    FLL
##  8 EV      N829AS  LGA    IAD
##  9 B6      N593JB  JFK    MCO
## 10 AA      N3ALAA  LGA    ORD
## # i 336,766 more rows
```

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”.
- `num_range("x", 1:3)`: matches x1, x2 and x3.

You can rename variables as you `select()` them by using `=`. The new name appears on the left hand side of the `=`, and the old variable appears on the right hand side.

```
flights |>
  select(tail_num = tailnum)
```

```
## # A tibble: 336,776 x 1
##    tail_num
##    <chr>
##  1 N14228
##  2 N24211
##  3 N619AA
##  4 N804JB
##  5 N668DN
##  6 N39463
##  7 N516JB
##  8 N829AS
##  9 N593JB
## 10 N3ALAA
## # i 336,766 more rows
```

6.2.3 `rename()`

If you want to keep all the existing variables and just want to rename a few, you can use `rename()` instead of `select()`:

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

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 336,766 more rows
```

```
## # i 11 more variables: 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 <dttm>
```

6.2.4 relocate()

Use `relocate()` to move variables around. You might want to collect related variables together or move important variables to the front. By default `relocate()` moves variables to the front:

```
flights |>
  relocate(time_hour, air_time)
```

```
## # A tibble: 336,776 x 19
##    time_hour           air_time  year month   day dep_time sched_dep_time
##    <dttm>                 <dbl> <int> <int> <int>    <int>          <int>
##  1 2013-01-01 05:00:00      227  2013     1     1      517            515
##  2 2013-01-01 05:00:00      227  2013     1     1      533            529
##  3 2013-01-01 05:00:00      160  2013     1     1      542            540
##  4 2013-01-01 05:00:00      183  2013     1     1      544            545
##  5 2013-01-01 06:00:00      116  2013     1     1      554            600
##  6 2013-01-01 05:00:00      150  2013     1     1      554            558
##  7 2013-01-01 06:00:00      158  2013     1     1      555            600
##  8 2013-01-01 06:00:00       53  2013     1     1      557            600
##  9 2013-01-01 06:00:00      140  2013     1     1      557            600
## 10 2013-01-01 06:00:00      138  2013     1     1      558            600
## # i 336,766 more rows
## # i 12 more variables: dep_delay <dbl>, arr_time <int>, sched_arr_time <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>, origin <chr>,
## #   dest <chr>, distance <dbl>, hour <dbl>, minute <dbl>
```

You can also specify where to put them using the `.before` and `.after` arguments, just like in `mutate()`:

```
flights |>
  relocate(year:dep_time, .after = time_hour)
```

```
## # A tibble: 336,776 x 19
##    sched_dep_time dep_delay arr_time sched_arr_time arr_delay carrier flight
##             <int>     <dbl>    <int>          <int>     <dbl> <chr>    <int>
##  1            515         2      830            819        11 UA        1545
##  2            529         4      850            830        20 UA        1714
##  3            540         2      923            850        33 AA        1141
##  4            545        -1     1004           1022       -18 B6         725
##  5            600        -6      812            837       -25 DL         461
##  6            558        -4      740            728        12 UA        1696
##  7            600        -5      913            854        19 B6         507
##  8            600        -3      709            723       -14 EV        5708
##  9            600        -3      838            846        -8 B6          79
## 10            600        -2      753            745         8 AA         301
## # i 336,766 more rows
## # i 12 more variables: tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
## #   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>, year <int>,
## #   month <int>, day <int>, dep_time <int>
```

```r
flights |>
  relocate(starts_with("arr"), .before = dep_time)
```

```
## # A tibble: 336,776 x 19
##     year month   day arr_time arr_delay dep_time sched_dep_time dep_delay
##    <int> <int> <int>    <int>     <dbl>    <int>          <int>     <dbl>
##  1  2013     1     1      830        11      517            515         2
##  2  2013     1     1      850        20      533            529         4
##  3  2013     1     1      923        33      542            540         2
##  4  2013     1     1     1004       -18      544            545        -1
##  5  2013     1     1      812       -25      554            600        -6
##  6  2013     1     1      740        12      554            558        -4
##  7  2013     1     1      913        19      555            600        -5
##  8  2013     1     1      709       -14      557            600        -3
##  9  2013     1     1      838        -8      557            600        -3
## 10  2013     1     1      753         8      558            600        -2
## # i 336,766 more rows
## # i 11 more variables: sched_arr_time <int>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

6.3 The Pipe

We've shown you simple examples of the pipe above, but its real power arises when you start to combine multiple verbs. For example, imagine that you wanted to find the fastest flights to Houston's IAH airport: you need to combine `filter()`, `mutate()`, `select()`, and `arrange()`:

```r
flights |>
  filter(dest =="IAH") |>
  mutate(speed = distance / air_time * 60) |>
  select(year:day, dep_time, carrier, flight, speed) |>
  arrange(desc(speed))
```

```
## # A tibble: 7,198 x 7
##     year month   day dep_time carrier flight speed
##    <int> <int> <int>    <int> <chr>    <int> <dbl>
##  1  2013     7     9      707 UA         226  522.
##  2  2013     8    27     1850 UA        1128  521.
##  3  2013     8    28      902 UA        1711  519.
##  4  2013     8    28     2122 UA        1022  519.
##  5  2013     6    11     1628 UA        1178  515.
##  6  2013     8    27     1017 UA         333  515.
##  7  2013     8    27     1205 UA        1421  515.
##  8  2013     8    27     1758 UA         302  515.
##  9  2013     9    27      521 UA         252  515.
## 10  2013     8    28      625 UA         559  515.
## # i 7,188 more rows
```

6.4 Groups

dplyr gets even more powerful when you add in the ability to work with groups. In this section, we'll focus on the most important functions: `group_by()`, `summarize()`, and the slice family of functions.

6.4.1 group_by

Use `group_by()` to divide your dataset into groups meaningful for your analysis:

```
flights |>
  group_by(month)
```

```
## # A tibble: 336,776 x 19
## # Groups:   month [12]
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 336,766 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

`group_by()` doesn't change the data but, if you look closely at the output, you'll notice that the output indicates that it is "grouped by" month (`Groups: month [12]`). This means subsequent operations will now work "by month". `group_by()` adds this grouped feature (referred to as class) to the data frame, which changes the behavior of the subsequent verbs applied to the data.

6.4.2 sumarize()

The most important grouped operation is a summary, which, if being used to calculate a single summary statistic, reduces the data frame to have a single row for each group. In dplyr, this operation is performed by `summarize()`, as shown by the following example, which computes the average departure delay by month.

```
flights |>
  group_by(month) |>
  summarize(
    avg_delay = mean(dep_delay, na.rm = TRUE)
  )
```

```
## # A tibble: 12 x 2
##    month avg_delay
##    <int>     <dbl>
##  1     1      10.0
##  2     2      10.8
##  3     3      13.2
##  4     4      13.9
##  5     5      13.0
##  6     6      20.8
```

```
## 7     7      21.7
## 8     8      12.6
## 9     9       6.72
## 10   10       6.24
## 11   11       5.44
## 12   12      16.6
```

You can create any number of summaries in a single call to `summarize()`. One very useful summary is `n()`, which returns the number of rows in each group.

```
flights |>
  group_by(month) |>
  summarize(
    avg_delay = mean(dep_delay, na.rm = TRUE),
    n = n()
  )
```

```
## # A tibble: 12 x 3
##    month avg_delay     n
##    <int>     <dbl> <int>
##  1     1     10.0  27004
##  2     2     10.8  24951
##  3     3     13.2  28834
##  4     4     13.9  28330
##  5     5     13.0  28796
##  6     6     20.8  28243
##  7     7     21.7  29425
##  8     8     12.6  29327
##  9     9      6.72 27574
## 10    10      6.24 28889
## 11    11      5.44 27268
## 12    12     16.6  28135
```

6.4.3 The `slice_` functions

There are five handy functions that allow you extract specific rows within each group:

- `df |> slice_head(n = 1)` takes the first row from each group.
- `df |> slice_tail(n = 1)` takes the last row in each group.
- `df |> slice_min(x, n = 1)` takes the row with the smallest value of column x.
- `df |> slice_max(x, n = 1)` takes the row with the largest value of column x.
- `df |> slice_sample(n = 1)` takes one random row.

You can vary `n` to select more than one row, or instead of `n =`, you can use `prop = 0.1` to select (e.g.) 10% of the rows in each group. For example, the following code finds the flights that are most delayed upon arrival at each destination:

```
flights |>
  group_by(dest) |>
  slice_max(arr_delay, n=1) |>
  relocate(dest)
```

```
## # A tibble: 108 x 19
## # Groups:   dest [105]
##    dest   year month   day dep_time sched_dep_time dep_delay arr_time
##    <chr> <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1 ABQ    2013     7    22     2145           2007        98      132
##  2 ACK    2013     7    23     1139            800       219     1250
##  3 ALB    2013     1    25      123           2000       323      229
##  4 ANC    2013     8    17     1740           1625        75     2042
##  5 ATL    2013     7    22     2257            759       898      121
##  6 AUS    2013     7    10     2056           1505       351     2347
##  7 AVL    2013     8    13     1156            832       204     1417
##  8 BDL    2013     2    21     1728           1316       252     1839
##  9 BGR    2013    12     1     1504           1056       248     1628
## 10 BHM    2013     4    10       25           1900       325      136
## # i 98 more rows
## # i 11 more variables: sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

Note that there are 105 destinations but we get 108 rows here. What's up? `slice_min()` and `slice_max()` keep tied values so `n = 1` means give us all rows with the highest value. If you want exactly one row per group you can set `with_ties = FALSE`.

6.4.4 Grouping by multiple variables

You can create groups using more than one variable. For example, we could make a group for each date.

```
daily <- flights |>
  group_by(year, month, day)
daily
```

```
## # A tibble: 336,776 x 19
## # Groups:   year, month, day [365]
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # i 336,766 more rows
## # i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

When you summarize a tibble grouped by more than one variable, each summary peels off the last group. In hindsight, this wasn't a great way to make this function work, but it's difficult to change without breaking existing code. To make it obvious what's happening, dplyr displays a message that tells you how you can change this behavior:

```
daily_flights <- daily |>
  summarize(n = n())
```

```
## `summarise()` has grouped output by 'year', 'month'. You can override using the
## `.groups` argument.
```

If you're happy with this behavior, you can explicitly request it in order to suppress the message:

```
daily_flights <- daily |>
  summarize(
    n = n(),
    .groups = "drop_last"
  )
```

7. Data Tidying

```
library(tidyverse)
```

There are three interrelated rules that make a dataset tidy:

1. Each variable is a column; each column is a variable.
2. Each observation is a row; each row is an observation.
3. Each value is a cell; each cell is a single value.

7.1. Lengthening data

`tidyr` provides two functions for pivoting data: `pivot_longer()` and `pivot_wider()`. We'll first start with `pivot_longer()` because it's the most common case. Let's dive into some examples.

7.1.1. `pivot_longer()`

The `billboard` dataset records the billboard rank of songs in the year 2000:

```
billboard
```

```
## # A tibble: 317 x 79
##    artist      track date.entered   wk1   wk2   wk3   wk4   wk5   wk6   wk7   wk8
##    <chr>       <chr> <date>       <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1 2 Pac       Baby~ 2000-02-26      87    82    72    77    87    94    99    NA
##  2 2Ge+her     The ~ 2000-09-02      91    87    92    NA    NA    NA    NA    NA
##  3 3 Doors D~ Kryp~ 2000-04-08      81    70    68    67    66    57    54    53
##  4 3 Doors D~ Loser 2000-10-21      76    76    72    69    67    65    55    59
##  5 504 Boyz    Wobb~ 2000-04-15      57    34    25    17    17    31    36    49
```

```
##  6 98^0       Give~ 2000-08-19      51    39    34    26    26    19     2     2
##  7 A*Teens    Danc~ 2000-07-08      97    97    96    95   100    NA    NA    NA
##  8 Aaliyah    I Do~ 2000-01-29      84    62    51    41    38    35    35    38
##  9 Aaliyah    Try ~ 2000-03-18      59    53    38    28    21    18    16    14
## 10 Adams, Yo~ Open~ 2000-08-26      76    76    74    69    68    67    61    58
## # i 307 more rows
## # i 68 more variables: wk9 <dbl>, wk10 <dbl>, wk11 <dbl>, wk12 <dbl>,
## #   wk13 <dbl>, wk14 <dbl>, wk15 <dbl>, wk16 <dbl>, wk17 <dbl>, wk18 <dbl>,
## #   wk19 <dbl>, wk20 <dbl>, wk21 <dbl>, wk22 <dbl>, wk23 <dbl>, wk24 <dbl>,
## #   wk25 <dbl>, wk26 <dbl>, wk27 <dbl>, wk28 <dbl>, wk29 <dbl>, wk30 <dbl>,
## #   wk31 <dbl>, wk32 <dbl>, wk33 <dbl>, wk34 <dbl>, wk35 <dbl>, wk36 <dbl>,
## #   wk37 <dbl>, wk38 <dbl>, wk39 <dbl>, wk40 <dbl>, wk41 <dbl>, wk42 <dbl>, ...
```

In this dataset, each observation is a song. The first three columns (`artist`, `track` and `date.entered`) are variables that describe the song. Then we have 76 columns (`wk1-wk76`) that describe the rank of the song in each week. Here, the column names are one variable (the `week`) and the cell values are another (the `rank`).

To tidy this data, we'll use `pivot_longer()`:

```
billboard |>
  pivot_longer(
    cols = starts_with("wk"),
    names_to = "week",
    values_to = "rank"
  )
```

```
## # A tibble: 24,092 x 5
##    artist track                   date.entered week   rank
##    <chr>  <chr>                   <date>       <chr> <dbl>
##  1 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk1      87
##  2 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk2      82
##  3 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk3      72
##  4 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk4      77
##  5 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk5      87
##  6 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk6      94
##  7 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk7      99
##  8 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk8      NA
##  9 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk9      NA
## 10 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk10     NA
## # i 24,082 more rows
```

After the data, there are three key arguments:

- `cols` specifies which columns need to be pivoted, i.e. which columns aren't variables. This argument uses the same syntax as `select()` so here we could use `!c(artist, track, date.entered)` or `starts_with("wk")`.
- `names_to` names the variable stored in the column names, we named that variable `week`.
- `values_to` names the variable stored in the cell values, we named that variable `rank`.

Note that in the code `"week"` and `"rank"` are quoted because those are new variables we're creating, they don't yet exist in the data when we run the `pivot_longer()` call.

Now let's turn our attention to the resulting, longer data frame. What happens if a song is in the top 100 for less than 76 weeks? Take 2 Pac's "Baby Don't Cry", for example. The above output suggests that it was only in the top 100 for 7 weeks, and all the remaining weeks are filled in with missing values. These NAs don't really represent unknown observations; they were forced to exist by the structure of the dataset2, so we can ask `pivot_longer()` to get rid of them by setting `values_drop_na = TRUE`:

```
billboard |>
  pivot_longer(
    cols = starts_with("wk"),
    names_to = "week",
    values_to = "rank",
    values_drop_na = TRUE
  )
```

```
## # A tibble: 5,307 x 5
##    artist  track                   date.entered week   rank
##    <chr>   <chr>                   <date>       <chr> <dbl>
##  1 2 Pac   Baby Don't Cry (Keep... 2000-02-26   wk1      87
##  2 2 Pac   Baby Don't Cry (Keep... 2000-02-26   wk2      82
##  3 2 Pac   Baby Don't Cry (Keep... 2000-02-26   wk3      72
##  4 2 Pac   Baby Don't Cry (Keep... 2000-02-26   wk4      77
##  5 2 Pac   Baby Don't Cry (Keep... 2000-02-26   wk5      87
##  6 2 Pac   Baby Don't Cry (Keep... 2000-02-26   wk6      94
##  7 2 Pac   Baby Don't Cry (Keep... 2000-02-26   wk7      99
##  8 2Ge+her The Hardest Part Of ... 2000-09-02   wk1      91
##  9 2Ge+her The Hardest Part Of ... 2000-09-02   wk2      87
## 10 2Ge+her The Hardest Part Of ... 2000-09-02   wk3      92
## # i 5,297 more rows
```

This data is now tidy, but we could make future computation a bit easier by converting values of week from character strings to numbers using `mutate()` and `readr::parse_number()`.

`parse_number()` is a handy function that will extract the first number from a string, ignoring all other text.

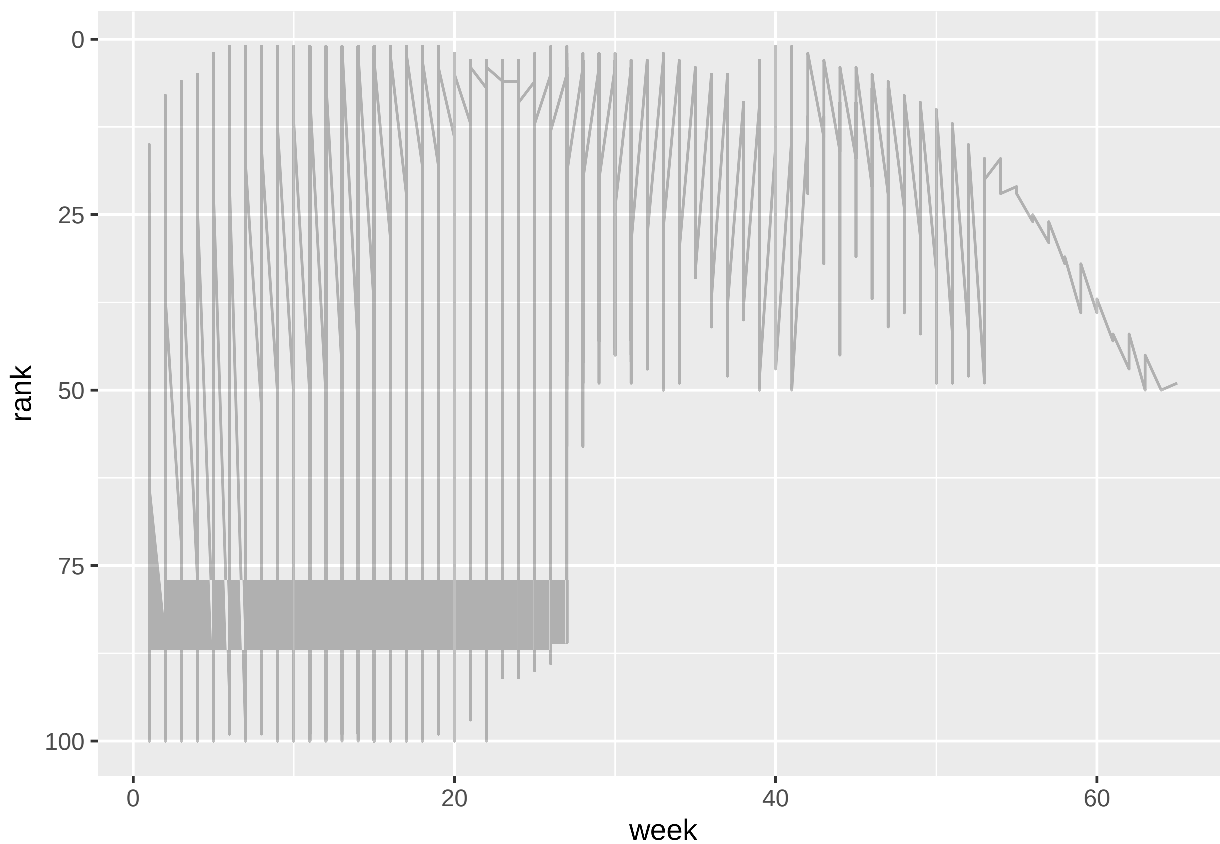
```
billboard_longer <- billboard |>
  pivot_longer(
    cols = starts_with("wk"),
    names_to = "week",
    values_to = "rank",
    values_drop_na = TRUE
  ) |>
  mutate(
    week = parse_number(week)
  )

billboard_longer
```

```
## # A tibble: 5,307 x 5
##    artist  track                   date.entered  week  rank
##    <chr>   <chr>                   <date>       <dbl> <dbl>
##  1 2 Pac   Baby Don't Cry (Keep... 2000-02-26       1    87
##  2 2 Pac   Baby Don't Cry (Keep... 2000-02-26       2    82
##  3 2 Pac   Baby Don't Cry (Keep... 2000-02-26       3    72
##  4 2 Pac   Baby Don't Cry (Keep... 2000-02-26       4    77
##  5 2 Pac   Baby Don't Cry (Keep... 2000-02-26       5    87
```

```
##   6 2 Pac    Baby Don't Cry (Keep... 2000-02-26       6    94
##   7 2 Pac    Baby Don't Cry (Keep... 2000-02-26       7    99
##   8 2Ge+her The Hardest Part Of ... 2000-09-02       1    91
##   9 2Ge+her The Hardest Part Of ... 2000-09-02       2    87
##  10 2Ge+her The Hardest Part Of ... 2000-09-02       3    92
## # i 5,297 more rows
```

Now that we have all the week numbers in one variable and all the rank values in another, we're in a good position to visualize how song ranks vary over time.

```
billboard_longer |>
  ggplot(aes(x = week,
             y = rank,
             group(track))) +
  geom_line(alpha = 0.25) +
  scale_y_reverse()
```



7.1.1.1. Many variables in column names A more challenging situation occurs when you have multiple pieces of information crammed into the column names, and you would like to store these in separate new variables. For example, take the `who2` dataset, the source of `table1` and friends that you saw above:

```
who2
```

```
## # A tibble: 7,240 x 58
##    country      year sp_m_014 sp_m_1524 sp_m_2534 sp_m_3544 sp_m_4554 sp_m_5564
##    <chr>       <dbl>    <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>
```

```
##  1 Afghanistan  1980       NA         NA         NA         NA         NA         NA
##  2 Afghanistan  1981       NA         NA         NA         NA         NA         NA
##  3 Afghanistan  1982       NA         NA         NA         NA         NA         NA
##  4 Afghanistan  1983       NA         NA         NA         NA         NA         NA
##  5 Afghanistan  1984       NA         NA         NA         NA         NA         NA
##  6 Afghanistan  1985       NA         NA         NA         NA         NA         NA
##  7 Afghanistan  1986       NA         NA         NA         NA         NA         NA
##  8 Afghanistan  1987       NA         NA         NA         NA         NA         NA
##  9 Afghanistan  1988       NA         NA         NA         NA         NA         NA
## 10 Afghanistan  1989       NA         NA         NA         NA         NA         NA
## # i 7,230 more rows
## # i 50 more variables: sp_m_65 <dbl>, sp_f_014 <dbl>, sp_f_1524 <dbl>,
## #   sp_f_2534 <dbl>, sp_f_3544 <dbl>, sp_f_4554 <dbl>, sp_f_5564 <dbl>,
## #   sp_f_65 <dbl>, sn_m_014 <dbl>, sn_m_1524 <dbl>, sn_m_2534 <dbl>,
## #   sn_m_3544 <dbl>, sn_m_4554 <dbl>, sn_m_5564 <dbl>, sn_m_65 <dbl>,
## #   sn_f_014 <dbl>, sn_f_1524 <dbl>, sn_f_2534 <dbl>, sn_f_3544 <dbl>,
## #   sn_f_4554 <dbl>, sn_f_5564 <dbl>, sn_f_65 <dbl>, ep_m_014 <dbl>, ...
```

This dataset, collected by the World Health Organisation, records information about tuberculosis diagnoses. There are two columns that are already variables and are easy to interpret: `country` and `year`. They are followed by 56 columns like `sp_m_014`, `ep_m_4554`, and `rel_m_3544`. If you stare at these columns for long enough, you'll notice there's a pattern. Each column name is made up of three pieces separated by `_`. The first piece, `sp/rel/ep`, describes the method used for the diagnosis, the second piece, `m/f` is the gender (coded as a binary variable in this dataset), and the third piece, `014/1524/2534/3544/4554/5564/65` is the age range (014 represents `0-14`, for example).

So in this case we have six pieces of information recorded in `who2`: the `country` and the `year` (already columns); the method of diagnosis, the gender category, and the age range category (contained in the other column names); and the count of patients in that category (cell values). To organize these six pieces of information in six separate columns, we use `pivot_longer()` with a vector of column names for `names_to` and instructors for splitting the original variable names into pieces for `names_sep` as well as a column name for `values_to`:

```
who2 |>
  pivot_longer(
    cols = !(country:year),
    names_to = c("diagnosis", "gender", "age"),
    names_sep = "_",
    values_to = "count"

  )
```

```
## # A tibble: 405,440 x 6
##    country      year diagnosis gender age   count
##    <chr>       <dbl> <chr>     <chr>  <chr> <dbl>
##  1 Afghanistan  1980 sp        m      014      NA
##  2 Afghanistan  1980 sp        m      1524     NA
##  3 Afghanistan  1980 sp        m      2534     NA
##  4 Afghanistan  1980 sp        m      3544     NA
##  5 Afghanistan  1980 sp        m      4554     NA
##  6 Afghanistan  1980 sp        m      5564     NA
##  7 Afghanistan  1980 sp        m      65       NA
##  8 Afghanistan  1980 sp        f      014      NA
##  9 Afghanistan  1980 sp        f      1524     NA
```

```
## 10 Afghanistan  1980 sp        f      2534     NA
## # i 405,430 more rows
```

An alternative to `names_sep` is `names_pattern`, which you can use to extract variables from more complicated naming scenarios.

This dataset contains data about five families, with the names and dates of birth of up to two children. The new challenge in this dataset is that the column names contain the names of two variables (`dob`, `name`) and the values of another (child, with values 1 or 2). To solve this problem we again need to supply a vector to names_to but this time we use the special "`.value`" sentinel; this isn't the name of a variable but a unique value that tells `pivot_longer()` to do something different. This overrides the usual `values_to` argument to use the first component of the pivoted column name as a variable name in the output.

```
household
```

```
## # A tibble: 5 x 5
##   family dob_child1 dob_child2 name_child1 name_child2
##    <int> <date>     <date>     <chr>       <chr>
## 1      1 1998-11-26 2000-01-29 Susan       Jose
## 2      2 1996-06-22 NA         Mark        <NA>
## 3      3 2002-07-11 2004-04-05 Sam         Seth
## 4      4 2004-10-10 2009-08-27 Craig       Khai
## 5      5 2000-12-05 2005-02-28 Parker      Gracie
```

```
household |>
  pivot_longer(
    cols = !family,
    names_to = c(".value", "child"),
    names_sep = "_",
    values_drop_na = TRUE
  )
```

```
## # A tibble: 9 x 4
##   family child  dob        name
##    <int> <chr>  <date>     <chr>
## 1      1 child1 1998-11-26 Susan
## 2      1 child2 2000-01-29 Jose
## 3      2 child1 1996-06-22 Mark
## 4      3 child1 2002-07-11 Sam
## 5      3 child2 2004-04-05 Seth
## 6      4 child1 2004-10-10 Craig
## 7      4 child2 2009-08-27 Khai
## 8      5 child1 2000-12-05 Parker
## 9      5 child2 2005-02-28 Gracie
```

When you use "`.value`" in names_to, the column names in the input contribute to both values and variable names in the output.

7.2. Data Widening

7.2.1 `pivot_wider()`

`pivot_wider()`, which makes datasets wider by increasing columns and reducing rows and helps when one observation is spread across multiple rows.

We'll start by looking at `cms_patient_experience`, a dataset from the Centers of Medicare and Medicaid services that collects data about patient experiences:

```
cms_patient_experience
```

```
## # A tibble: 500 x 5
##    org_pac_id org_nm                           measure_cd measure_title prf_rate
##    <chr>      <chr>                            <chr>      <chr>            <dbl>
##  1 0446157747 USC CARE MEDICAL GROUP INC       CAHPS_GRP~ CAHPS for MI~       63
##  2 0446157747 USC CARE MEDICAL GROUP INC       CAHPS_GRP~ CAHPS for MI~       87
##  3 0446157747 USC CARE MEDICAL GROUP INC       CAHPS_GRP~ CAHPS for MI~       86
##  4 0446157747 USC CARE MEDICAL GROUP INC       CAHPS_GRP~ CAHPS for MI~       57
##  5 0446157747 USC CARE MEDICAL GROUP INC       CAHPS_GRP~ CAHPS for MI~       85
##  6 0446157747 USC CARE MEDICAL GROUP INC       CAHPS_GRP~ CAHPS for MI~       24
##  7 0446162697 ASSOCIATION OF UNIVERSITY PHYSI~ CAHPS_GRP~ CAHPS for MI~       59
##  8 0446162697 ASSOCIATION OF UNIVERSITY PHYSI~ CAHPS_GRP~ CAHPS for MI~       85
##  9 0446162697 ASSOCIATION OF UNIVERSITY PHYSI~ CAHPS_GRP~ CAHPS for MI~       83
## 10 0446162697 ASSOCIATION OF UNIVERSITY PHYSI~ CAHPS_GRP~ CAHPS for MI~       63
## # i 490 more rows
```

The core unit being studied is an organization, but each organization is spread across six rows, with one row for each measurement taken in the survey organization. We can see the complete set of values for `measure_cd` and `measure_title` by using `distinct()`:

```
cms_patient_experience |>
  distinct(measure_cd, measure_title)
```

```
## # A tibble: 6 x 2
##   measure_cd   measure_title
##   <chr>        <chr>
## 1 CAHPS_GRP_1  CAHPS for MIPS SSM: Getting Timely Care, Appointments, and Infor~
## 2 CAHPS_GRP_2  CAHPS for MIPS SSM: How Well Providers Communicate
## 3 CAHPS_GRP_3  CAHPS for MIPS SSM: Patient's Rating of Provider
## 4 CAHPS_GRP_5  CAHPS for MIPS SSM: Health Promotion and Education
## 5 CAHPS_GRP_8  CAHPS for MIPS SSM: Courteous and Helpful Office Staff
## 6 CAHPS_GRP_12 CAHPS for MIPS SSM: Stewardship of Patient Resources
```

`pivot_wider()` has the opposite interface to `pivot_longer()`: instead of choosing new column names, we need to provide the existing columns that define the values (`values_from`) and the column name (`names_from`):

```
cms_patient_experience |>
  pivot_wider(
    names_from = measure_cd,
    values_from = prf_rate
  )
```

```
## # A tibble: 500 x 9
##    org_pac_id org_nm           measure_title CAHPS_GRP_1 CAHPS_GRP_2 CAHPS_GRP_3
##    <chr>      <chr>            <chr>               <dbl>       <dbl>       <dbl>
##  1 0446157747 USC CARE MEDICA~ CAHPS for MI~          63          NA          NA
##  2 0446157747 USC CARE MEDICA~ CAHPS for MI~          NA          87          NA
```

```
##  3 0446157747 USC CARE MEDICA~ CAHPS for MI~          NA          NA          86
##  4 0446157747 USC CARE MEDICA~ CAHPS for MI~          NA          NA          NA
##  5 0446157747 USC CARE MEDICA~ CAHPS for MI~          NA          NA          NA
##  6 0446157747 USC CARE MEDICA~ CAHPS for MI~          NA          NA          NA
##  7 0446162697 ASSOCIATION OF ~ CAHPS for MI~          59          NA          NA
##  8 0446162697 ASSOCIATION OF ~ CAHPS for MI~          NA          85          NA
##  9 0446162697 ASSOCIATION OF ~ CAHPS for MI~          NA          NA          83
## 10 0446162697 ASSOCIATION OF ~ CAHPS for MI~          NA          NA          NA
## # i 490 more rows
## # i 3 more variables: CAHPS_GRP_5 <dbl>, CAHPS_GRP_8 <dbl>, CAHPS_GRP_12 <dbl>
```

The output doesn't look quite right; we still seem to have multiple rows for each organization. That's because, we also need to tell `pivot_wider()` which column or columns have values that uniquely identify each row; in this case those are the variables starting with "`org`":

```
cms_patient_experience |>
  pivot_wider(
    id_cols = starts_with("org"),
    names_from = measure_cd,
    values_from = prf_rate
  )
```

```
## # A tibble: 95 x 8
##    org_pac_id org_nm CAHPS_GRP_1 CAHPS_GRP_2 CAHPS_GRP_3 CAHPS_GRP_5 CAHPS_GRP_8
##    <chr>      <chr>        <dbl>       <dbl>       <dbl>       <dbl>       <dbl>
##  1 0446157747 USC C~          63          87          86          57          85
##  2 0446162697 ASSOC~          59          85          83          63          88
##  3 0547164295 BEAVE~          49          NA          75          44          73
##  4 0749333730 CAPE ~          67          84          85          65          82
##  5 0840104360 ALLIA~          66          87          87          64          87
##  6 0840109864 REX H~          73          87          84          67          91
##  7 0840513552 SCL H~          58          83          76          58          78
##  8 0941545784 GRITM~          46          86          81          54          NA
##  9 1052612785 COMMU~          65          84          80          58          87
## 10 1254237779 OUR L~          61          NA          NA          65          NA
## # i 85 more rows
## # i 1 more variable: CAHPS_GRP_12 <dbl>
```

8. Reading data from a file

8.1. `read.csv()`

We can read this file into R using `read_csv()`.

```
students <- read.csv("https://pos.it/r4ds-students-csv")
students
```

```
##   Student.ID        Full.Name     favourite.food           mealPlan  AGE
## 1          1   Sunil Huffmann Strawberry yoghurt          Lunch only    4
## 2          2     Barclay Lynn       French fries          Lunch only    5
## 3          3    Jayendra Lyne                N/A Breakfast and lunch    7
```

```
## 4           4     Leon Rossini           Anchovies           Lunch only
## 5           5 Chidiegwu Dunkel               Pizza Breakfast and lunch five
## 6           6    Güvenç Attila           Ice cream           Lunch only    6
```

Once you read data in, the first step usually involves transforming it in some way to make it easier to work with in the rest of your analysis.

8.1.1. `read.csv(file, na = "")`

In the `favourite.food` column, there are a bunch of food items, and then the character string `N/A`, which should have been a real `NA` that R will recognize as "not available". This is something we can address using the `na` argument. By default, `read_csv()` only recognizes empty strings (`""`) in this dataset as `NA`s, we want it to also recognize the character string `"N/A"`.

```
students <- read.csv("https://pos.it/r4ds-students-csv", na = c("N/A", ""))
students
```

```
##   Student.ID         Full.Name     favourite.food            mealPlan  AGE
## 1          1   Sunil Huffmann Strawberry yoghurt           Lunch only    4
## 2          2      Barclay Lynn       French fries           Lunch only    5
## 3          3    Jayendra Lyne               <NA> Breakfast and lunch    7
## 4          4     Leon Rossini          Anchovies           Lunch only <NA>
## 5          5 Chidiegwu Dunkel              Pizza Breakfast and lunch five
## 6          6    Güvenç Attila          Ice cream           Lunch only    6
```

8.1.2. `factor()`

Another common task after reading in data is to consider variable types. For example, `meal_plan` is a categorical variable with a known set of possible values, which in R should be represented as a factor:

```
students |>
  mutate(
    mealPlan = factor(mealPlan)
  )
```

```
##   Student.ID         Full.Name     favourite.food            mealPlan  AGE
## 1          1   Sunil Huffmann Strawberry yoghurt           Lunch only    4
## 2          2      Barclay Lynn       French fries           Lunch only    5
## 3          3    Jayendra Lyne               <NA> Breakfast and lunch    7
## 4          4     Leon Rossini          Anchovies           Lunch only <NA>
## 5          5 Chidiegwu Dunkel              Pizza Breakfast and lunch five
## 6          6    Güvenç Attila          Ice cream           Lunch only    6
```

Before you analyze these data, you'll probably want to fix the `age` and `id` columns. Currently, `age` is a character variable because one of the observations is typed out as five instead of a numeric 5.

```
students <- students |>
  mutate(
    mealPlan = factor(mealPlan),
    AGE = parse_number(ifelse(AGE == "five", 5, AGE))
  )

students
```

```
##   Student.ID         Full.Name     favourite.food            mealPlan AGE
## 1          1   Sunil Huffmann Strawberry yoghurt          Lunch only   4
## 2          2     Barclay Lynn       French fries          Lunch only   5
## 3          3    Jayendra Lyne               <NA> Breakfast and lunch   7
## 4          4     Leon Rossini          Anchovies          Lunch only  NA
## 5          5 Chidiegwu Dunkel              Pizza Breakfast and lunch   5
## 6          6    Güvenç Attila          Ice cream          Lunch only   6
```

A new function here is `if_else()`, which has three arguments. The first argument test should be a logical vector. The result will contain the value of the second argument, `yes`, when `test` is `TRUE`, and the value of the third argument, `no`, when it is `FALSE.` Here we're saying if age is the character string "five", make it "5", and if not leave it as age.