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.

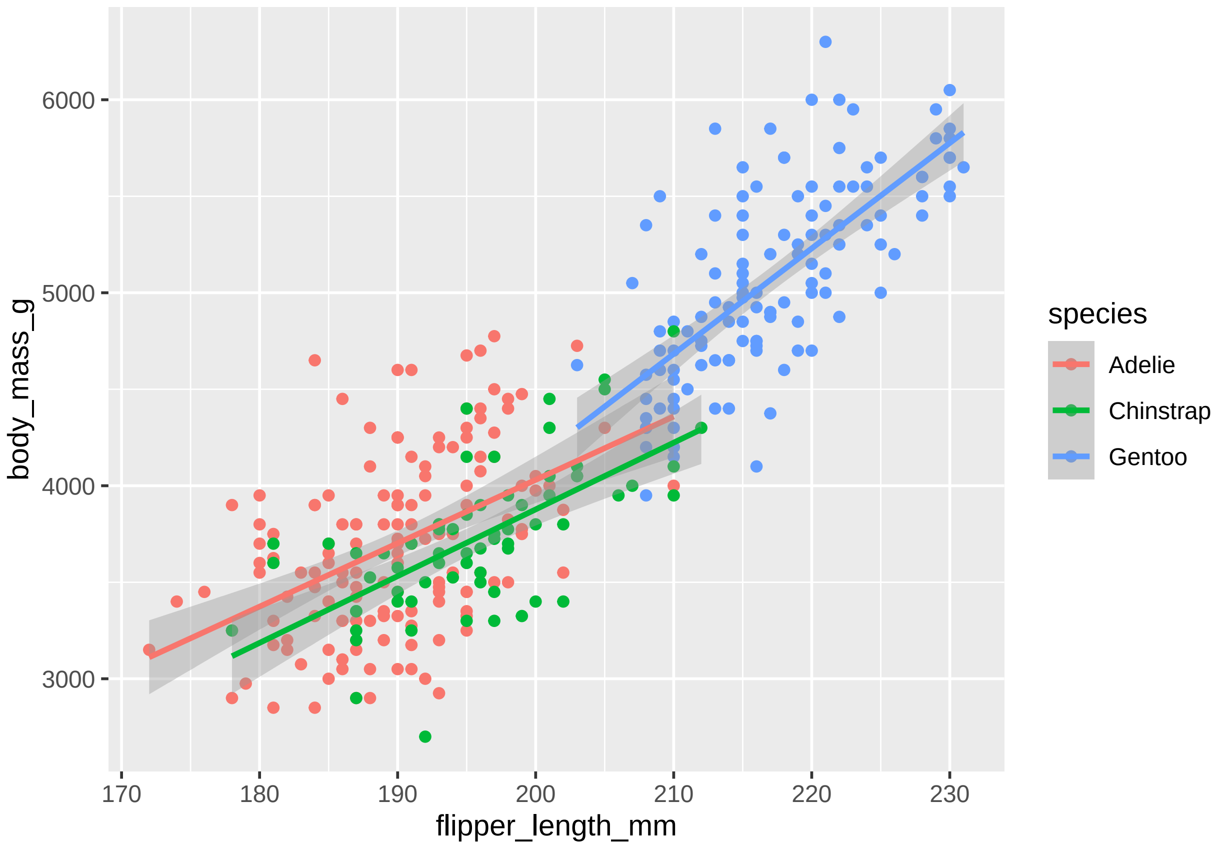
The function `geom_point()` adds a layer of points to your plot, which creates a scatterplot.

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'
```



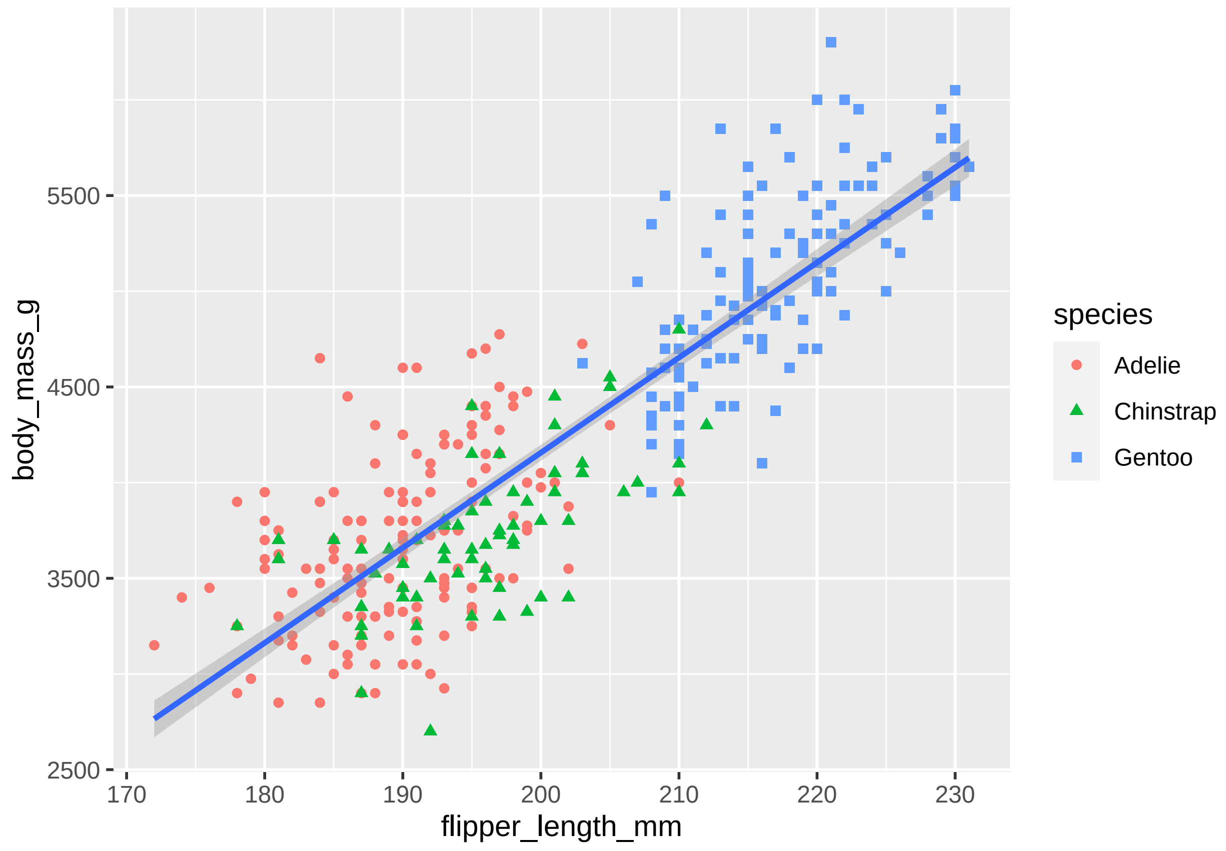
When aesthetic mappings are defined in `ggplot()`, at the global level, they're passed down to each of the subsequent geom layers of the plot. However, each geom function in ggplot2 can also take a `mapping` argument, which allows for aesthetic mappings at the local level that are added to those inherited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

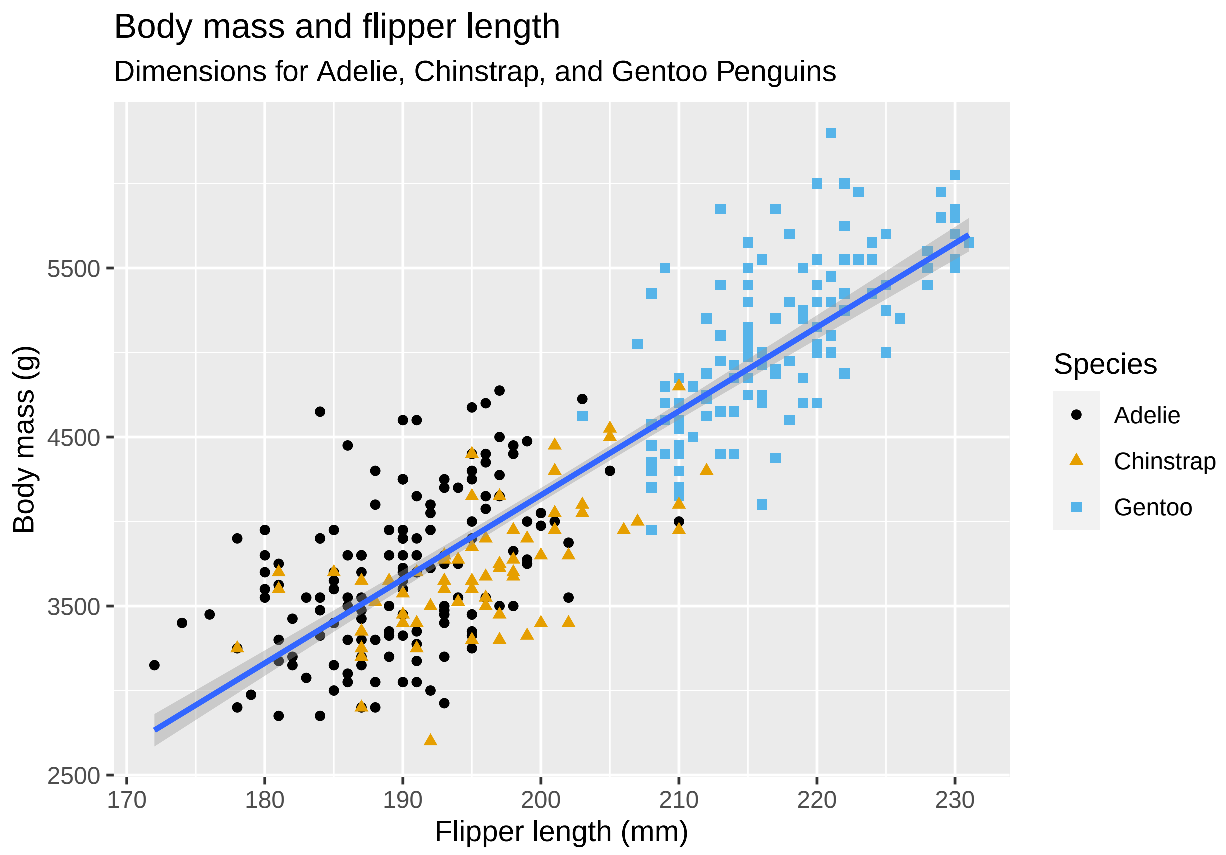
```
## `geom_smooth()` using formula = 'y ~ x'
```



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.

```
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()
```

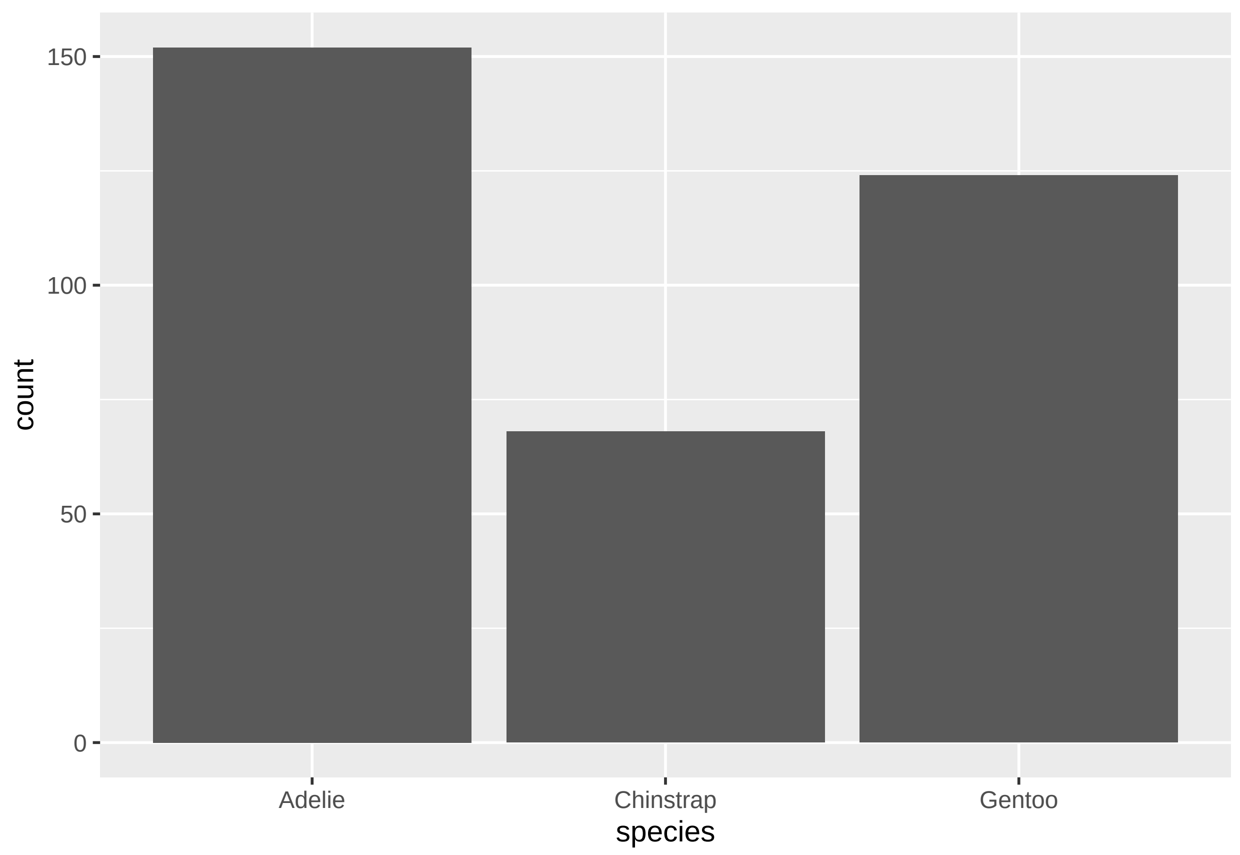
```
## `geom_smooth()` using formula = 'y ~ x'
```



3. Visualizing distributions

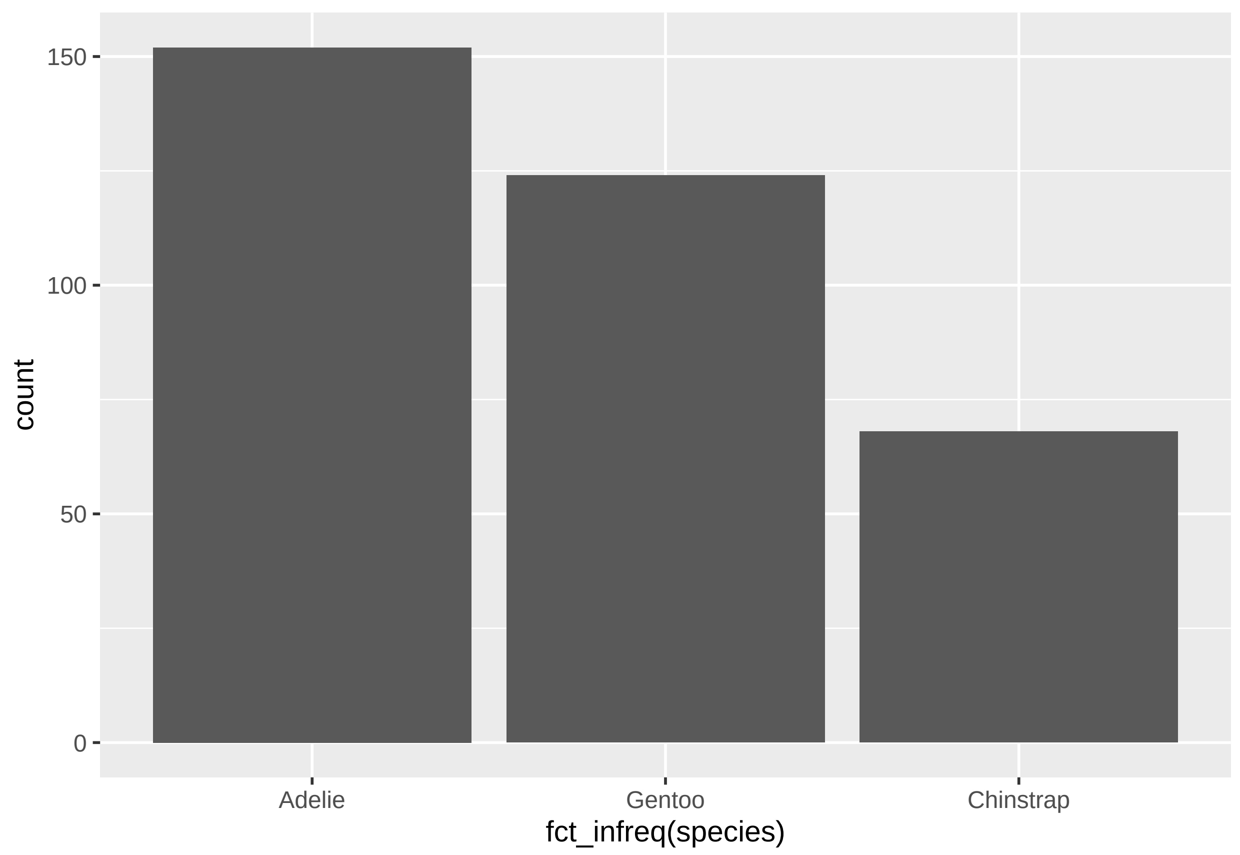
A variable is *categorical* if it can only take one of a small set of values. To examine the distribution of a categorical variable, you can use a bar chart. The height of the bars displays how many observations occurred with each x value.

```
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()
```

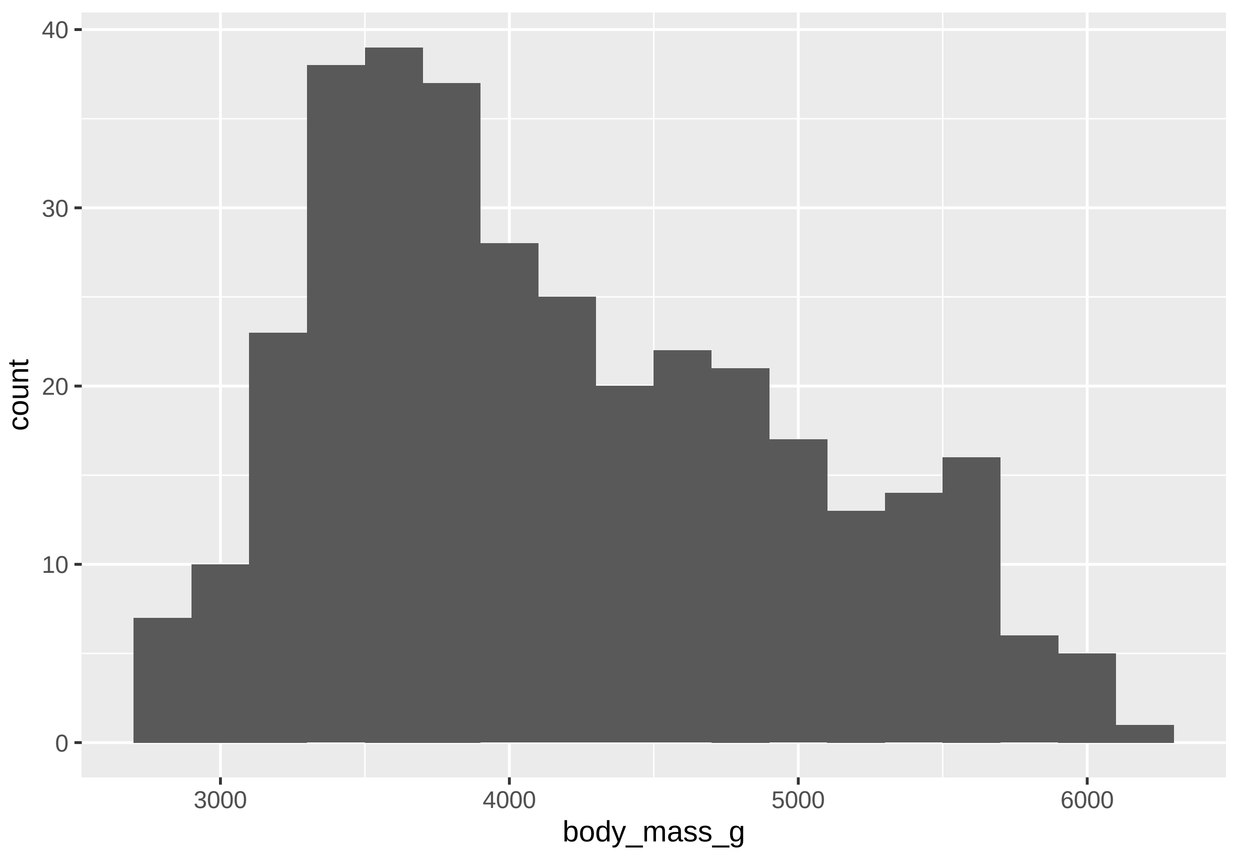


A variable is *numerical* (or quantitative) if it can take on a wide range of numerical values, and it is sensible to add, subtract, or take averages with those values. Numerical variables can be continuous or discrete.

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.

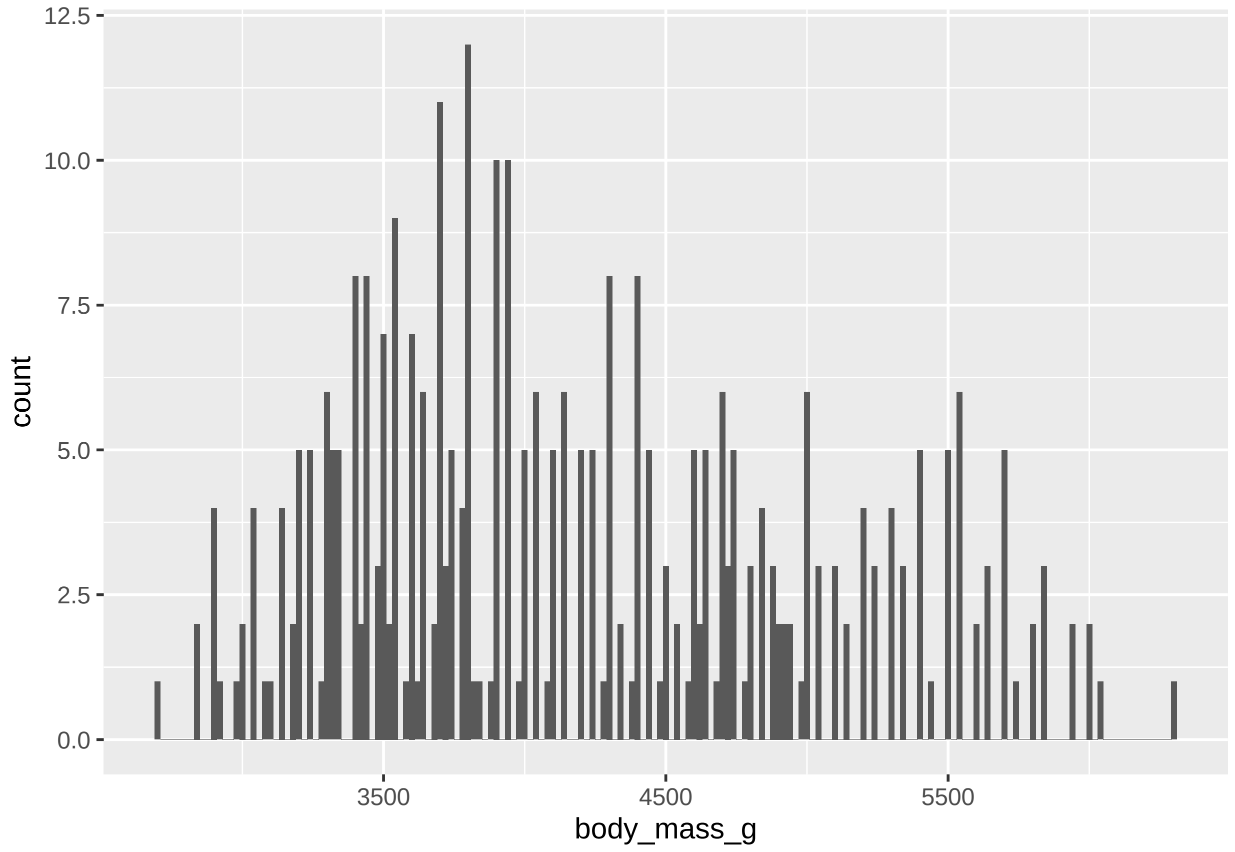
```
ggplot(penguins,
       aes(x = body_mass_g)) +
  geom_histogram(binwidth = 200)
```



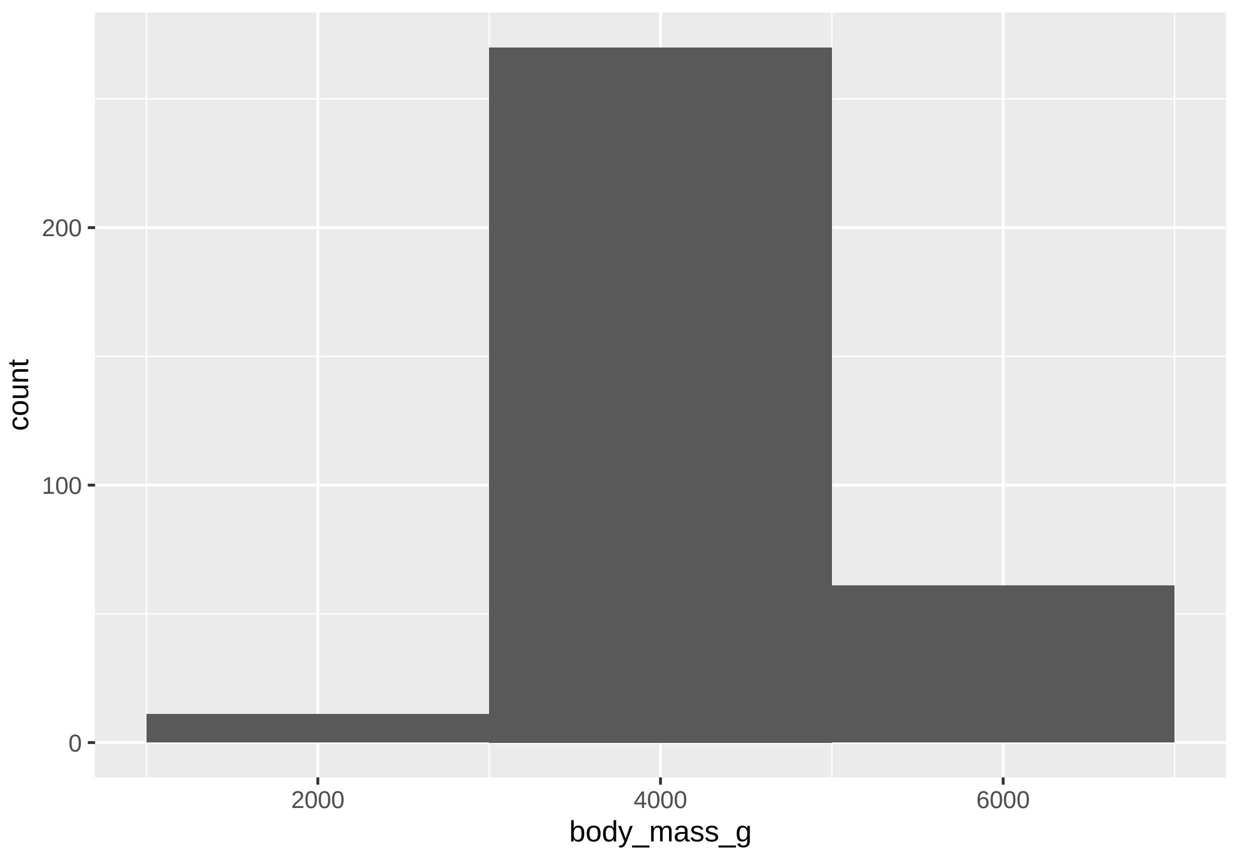
You should always explore a variety of binwidths when working with histograms, as different binwidths can reveal different patterns.

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)
```

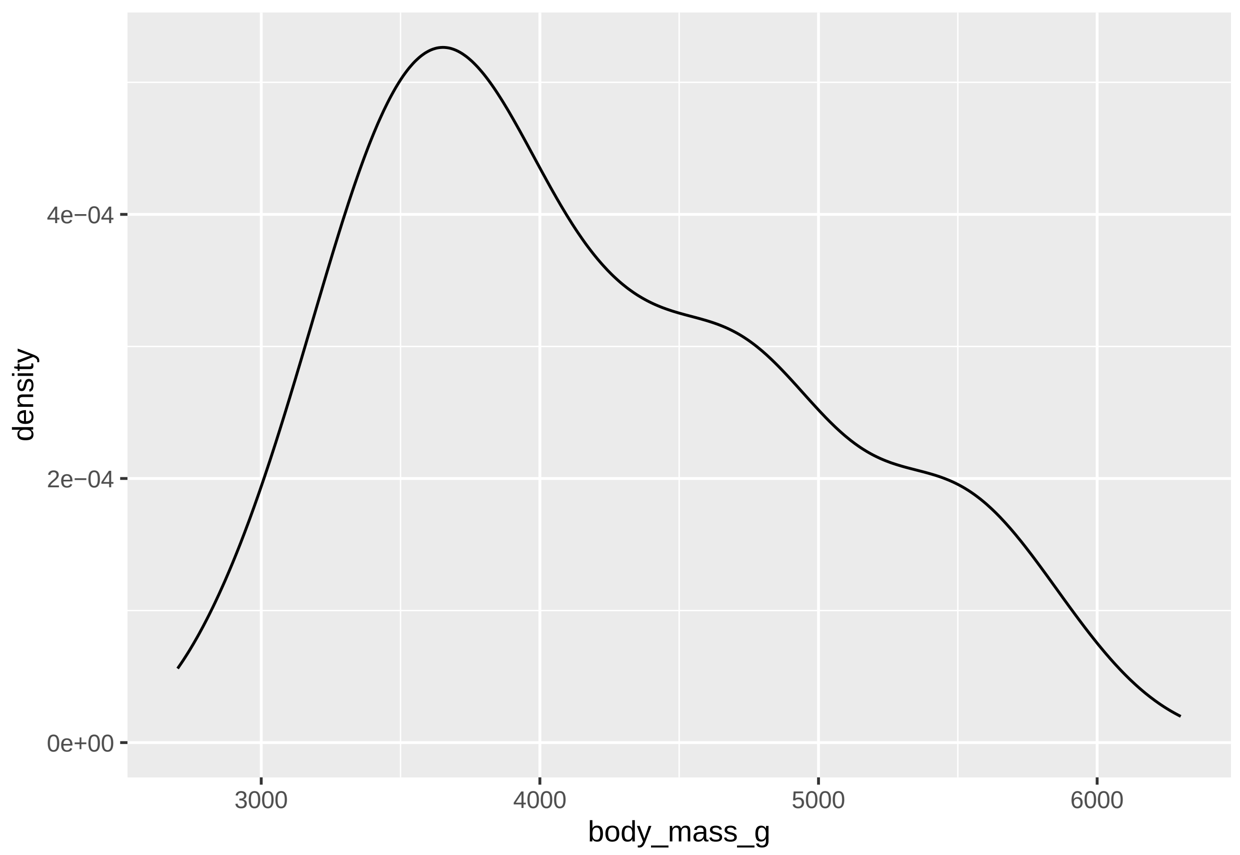


```r
ggplot(penguins,
       aes(x = body_mass_g)) +
  geom_histogram(binwidth = 2000)
```



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()
```



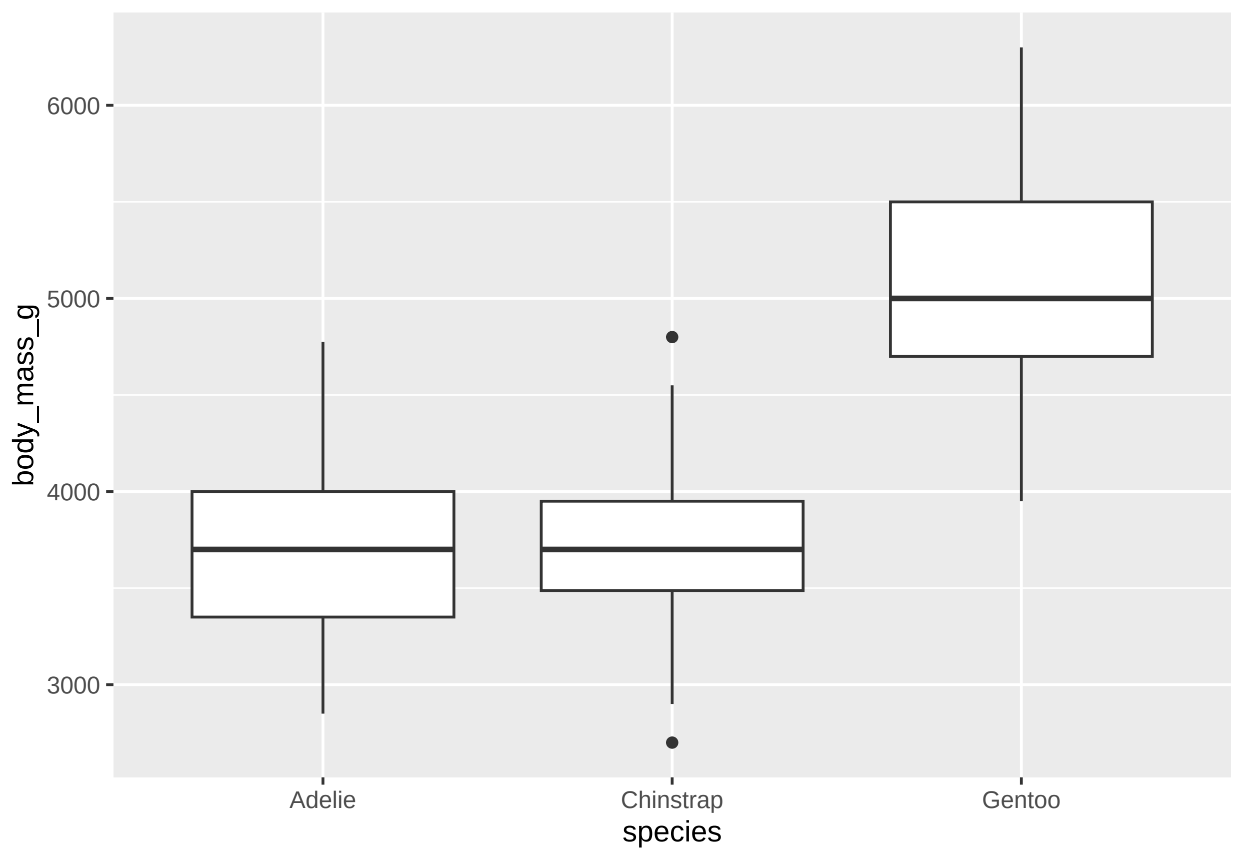
4. Visualizing relationships

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.

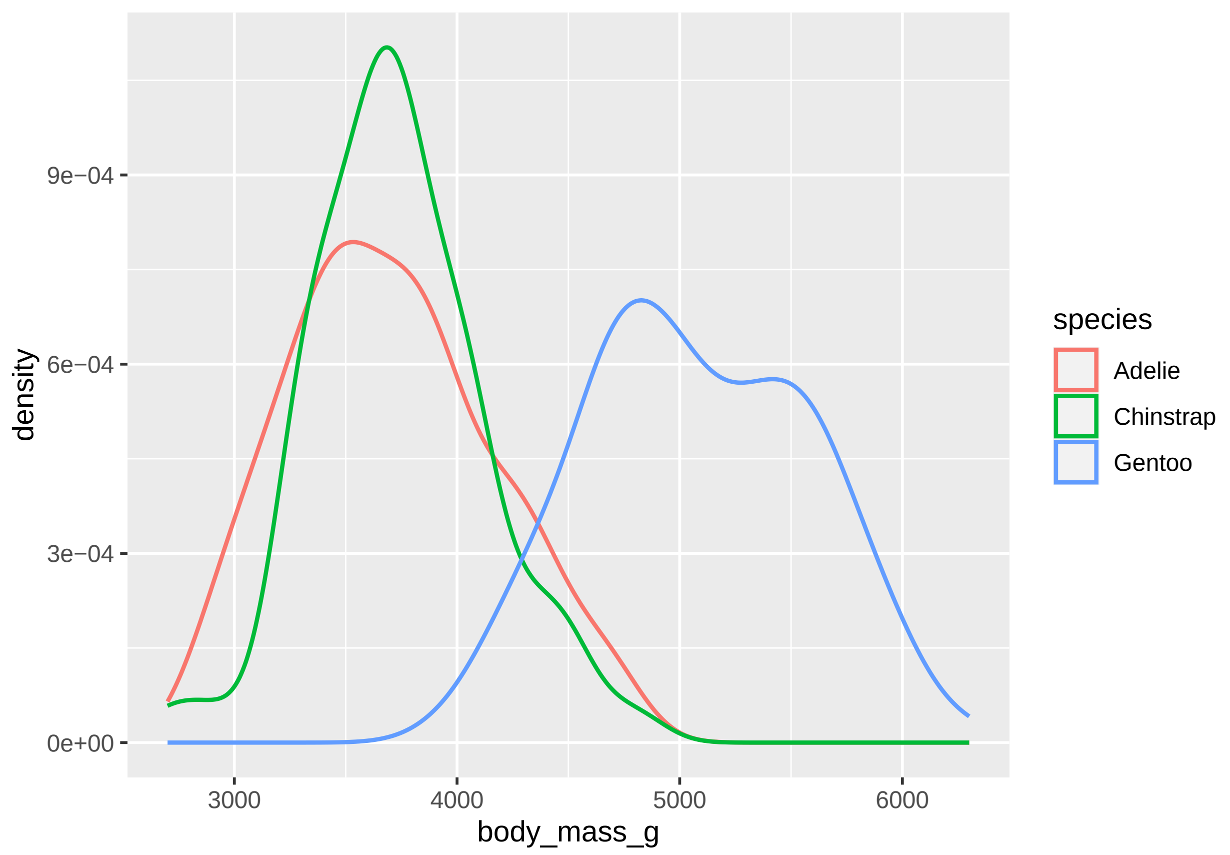
- A box that indicates the range of the middle half of the data, a distance known as the interquartile range (IQR). The 25th, 75th, and the median lines give you a sense of the spread of the distribution and whether or not the distribution is symmetric about the median or skewed to one side.
- A line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

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



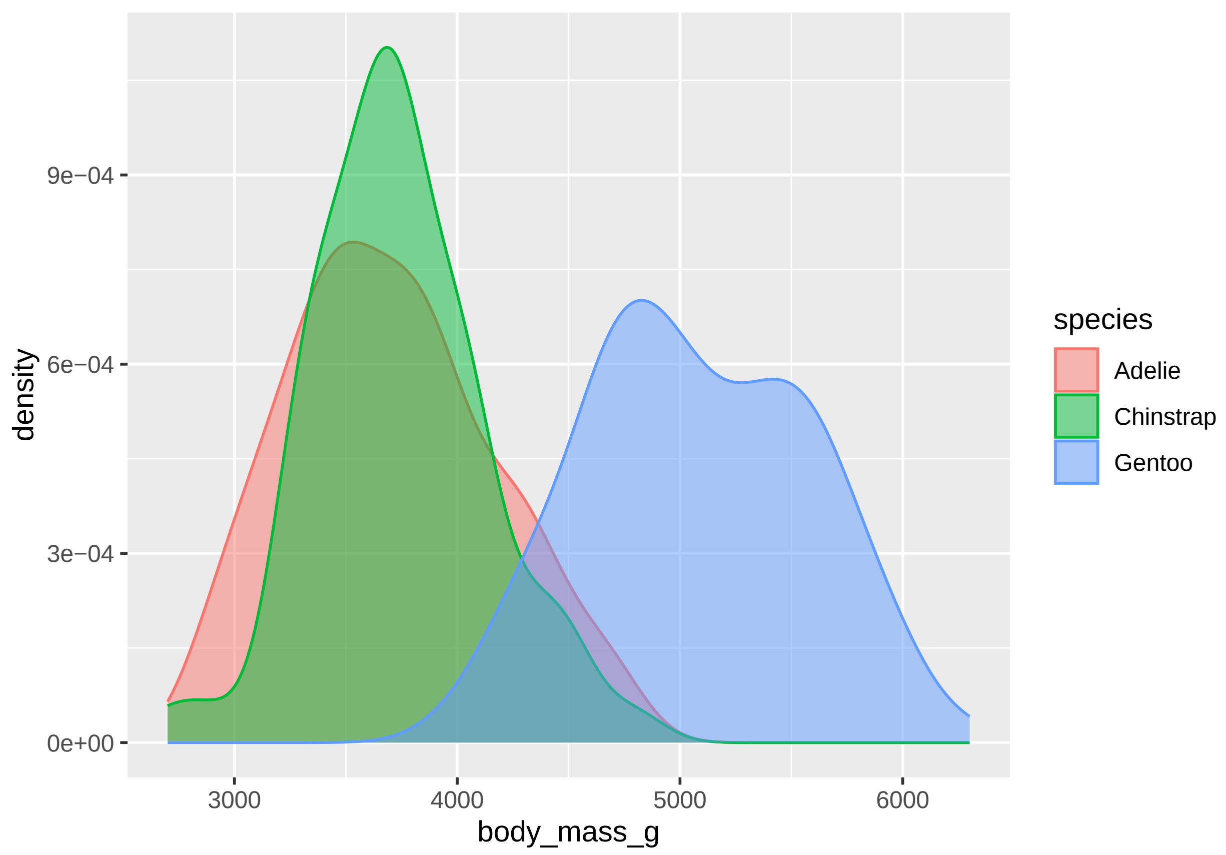
Alternatively, we can make density plots with `geom_density()`. You can customize the thickness of the lines using the `linewidth` argument in order to make them stand out a bit more against the background.

```
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).

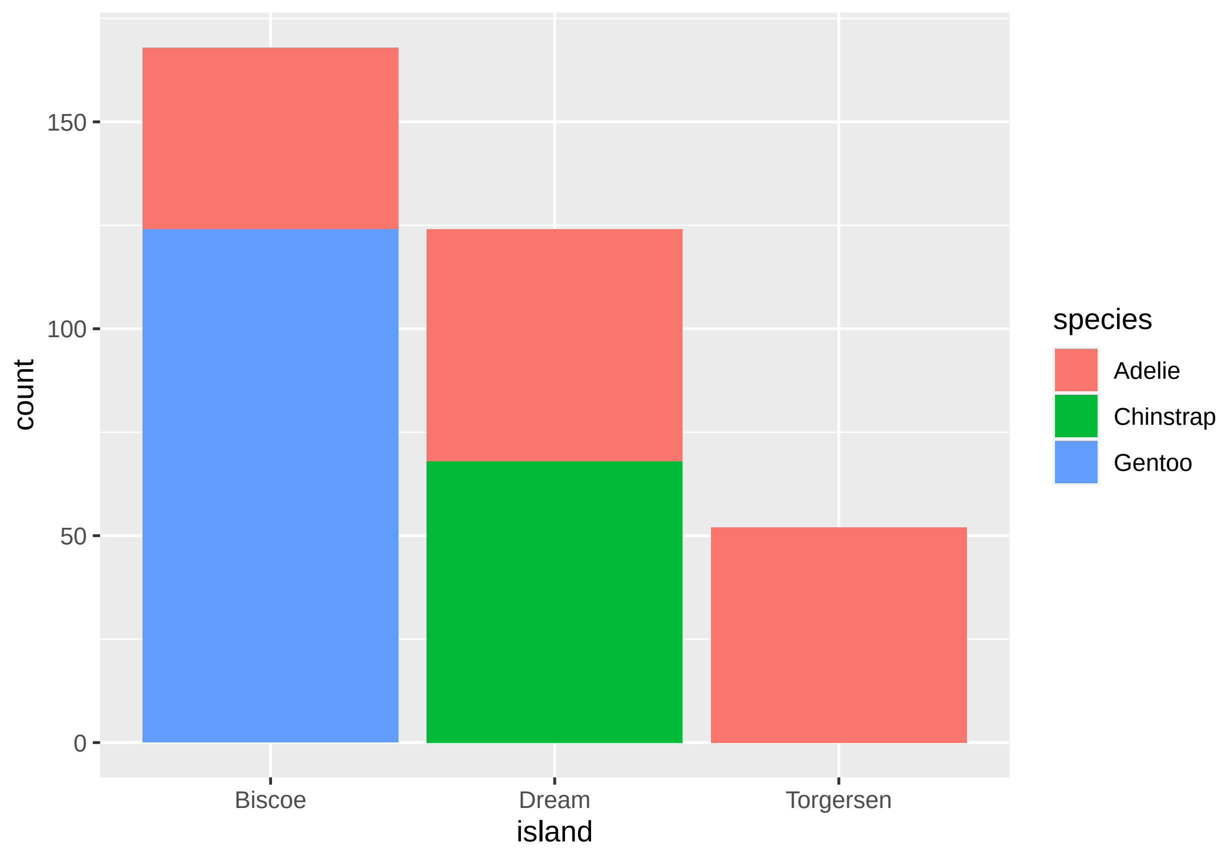
```
ggplot(penguins,
       aes(x = body_mass_g,
           color = species,
           fill = species)) +
  geom_density(alpha = 0.5)
```



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.

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

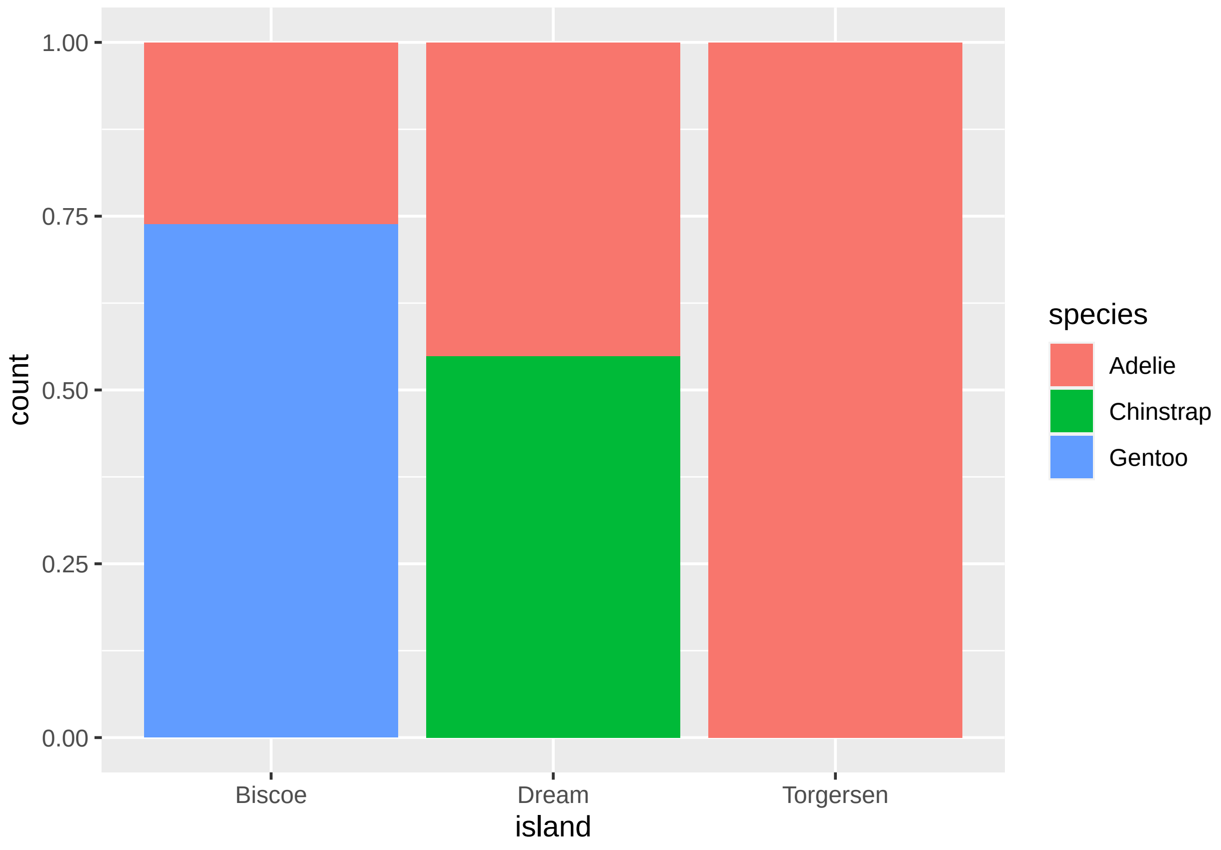


The second plot, a relative frequency plot created by setting `position = "fill"` in the geom, is more useful for comparing species distributions across islands since it's not affected by the unequal numbers of penguins across the islands.

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.

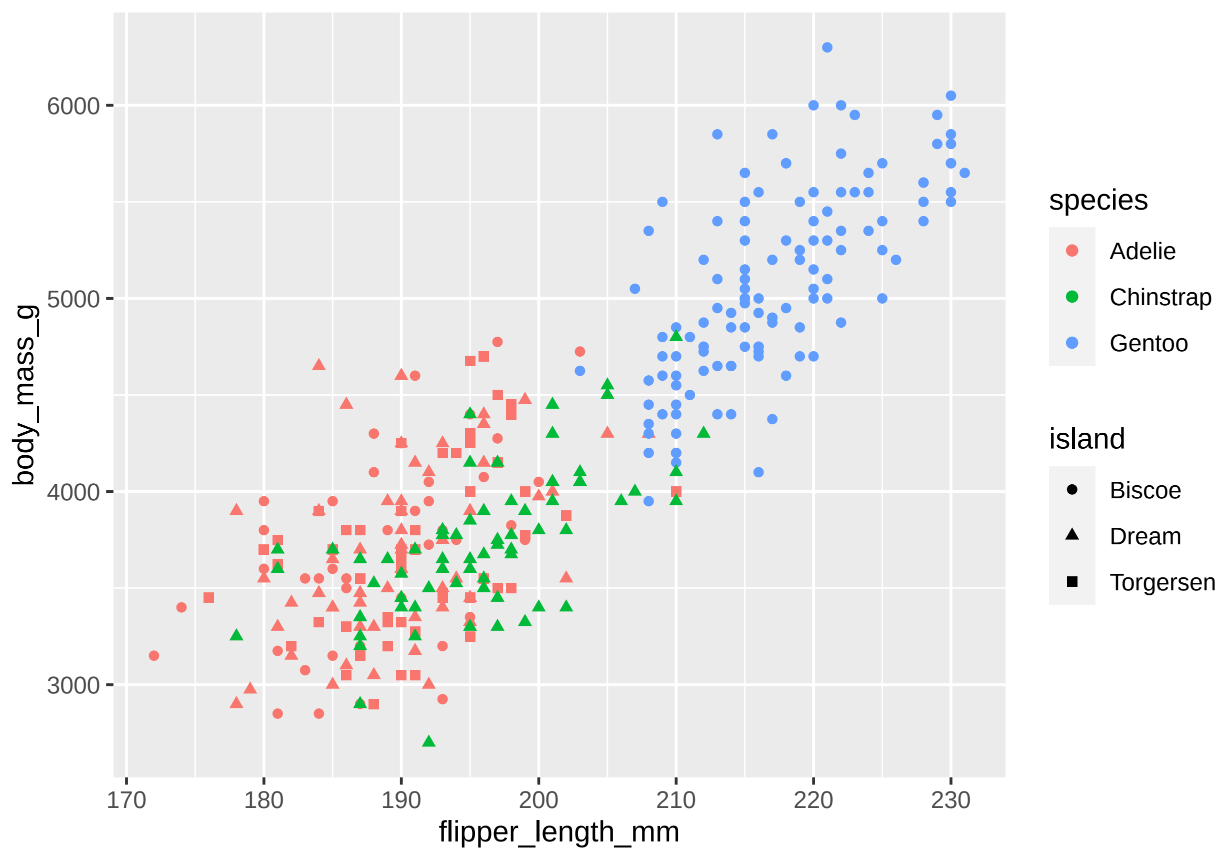
```r
ggplot(penguins,
       aes(x = island,
           fill = species)) +
  geom_bar(position = "fill")
```



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.

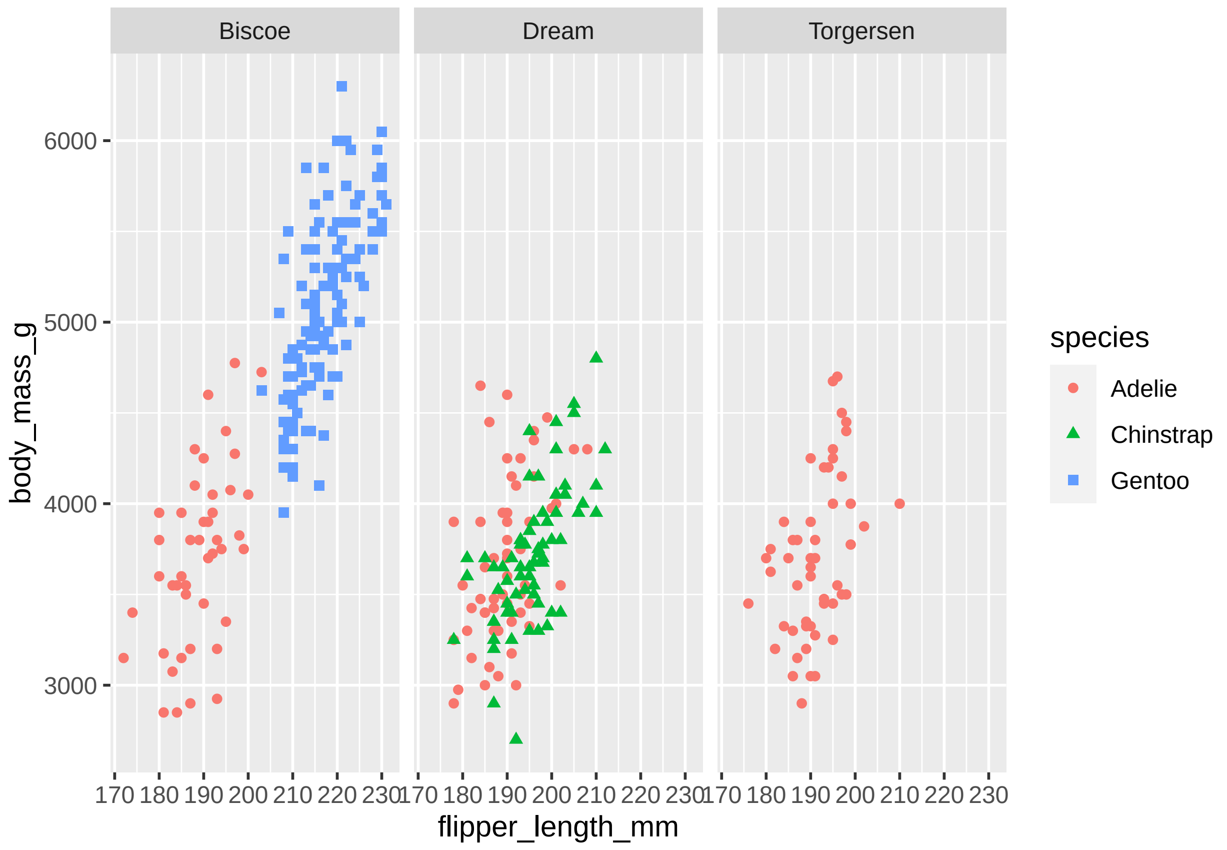
```
ggplot(penguins,
       aes(x = flipper_length_mm,
           y = body_mass_g)) +
  geom_point(aes(color = species,
                 shape = island))
```



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.

```
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.

```
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.

```
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.

```
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`.

```r
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.

```r
# 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
```

```r
# 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>
```