R

To download R, go to CRAN, the *comprehensive R archive network*. CRAN is composed of a set of mirror servers distributed around the world and is used to distribute R and R packages. Don't try and pick a mirror that's close to you: instead use the cloud mirror, *https://cloud.r-project.org*, which automatically figures it out for you.

A new major version of R comes out once a year, and there are 2–3 minor releases each year. It's a good idea to update regularly. Upgrading can be a bit of a hassle, especially for major versions, which require you to reinstall all your packages, but putting it off only makes it worse.

RStudio

RStudio is an integrated development environment, or IDE, for R programming. Download and install it from *http://www.rstudio.com/download*. RStudio is updated a couple of times a year. When a new version is available, RStudio will let you know. It's a good idea to upgrade regularly so you can take advantage of the latest and greatest features. For this book, make sure you have RStudio 1.0.0.

Data Visualization with ggplot2

Introduction

> The simple graph has brought more information to the data analyst's mind than any other device.
>
> —John Tukey

This Lab will teach you how to visualize your data using **ggplot2**. R has several systems for making graphs, but **ggplot2** is one of the most elegant and most versatile. **ggplot2** implements the *grammar of graphics*, a coherent system for describing and buildinggraphs. With **ggplot2**, you can do more faster by learning one sys- tem and applying it in many places.

If you'd like to learn more about the theoretical underpinnings of **ggplot2** before you start, I'd recommend reading "A Layered Gram- mar of Graphics".

Prerequisites

This Lab focuses on **ggplot2**, one of the core members of the tidyverse. To access the datasets, help pages, and functions that we will use in this chapter, load the tidyverse by running this code:

```
library(tidyverse)
#> Loading tidyverse: ggplot2
#> Loading tidyverse: tibble
#> Loading tidyverse: tidyr
#> Loading tidyverse: readr
#> Loading tidyverse: purrr
#> Loading tidyverse: dplyr
#> Conflicts with tidy packages ----------------------------------------------
#> filter(): dplyr, stats
#> lag():    dplyr, stats
```

That one line of code loads the core tidyverse, packages that you will use in almost every data analysis. It also tells you which functions from the tidyverse conflict with functions in base R (or from other packages you might have loaded).

If you run this code and get the error message "there is no package called 'tidyverse'," you'll need to first install it, then run `library()` once again:

```
install.packages("tidyverse")
library(tidyverse)
```

You only need to install a package once, but you need to reload it every time you start a new session.

If we need to be explicit about where a function (or dataset) comes from, we'll use the special form `package::function()`. For example, `ggplot2::ggplot()` tells you explicitly that we're using the `ggplot()` function from the **ggplot2** package.

First Steps

Let's use our first graph to answer a question: do cars with big engines use more fuel than cars with small engines? You probably already have an answer, but try to make your answer precise. What does the relationship between engine size and fuel efficiency look like? Is it positive? Negative? Linear? Nonlinear?

The mpg Data Frame

You can test your answer with the `mpg` data frame found in **ggplot2** (aka `ggplot2::mpg`). A *data frame* is a rectangular collection of variables (in the columns) and observations (in the rows). `mpg` contains observations collected by the US Environment Protection Agency on 38 models of cars:

```
mpg
#> # A tibble: 234 × 11
#>   manufacturer model displ  year   cyl     trans   drv
#>         <chr> <chr> <dbl> <int> <int>     <chr> <chr>#>
1        audi    a4   1.8  1999     4   auto(l5)     f
#> 2        audi    a4   1.8  1999     4 manual(m5)     f
#> 3        audi    a4   2.0  2008     4 manual(m6)     f
#> 4        audi    a4   2.0  2008     4  auto(av)     f
#> 5        audi    a4   2.8  1999     6  auto(l5)     f
#> 6        audi    a4   2.8  1999     6 manual(m5)     f
#> # ... with 228 more rows, and 4 more variables:
#> # cty <int>, hwy <int>, fl <chr>, class <chr>
```

Among the variables in `mpg` are:

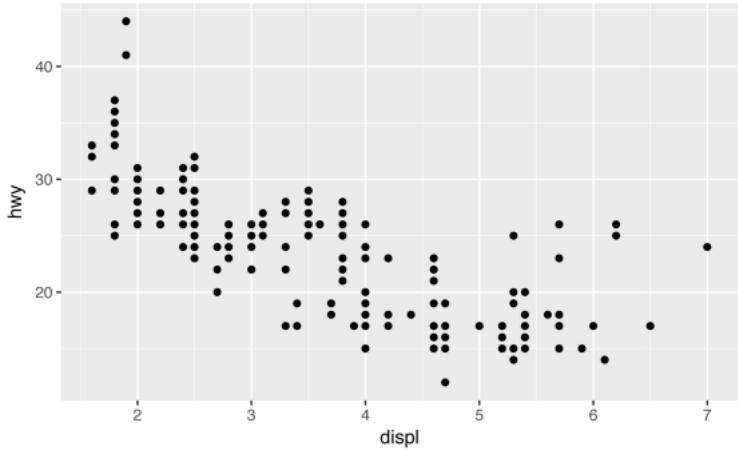
- `displ`, a car's engine size, in liters.
- `hwy`, a car's fuel efficiency on the highway, in miles per gallon (mpg). A car with a low fuel efficiency consumes more fuel than a car with a high fuel efficiency when they travel the same distance.

To learn more about `mpg`, open its help page by running `?mpg`.

Creating a ggplot

To plot `mpg`, run this code to put `displ` on the x-axis and `hwy` on the y-axis:

```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy))
```



The plot shows a negative relationship between engine size (`displ`) and fuel efficiency (`hwy`). In other words, cars with big engines use more fuel. Does this confirm or refute your hypothesis about fuel efficiency and engine size?

With **ggplot2**, you begin a plot with the function `ggplot()`. `ggplot()` creates a coordinate system that you can add layers to. The first argument of `ggplot()` is the dataset to use in the graph. So `ggplot(data = mpg)` creates an empty graph, but it's not very interesting so I'm not going to show it here.

You complete your graph by adding one or more layers to `ggplot()`. The function `geom_point()` adds a layer of points to your plot, which creates a scatterplot. **ggplot2** comes with many geom func- tions that each add a different type of layer to a plot. You'll learn a whole bunch of them throughout this chapter.

Each geom function in **ggplot2** takes a `mapping` argument. This defines how variables in your dataset are mapped to visual properties. The `mapping` argument is always paired with `aes()`, and the `x` and `y` arguments of `aes()` specify which variables to map to the x- and y-axes. **ggplot2** looks for the mapped variable in the `data` argument, in this case, `mpg`.

A Graphing Template

Let's turn this code into a reusable template for making graphs with **ggplot2**. To make a graph, replace the bracketed sections in the following code with a dataset, a geom function, or a collection of mappings:

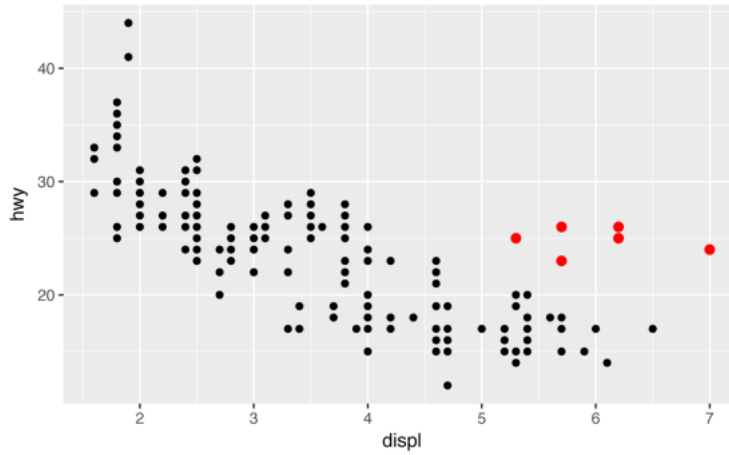
```
ggplot(data = <DATA>) +
  <GEOM_FUNCTION>(mapping = aes(<MAPPINGS>))
```

The rest of this chapter will show you how to complete and extend this template to make different types of graphs. We will begin with the `<MAPPINGS>` component.

Aesthetic Mappings

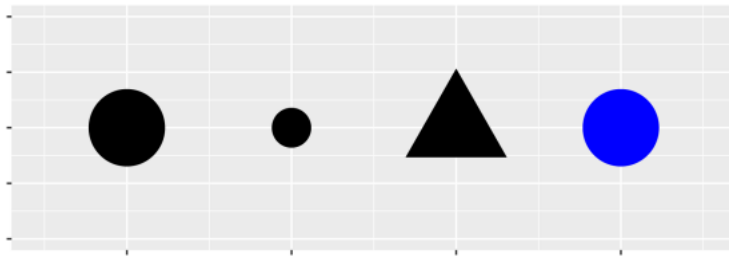
> The greatest value of a picture is when it forces us to notice what we never expected to see.
>
> —John Tukey

In the following plot, one group of points (highlighted in red) seems to fall outside of the linear trend. These cars have a higher mileage than you might expect. How can you explain these cars?



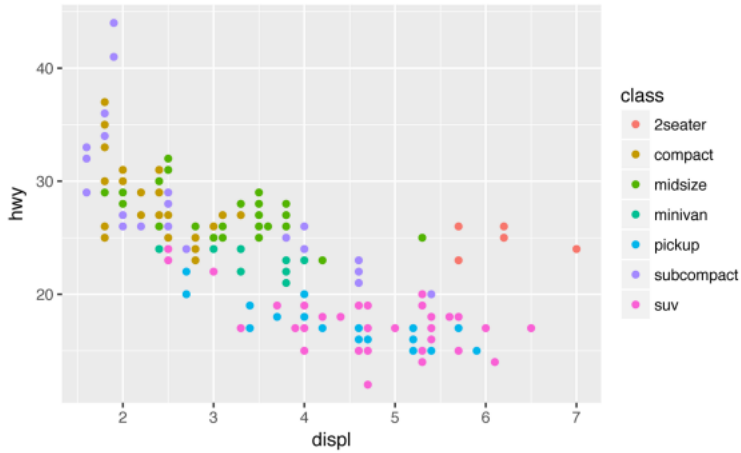
Let's hypothesize that the cars are hybrids. One way to test this hypothesis is to look at the `class` value for each car. The `class` variable of the `mpg` dataset classifies cars into groups such as compact, midsize, and SUV. If the outlying points are hybrids, they should be classified as compact cars or, perhaps, subcompact cars (keep in mind that this data was collected before hybrid trucks and SUVs became popular).

You can add a third variable, like `class`, to a two-dimensional scatterplot by mapping it to an *aesthetic*. An aesthetic is a visual property of the objects in your plot. Aesthetics include things like the size, the shape, or the color of your points. You can display a point (like the one shown next) in different ways by changing the values ofits aesthetic properties. Since we already use the word "value" to describe data, let's use the word "level" to describe aesthetic properties. Here we change the levels of a point's size, shape, and color to make the point small, triangular, or blue:



You can convey information about your data by mapping the aesthetics in your plot to the variables in your dataset. For example, you can map the colors of your points to the `class` variable to reveal the class of each car:

```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy, color = class))
```



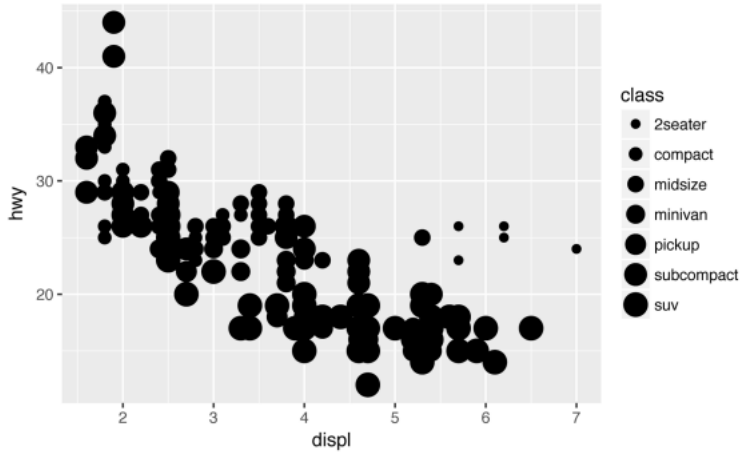
(If you prefer British English, like Hadley, you can use `colour` instead of `color`.)

To map an aesthetic to a variable, associate the name of the aesthetic to the name of the variable inside `aes()`. **ggplot2** will automatically assign a unique level of the aesthetic (here a unique color) to each unique value of the variable, a process known as *scaling*. **ggplot2** will also add a legend that explains which levels correspond to which values.

The colors reveal that many of the unusual points are two-seater cars. These cars don't seem like hybrids, and are, in fact, sports cars!Sports cars have large engines like SUVs and pickup trucks, but small bodies like midsize and compact cars, which improves their gas mileage. In hindsight, these cars were unlikely to be hybrids since they have large engines.

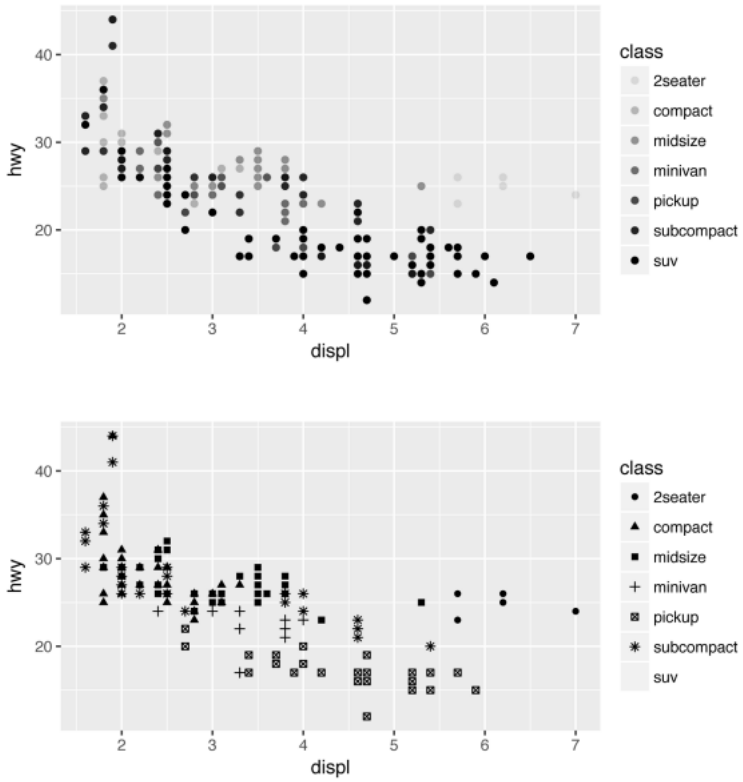
In the preceding example, we mapped `class` to the color aesthetic, but we could have mapped `class` to the size aesthetic in the same way. In this case, the exact size of each point would reveal its class affiliation. We get a *warning* here, because mapping an unordered variable (`class`) to an ordered aesthetic (`size`) is not a good idea:

```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy, size = class))
#> Warning: Using size for a discrete variable is not advised.
```



Or we could have mapped `class` to the *alpha* aesthetic, which controls the transparency of the points, or the shape of the points:

```
# Top
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy, alpha = class))

# Bottom
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy, shape = class))
```



What happened to the SUVs? **ggplot2** will only use six shapes at a time. By default, additional groups will go unplotted when you use this aesthetic.

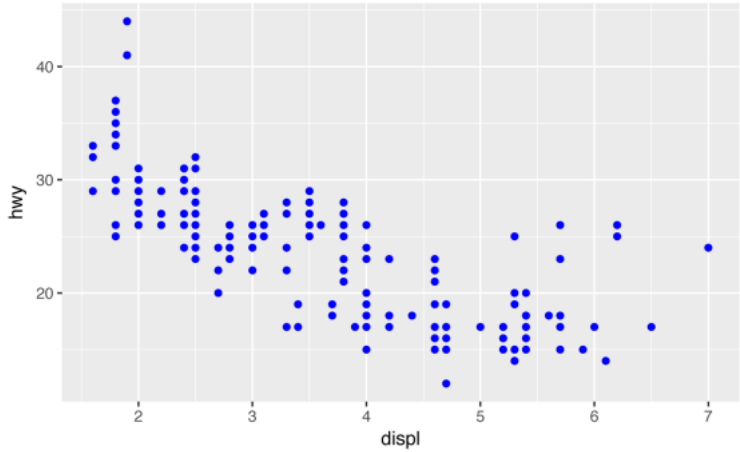
For each aesthetic you use, the `aes()` to associate the name of the aesthetic with a variable to display. The `aes()` function gathers together each of the aesthetic mappings used by a layer and passes them to the layer's mapping argument. The syntax highlights a useful insight about `x` and `y`: the x and y locations of a point are themselves aesthetics, visual properties that you can map to variables to display information about the data.

Once you map an aesthetic, **ggplot2** takes care of the rest. It selects a reasonable scale to use with the aesthetic, and it constructs a legend that explains the mapping between levels and values. For x and y aesthetics, **ggplot2** does not create a legend, but it creates an axis

line with tick marks and a label. The axis line acts as a legend; it explains the mapping between locations and values.

You can also *set* the aesthetic properties of your geom manually. For example, we can make all of the points in our plot blue:

```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy), color = "blue")
```



Here, the color doesn't convey information about a variable, but only changes the appearance of the plot. To set an aesthetic man- ually, set the aesthetic by name as an argument of your geom func- tion; i.e., it goes *outside* of `aes()`. You'll need to pick a value that makes sense for that aesthetic:

- The name of a color as a character string.
- The size of a point in mm.
- The shape of a point as a number, as shown in Figure 1-1. There are some seeming duplicates: for example, 0, 15, and 22 are all squares. The difference comes from the interaction of the `color` and `fill` aesthetics. The hollow shapes (0–14) have a border determined by `color`; the solid shapes (15–18) are filled with `color`; and the filled shapes (21–24) have a border of `color` and are filled with `fill`.

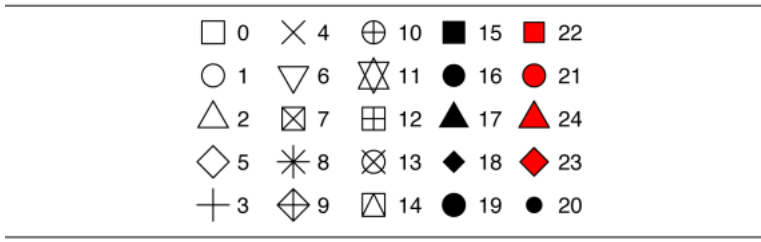


Figure 1-1. R has 25 built-in shapes that are identified by numbers

Common Problems

As you start to run R code, you're likely to run into problems. Don't worry—it happens to everyone. I have been writing R code for years, and every day I still write code that doesn't work!

Start by carefully comparing the code that you're running to the code in the book. R is extremely picky, and a misplaced character can make all the difference. Make sure that every (is matched witha) and every " is paired with another ". Sometimes you'll run the code and nothing happens. Check the left-hand side of your con- sole: if it's a +, it means that R doesn't think you've typed a complete expression and it's waiting for you to finish it. In this case, it's usually easy to start from scratch again by pressing Esc to abort processing the current command.

One common problem when creating **ggplot2** graphics is to put the + in the wrong place: it has to come at the end of the line, not the start. In other words, make sure you haven't accidentally written code like this:

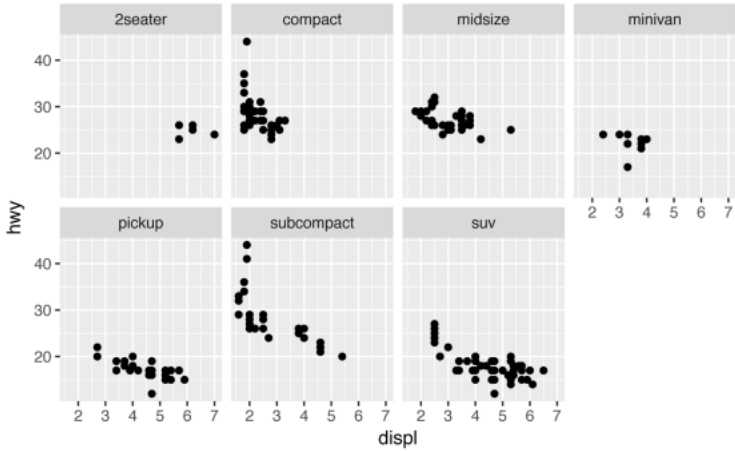
```
ggplot(data = mpg)
+ geom_point(mapping = aes(x = displ, y = hwy))
```

If you're still stuck, try the help. You can get help about any R function by running `?function_name` in the console, or selecting the function name and pressing F1 in RStudio. Don't worry if the help doesn't seem that helpful—instead skip down to the examples and look for code that matches what you're trying to do.

If that doesn't help, carefully read the error message. Sometimes the answer will be buried there! But when you're new to R, the answer might be in the error message but you don't yet know how to understand it. Another great tool is Google: trying googling the error message, as it's likely someone else has had the same problem, and has received help online.

Facets

One way to add additional variables is with aesthetics. Another way, particularly useful for categorical variables, is to split your plot into *facets*, subplots that each display one subset of the data.

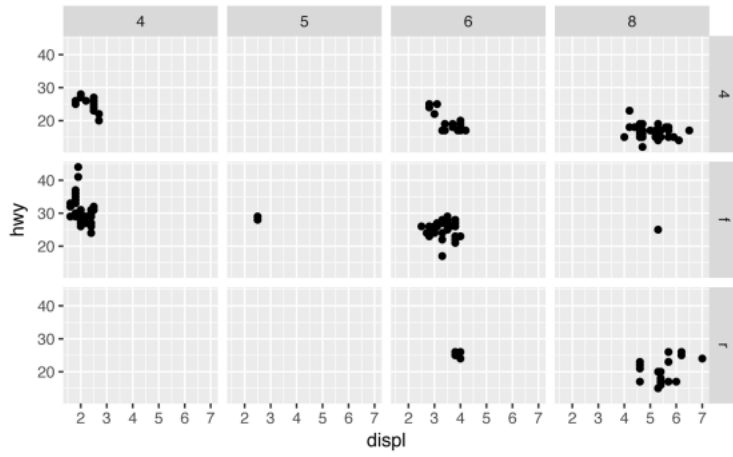


To facet your plot by a single variable, use `facet_wrap()`. The first argument of `facet_wrap()` should be a formula, which you create with `~` followed by a variable name (here "formula" is the name of a data structure in R, not a synonym for "equation"). The variable thatyou pass to `facet_wrap()` should be discrete:

```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy)) +
  facet_wrap(~ class, nrow = 2)
```

To facet your plot on the combination of two variables, add `facet_grid()` to your plot call. The first argument of `facet_grid()` is also a formula. This time the formula should contain two variable names separated by a `~`:

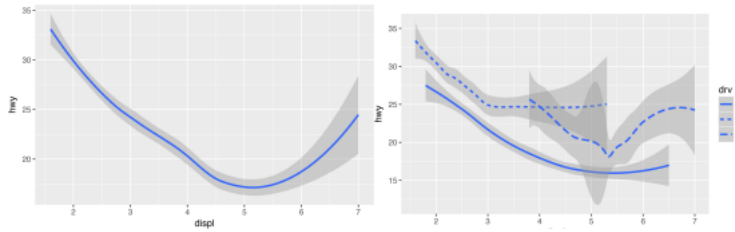
```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy)) +
  facet_grid(drv ~ cyl)
```



If you prefer to not facet in the rows or columns dimension, use a . instead of a variable name, e.g., `+ facet_grid(. ~ cyl)`.

Geometric Objects

How are these two plots similar?



Both plots contain the same `x` variable and the same `y` variable, and both describe the same data. But the plots are not identical. Each plot uses a different visual object to represent the data. In **ggplot2** syntax, we say that they use different *geoms*.

A *geom* is the geometrical object that a plot uses to represent data. People often describe plots by the type of geom that the plot uses. For example, bar charts use bar geoms, line charts use line geoms, boxplots use boxplot geoms, and so on. Scatterplots break the trend; they use the point geom. As we see in the preceding plots, you can use different geoms to plot the same data. The plot on the left uses the point geom, and the plot on the right uses the smooth geom, a smooth line fitted to the data.

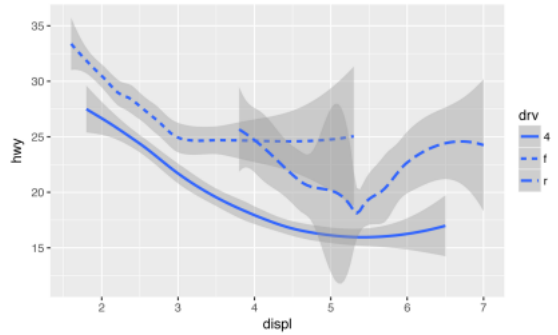
To change the geom in your plot, change the geom function that you

add to `ggplot()`. For instance, to make the preceding plots, you can use this code:

```
# left
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy))

# right
ggplot(data = mpg) +
  geom_smooth(mapping = aes(x = displ, y = hwy))
```

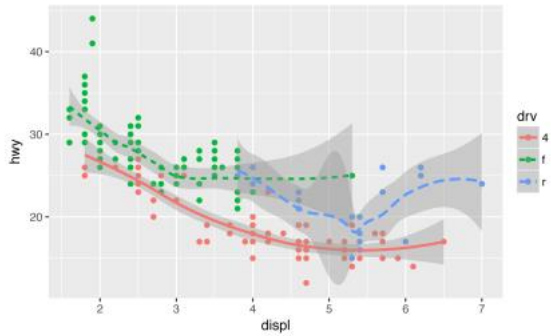
Every geom function in **ggplot2** takes a `mapping` argument. How-ever, not every aesthetic works with every geom. You could set the shape of a point, but you couldn't set the "shape" of a line. On the other hand, you *could* set the linetype of a line. `geom_smooth()` will draw a different line, with a different linetype, for each unique valueof the variable that you map to linetype:

```
ggplot(data = mpg) +
  geom_smooth(mapping = aes(x = displ, y = hwy, linetype = drv))
```



Here `geom_smooth()` separates the cars into three lines based on their `drv` value, which describes a car's drivetrain. One line describes all of the points with a `4` value, one line describes all of the points with an `f` value, and one line describes all of the points with an `r` value. Here, `4` stands for four-wheel drive, `f` for front-wheel drive, and `r` for rear-wheel drive.

If this sounds strange, we can make it more clear by overlaying the lines on top of the raw data and then coloring everything according to `drv`.

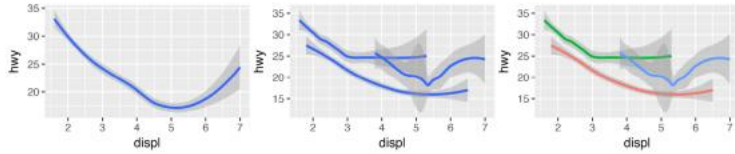


Notice that this plot contains two geoms in the same graph! If this makes you excited, buckle up. In the next section, we will learn how to place multiple geoms in the same plot.

ggplot2 provides over 30 geoms, and extension packages provide even more (see *https://www.ggplot2-exts.org* for a sampling). The best way to get a comprehensive overview is the **ggplot2** cheatsheet, which you can find at *http://rstudio.com/cheatsheets*. To learn more about any single geom, use help: `?geom_smooth`.

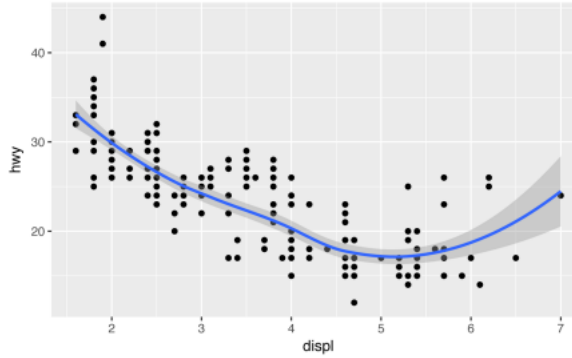
Many geoms, like `geom_smooth()`, use a single geometric object to display multiple rows of data. For these geoms, you can set the `group` aesthetic to a categorical variable to draw multiple objects. **ggplot2** will draw a separate object for each unique value of the grouping variable. In practice, **ggplot2** will automatically group the data for these geoms whenever you map an aesthetic to a discrete variable (as in the `linetype` example). It is convenient to rely on this feature because the group aesthetic by itself does not add a legend or distinguishing features to the geoms:

```
ggplot(data = mpg) +
  geom_smooth(mapping = aes(x = displ, y = hwy))

ggplot(data = mpg) +
  geom_smooth(mapping = aes(x = displ, y = hwy, group = drv))

ggplot(data = mpg) +
  geom_smooth(
    mapping = aes(x = displ, y = hwy, color = drv),
    show.legend = FALSE
  )
```



To display multiple geoms in the same plot, add multiple geom functions to `ggplot()`:

```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy)) +
  geom_smooth(mapping = aes(x = displ, y = hwy))
```

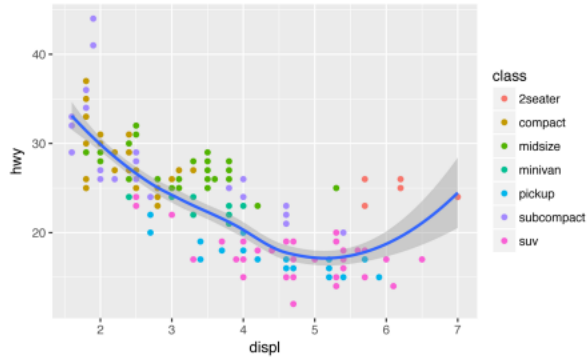


This, however, introduces some duplication in our code. Imagine if you wanted to change the y-axis to display `cty` instead of `hwy`. You'd need to change the variable in two places, and you might forget to update one. You can avoid this type of repetition by passing a set of mappings to `ggplot()`. **ggplot2** will treat these mappings as global mappings that apply to each geom in the graph. In other words, this code will produce the same plot as the previous code:

```
ggplot(data = mpg, mapping = aes(x = displ, y = hwy)) +
  geom_point() +
  geom_smooth()
```

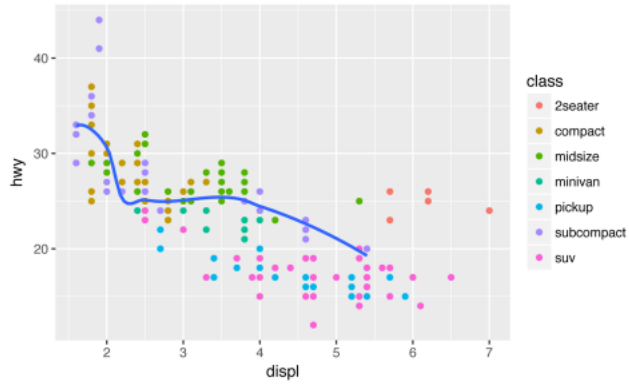
If you place mappings in a geom function, **ggplot2** will treat them as local mappings for the layer. It will use these mappings to extend or overwrite the global mappings *for that layer only*. This makes it possible to display different aesthetics in different layers:

```
ggplot(data = mpg, mapping = aes(x = displ, y = hwy)) +
  geom_point(mapping = aes(color = class)) +
  geom_smooth()
```



You can use the same idea to specify different `data` for each layer. Here, our smooth line displays just a subset of the `mpg` dataset, the subcompact cars. The local data argument in `geom_smooth()` overrides the global data argument in `ggplot()` for that layer only:

```
ggplot(data = mpg, mapping = aes(x = displ, y = hwy)) +
  geom_point(mapping = aes(color = class)) +
  geom_smooth(
    data = filter(mpg, class == "subcompact"),
    se = FALSE
  )
```

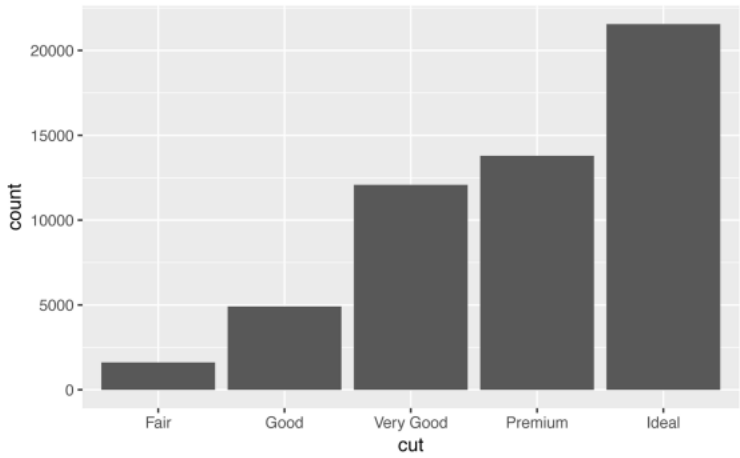


(You'll learn how `filter()` works in the next chapter: for now, just know that this command selects only the subcompact cars.)

Statistical Transformations

Next, let's take a look at a bar chart. Bar charts seem simple, but they are interesting because they reveal something subtle about plots. Consider a basic bar chart, as drawn with `geom_bar()`. The following chart displays the total number of diamonds in the `diamonds` dataset, grouped by `cut`. The `diamonds` dataset comes in **ggplot2** and contains information about ~54,000 diamonds, including the `price`, `carat`, `color`, `clarity`, and `cut` of each diamond. The chart shows that more diamonds are available with high-quality cuts than with low quality cuts:

```
ggplot(data = diamonds) +
  geom_bar(mapping = aes(x = cut))
```

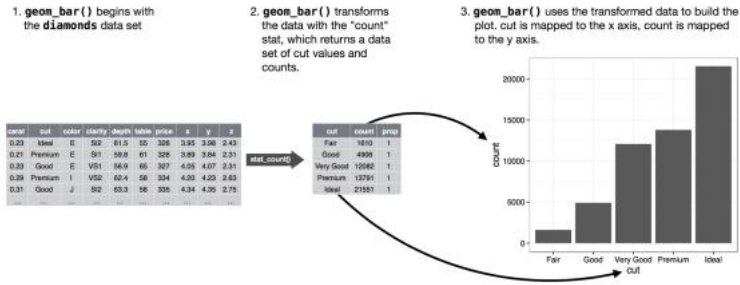


On the x-axis, the chart displays `cut`, a 'variable from `diamonds`. On the y-axis, it displays `count`, but `count` is not a variable in `diamonds`! Where does `count` come from? Many graphs, like scatterplots, plot the raw values of your dataset. Other graphs, like bar charts, calculate new values to plot:

- Bar charts, histograms, and frequency polygons bin your data and then plot bin counts, the number of points that fall in each bin.
- Smoothers fit a model to your data and then plot predictions from the model.

- Boxplots compute a robust summary of the distribution and display a specially formatted box.

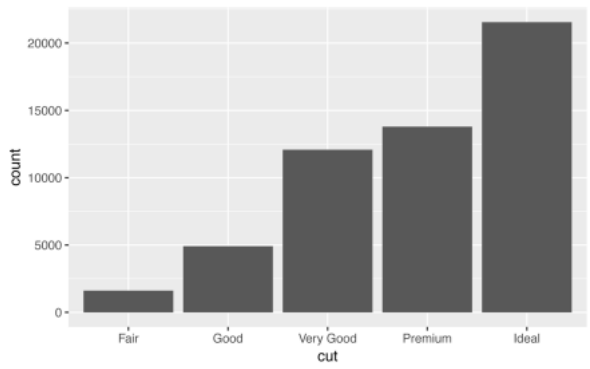
The algorithm used to calculate new values for a graph is called a *stat*, short for statistical transformation. The following figure describes how this process works with `geom_bar()`.



You can learn which stat a geom uses by inspecting the default value for the `stat` argument. For example, `?geom_bar` shows the default value for `stat` is "count," which means that `geom_bar()` uses `stat_count()`. `stat_count()` is documented on the same page as `geom_bar()`, and if you scroll down you can find a section called "Computed variables." That tells that it computes two new variables: `count` and `prop`.

You can generally use geoms and stats interchangeably. For example, you can re-create the previous plot using `stat_count()` instead of `geom_bar()`:

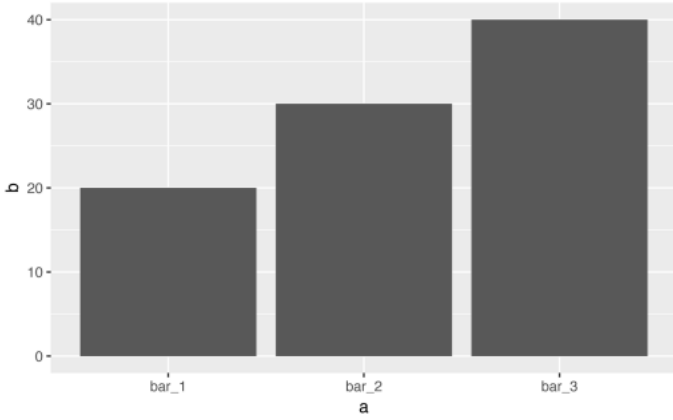
```
ggplot(data = diamonds) +
  stat_count(mapping = aes(x = cut))
```



This works because every geom has a default stat, and every stat has a default geom. This means that you can typically use geoms without worrying about the underlying statistical transformation.There are three reasons you might need to use a stat explicitly:

- You might want to override the default stat. In the following code, I change the stat of `geom_bar()` from count (the default) to identity. This lets me map the height of the bars to the raw values of a *y* variable. Unfortunately when people talk about barcharts casually, they might be referring to this type of bar chart, where the height of the bar is already present in the data, or the previous bar chart where the height of the bar is generated by counting rows.

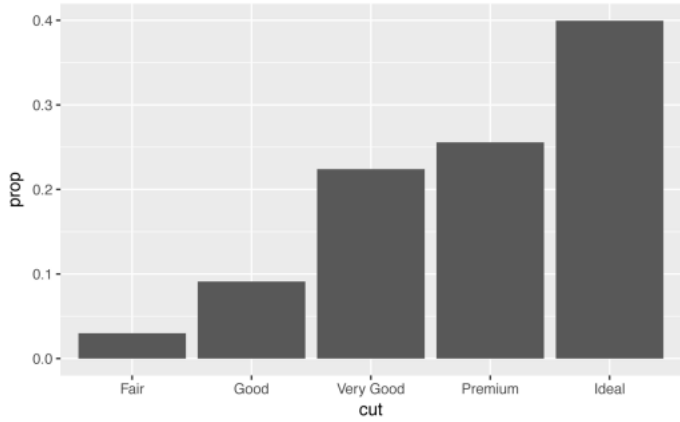
```
demo <- tribble(
  ~a,      ~b,
  "bar_1", 20,
  "bar_2", 30,
  "bar_3", 40
)

ggplot(data = demo) +
  geom_bar(
    mapping = aes(x = a, y = b), stat = "identity"
  )
```



(Don't worry that you haven't seen `<-` or `tibble()` before. You might be able to guess at their meaning from the context, and you'll learn exactly what they do soon!)

- You might want to override the default mapping from transformed variables to aesthetics. For example, you might want to display a bar chart of proportion, rather than count:

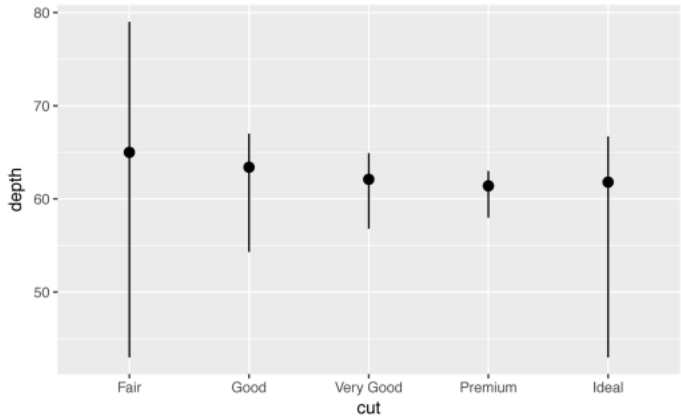
```
ggplot(data = diamonds) +
  geom_bar(
    mapping = aes(x = cut, y = ..prop.., group = 1)
  )
```



To find the variables computed by the stat, look for the help section titled "Computed variables."

- You might want to draw greater attention to the statistical transformation in your code. For example, you might use `stat_summary()`, which summarizes the `y` values for each unique `x` value, to draw attention to the summary that you're computing:

```
ggplot(data = diamonds) +
  stat_summary(
    mapping = aes(x = cut, y = depth),
    fun.ymin = min,
    fun.ymax = max,
    fun.y = median
  )
```

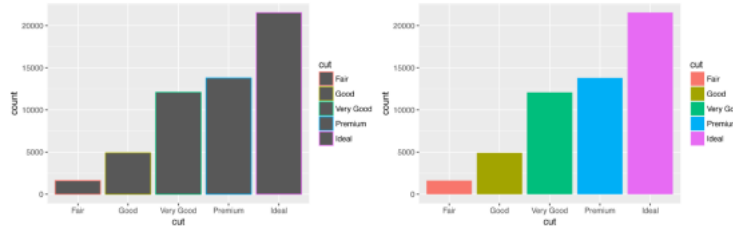


ggplot2 provides over 20 stats for you to use. Each stat is a function, so you can get help in the usual way, e.g., `?stat_bin`. To see a complete list of stats, try the **ggplot2** cheatsheet.

Position Adjustments

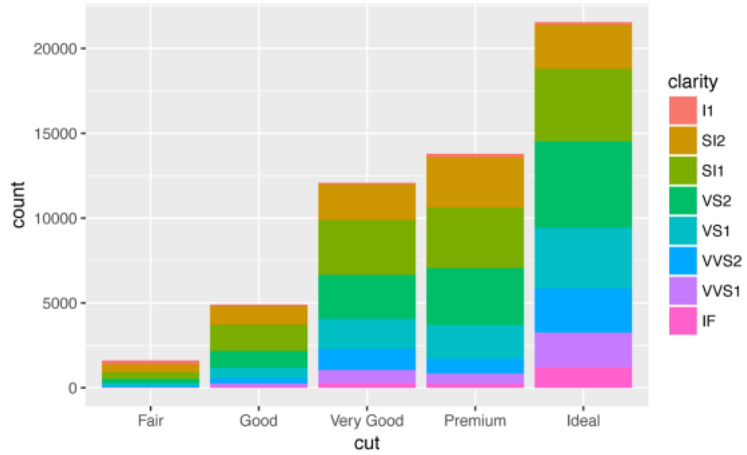
There's one more piece of magic associated with bar charts. You can color a bar chart using either the `color` aesthetic, or more usefully, `fill`:

```
ggplot(data = diamonds) +
  geom_bar(mapping = aes(x = cut, color = cut))
ggplot(data = diamonds) +
  geom_bar(mapping = aes(x = cut, fill = cut))
```



Note what happens if you map the `fill` aesthetic to another variable, like `clarity`: the bars are automatically stacked. Each colored rectangle represents a combination of `cut` and `clarity`:

```
ggplot(data = diamonds) +
  geom_bar(mapping = aes(x = cut, fill = clarity))
```



The stacking is performed automatically by the *position adjustment* specified by the `position` argument. If you don't want a stacked bar

chart, you can use one of three other options: `"identity"`, `"dodge"` or `"fill"`:

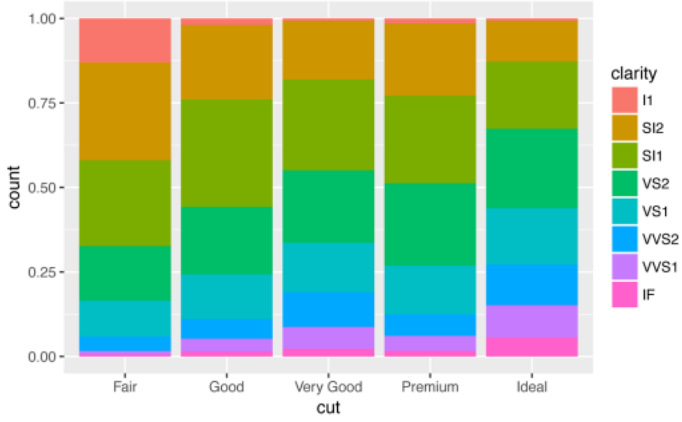
- `position = "identity"` will place each object exactly where it falls in the context of the graph. This is not very useful for bars, because it overlaps them. To see that overlapping we either need to make the bars slightly transparent by setting `alpha` to a small value, or completely transparent by setting `fill = NA`:

```
ggplot(
  data = diamonds,
  mapping = aes(x = cut, fill = clarity)
) +
  geom_bar(alpha = 1/5, position = "identity")
ggplot(
  data = diamonds,
  mapping = aes(x = cut, color = clarity)
) +
  geom_bar(fill = NA, position = "identity")
```

  The identity position adjustment is more useful for 2D geoms, like points, where it is the default.

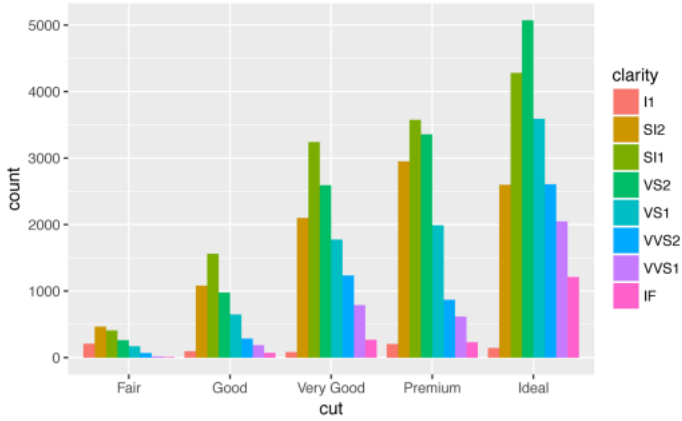
- `position = "fill"` works like stacking, but makes each set of stacked bars the same height. This makes it easier to compare proportions across groups:

```
ggplot(data = diamonds) +
  geom_bar(
    mapping = aes(x = cut, fill = clarity),
    position = "fill"
  )
```

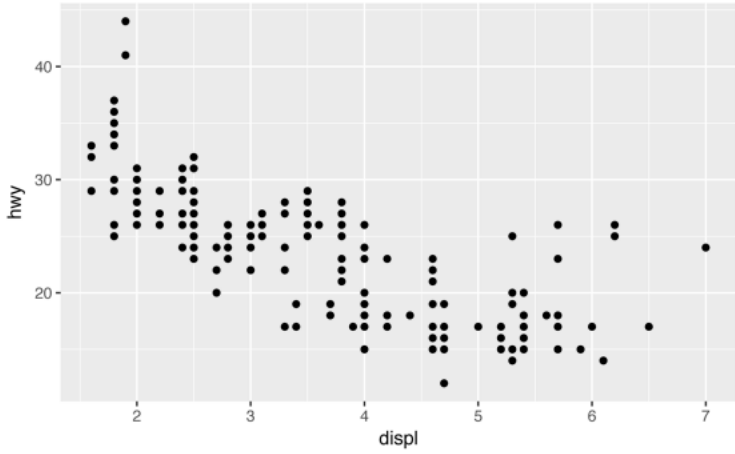


- `position = "dodge"` places overlapping objects directly *beside* one another. This makes it easier to compare individual values:

```
ggplot(data = diamonds) +
  geom_bar(
    mapping = aes(x = cut, fill = clarity),
    position = "dodge"
  )
```



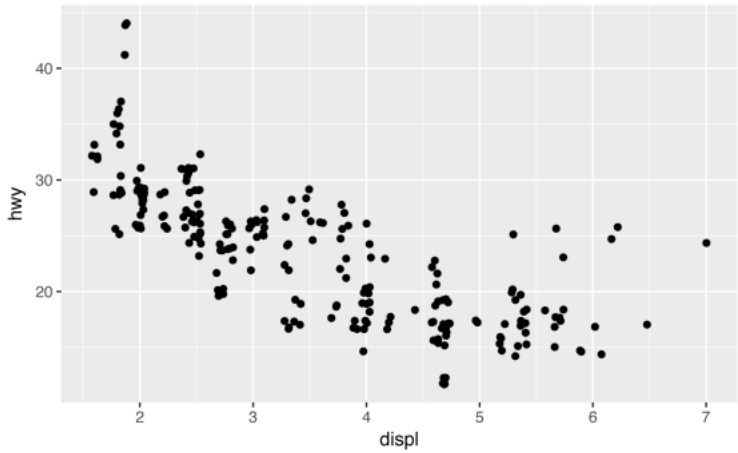
There's one other type of adjustment that's not useful for bar charts, but it can be very useful for scatterplots. Recall our first scatterplot. Did you notice that the plot displays only 126 points, even though there are 234 observations in the dataset?



The values of `hwy` and `displ` are rounded so the points appear on a grid and many points overlap each other. This problem is known as *overplotting*. This arrangement makes it hard to see where the mass of the data is. Are the data points spread equally throughout the graph, or is there one special combination of `hwy` and `displ` that contains 109 values?

You can avoid this gridding by setting the position adjustment to "jitter." `position = "jitter"` adds a small amount of random noise to each point. This spreads the points out because no two points are likely to receive the same amount of random noise:

```
ggplot(data = mpg) +
  geom_point(
    mapping = aes(x = displ, y = hwy),
    position = "jitter"
  )
```



Adding randomness seems like a strange way to improve your plot, but while it makes your graph less accurate at small scales, it makes your graph *more* revealing at large scales. Because this is such a useful operation, **ggplot2** comes with a shorthand for `geom_point(position = "jitter")`: `geom_jitter()`.

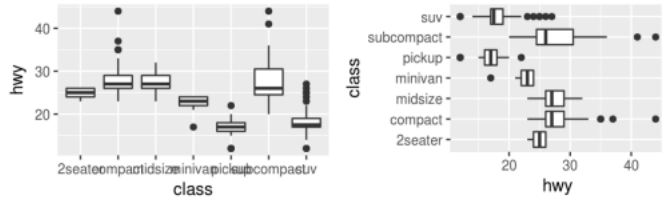
To learn more about a position adjustment, look up the help page associated with each adjustment: `?position_dodge`, `?position_fill`, `?position_identity`, `?position_jitter`, and `?position_stack`.

Coordinate Systems

Coordinate systems are probably the most complicated part of **ggplot2**. The default coordinate system is the Cartesian coordinate system where the x and y position act independently to find the location of each point. There are a number of other coordinate systems that are occasionally helpful:

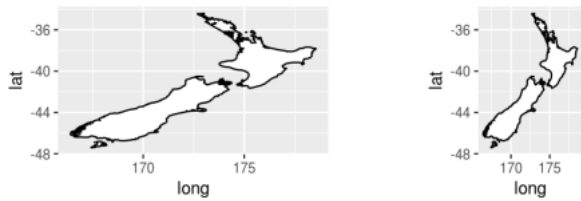
- `coord_flip()` switches the x- and y-axes. This is useful (for example) if you want horizontal boxplots. It's also useful for long labels—it's hard to get them to fit without overlapping on the x-axis:

```
ggplot(data = mpg, mapping = aes(x = class, y = hwy)) +
  geom_boxplot()
ggplot(data = mpg, mapping = aes(x = class, y = hwy)) +
  geom_boxplot() +
  coord_flip()
```



- `coord_quickmap()` sets the aspect ratio correctly for maps. This is very important if you're plotting spatial data with **ggplot2** (which unfortunately we don't have the space to cover in this book):

```
nz <- map_data("nz")

ggplot(nz, aes(long, lat, group = group)) +
  geom_polygon(fill = "white", color = "black")

ggplot(nz, aes(long, lat, group = group)) +
  geom_polygon(fill = "white", color = "black") +
  coord_quickmap()
```



- `coord_polar()` uses polar coordinates. Polar coordinates reveal

an interesting connection between a bar chart and a Coxcomb chart:

```
bar <- ggplot(data = diamonds) +
  geom_bar(
    mapping = aes(x = cut, fill = cut),
    show.legend = FALSE,
    width = 1
  ) +
  theme(aspect.ratio = 1) +
  labs(x = NULL, y = NULL)

bar + coord_flip()
bar + coord_polar()
```

Reference

Hadley Wickham & Garrett Grolemund, R for Data Science IMPORT, TIDY, TRANSFORM, VISUALIZE, AND MODEL DATA, Import, Tidy, Transform, Visualize, and Model Data. 2017.