Section 6: Figures with `ggplot2`

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Contents

1 Admin

1.1 What you will need

Packages:

- Previously used: `dplyr`, `lfe`, `readr`, `magrittr` and `parallel`
- New: `ggplot2`, `ggthemes`, `viridis`

Data: The `auto.csv` file.

1.2 Last week

Last week we discussed statistical inference—specifically using t and F statistics to conduct hypothesis tests. We also talked about simulations and parallelizing your R code.

1.3 This week

We will discuss how to utilize R's powerful figure-making package `ggplot2`.

2 Quality figures

Economics journals are not always filled with the most aesthetically pleasing figures.[1] To make matters worse, the same journals often feature fairly unhelpful images with equally uninformative captions. One might rationalize this behavior by saying that producing informative and aesthetically pleasing figures requires a lot of time and effort—and is just really hard.

In this section—and in future sections—I hope to demonstrate that while producing informative and pleasing figures probably takes more time that producing uninformative and ugly figures, it does not take *that much* time and effort, once you learn the basics of `ggplot2`. There is the cost-side argument; now for the benefit-side argument….

Figures *can* be very powerful. We have all seen bad figures that shed approximately zero light on their topic. Well-made figures can quickly and clearly communicate ideas that would take several paragraphs to describe. In general, most applied (empirical) economics papers should be able to describe the main results in a single graph.[2] Audiences generally love figures. And hopefully your papers and presentations are attempting to communicate to an audience.[Again, if this is not the case, as yourself why not. And try to fix it.]

Finally, you might actually want to look at your data once in a while. Regression is a helpful tool, but don't forget that there are other tools for analyzing your data. Here is a pretty famous example known as Anscombe's Quartet.

The setup:

```
# Setup ----
# Options
options(stringsAsFactors = F)
# Packages
library(dplyr)
library(magrittr)
library(ggplot2)
library(ggthemes)
```

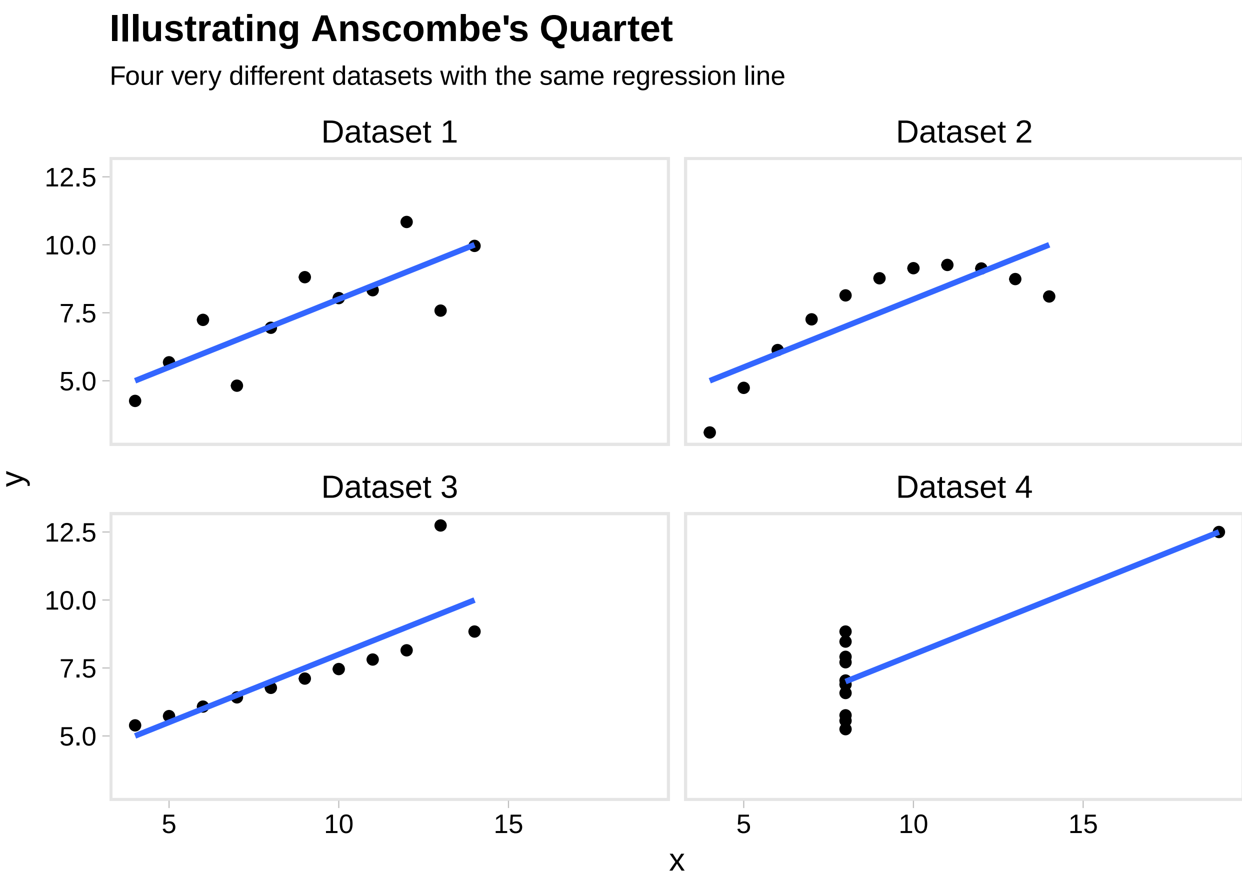
The plot (don't worry about the syntax for now):

```
# Reformat Anscombe's dataset
a_df <- bind_rows(
  select(anscombe, x = x1, y = y1),
```

[1]This sentence is probably true for most disciplines.

[2]If you cannot achieve this task, ask yourself why not. And try to fix it.

```
  select(anscombe, x = x2, y = y2),
  select(anscombe, x = x3, y = y3),
  select(anscombe, x = x4, y = y4))
# Add group identifier
a_df %<>% mutate(group = rep(paste0("Dataset ", 1:4), each = 11))
# The plot
ggplot(data = a_df, aes(x, y)) +
  # Plot the points
  geom_point() +
  # Add the regression line (without S.E. shading)
  geom_smooth(method = "lm", formula = y ~ x, se = F) +
  # Change the theme
  theme_pander() +
  theme(panel.border = element_rect(color = "grey90", fill=NA, size=1)) +
  # Plot by group
  facet_wrap(~group, nrow = 2, ncol = 2) +
  ggtitle("Illustrating Anscombe's Quartet",
    subtitle = "Four very different datasets with the same regression line")
```



So quality figures can take a little time and effort, but it is likely a use of your time and effort with particularly high yields. And you might learn something.

3 ggplot2

Having sold you on the creating high-quality figures, let's talk about R's `ggplot2` package—many people's go-to figure-making package in R.

3.1 Why ggplot2?

First, why aren't we using R's base plotting functions? While R's base package for making graphs is comprehensive and fairly powerful, it has a few drawbacks:

- It is often a bit difficult to manipulate
- Parameters are not named in a helpful way (*e.g.* to change the line type, you need to remember its abbreviation, `lty`)
- Coloring or filling by group is not very straightforward
- Limited in scope, relative to `ggplot2` and the packages that support `ggplot2`
- Saving is a bit strange

3.2 Introduction

So, what is `ggplot2`?

Short answer: `ggplot2` it a package for creating plots in R.[3]

Longer answer: (copied from the `ggplot2` home page) "ggplot2 is a plotting system for R, based on the grammar of graphics, which tries to take the good parts of base and lattice graphics and none of the bad parts. It takes care of many of the fiddly details that make plotting a hassle (like drawing legends) as well as providing a powerful model of graphics that makes it easy to produce complex multi-layered graphics."

More information: `ggplot2` is yet another package created by Hadley Wickham—yes *the* Hadley Wickham.

3.3 Setup

Let's load the packages and functions that we will want during this section.

My setup…

```
# Setup ----
# Options
options(stringsAsFactors = F)
# Packages
library(readr)
library(dplyr)
library(magrittr)
library(ggplot2)
library(ggthemes)
library(viridis)
# Set working directory
```

[3] You should install it (`install.package("ggplot2")`).

```r
setwd("/Users/edwardarubin/Dropbox/Teaching/ARE212/Section06")
# Load data
cars <- read_csv("auto.csv")
```

Our functions…

```r
# Functions ----
# Function to convert tibble, data.frame, or tbl_df to matrix
to_matrix <- function(the_df, vars) {
  # Create a matrix from variables in var
  new_mat <- the_df %>%
    # Select the columns given in 'vars'
    select_(.dots = vars) %>%
    # Convert to matrix
    as.matrix()
  # Return 'new_mat'
  return(new_mat)
}
# Function for OLS coefficient estimates
b_ols <- function(data, y_var, X_vars, intercept = TRUE) {
  # Require the 'dplyr' package
  require(dplyr)
  # Create the y matrix
  y <- to_matrix(the_df = data, vars = y_var)
  # Create the X matrix
  X <- to_matrix(the_df = data, vars = X_vars)
  # If 'intercept' is TRUE, then add a column of ones
  if (intercept == T) {
    # Bind a column of ones to X
    X <- cbind(1, X)
    # Name the new column "intercept"
    colnames(X) <- c("intercept", X_vars)
  }
  # Calculate beta hat
  beta_hat <- solve(t(X) %*% X) %*% t(X) %*% y
  # Return beta_hat
  return(beta_hat)
}
# Function for OLS table
ols <- function(data, y_var, X_vars, intercept = T) {
  # Turn data into matrices
  y <- to_matrix(data, y_var)
  X <- to_matrix(data, X_vars)
  # Add intercept if requested
  if (intercept == T) X <- cbind(1, X)
  # Calculate n and k for degrees of freedom
  n <- nrow(X)
  k <- ncol(X)
  # Estimate coefficients
```

```r
  b <- b_ols(data, y_var, X_vars, intercept)
  # Calculate OLS residuals
  e <- y - X %*% b
  # Calculate s^2
  s2 <- (t(e) %*% e) / (n-k)
  # Inverse of X'X
  XX_inv <- solve(t(X) %*% X)
  # Standard error
  se <- sqrt(s2 * diag(XX_inv))
  # Vector of _t_ statistics
  t_stats <- (b - 0) / se
  # Calculate the p-values
  p_values = pt(q = abs(t_stats), df = n-k, lower.tail = F) * 2
  # Nice table (data.frame) of results
  results <- data.frame(
    # The rows have the coef. names
    effect = rownames(b),
    # Estimated coefficients
    coef = as.vector(b) %>% round(3),
    # Standard errors
    std_error = as.vector(se) %>% round(3),
    # t statistics
    t_stat = as.vector(t_stats) %>% round(3),
    # p-values
    p_value = as.vector(p_values) %>% round(4)
    )
  # Return the results
  return(results)
}
```

3.4 Basic syntax

Alright. Let's talk about the syntax of `ggplot2`. As mentioned above, `ggplot2` is "based on the grammar of graphics." What does that mean? It means that you will *build* plots like the English language *builds* sentences.[4] In a sense, you will start with a subject—your data—and then apply different modifiers to it, creating layers in your plot and changing various plotting parameters.

This syntax certainly deviates a bit from many other plotting methods out there, but once you see how it works, I think you will also see how clean and powerful it can be.

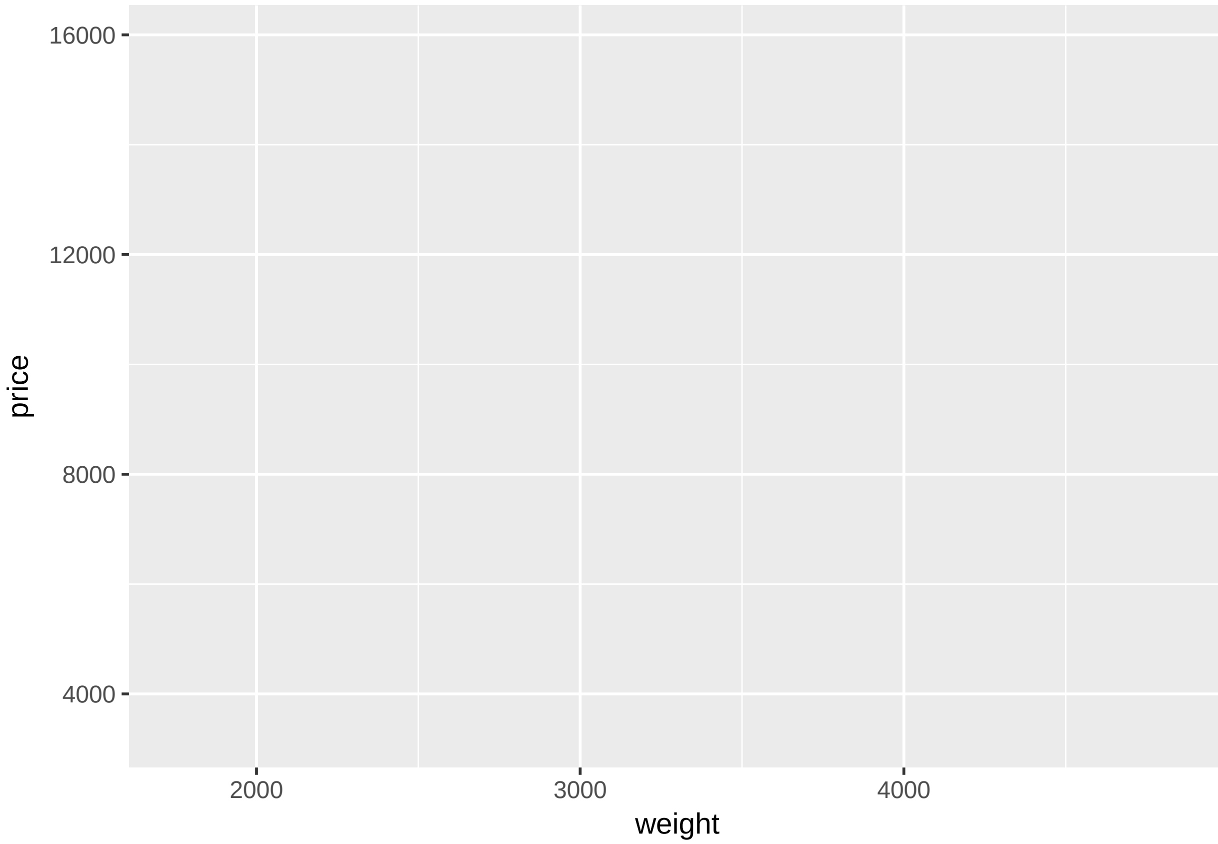
3.5 `ggplot()`

To start a plot, we use the function `ggplot()`. This function passes the data to the other layers of the plot. You can also use the `ggplot()` function to define which variable is your `x` variable (in terms of `x` and `y` axes), which variable is your `y` variable, and a number of other parameter tweaks.

[4] This paradigm is similar to the verb constructions in `dplyr`.

Let's see what happens when we feed `ggplot()` our `cars` dataset and define `x` as weight and `y` as price.

```
ggplot(data = cars, aes(x = weight, y = price))
```



A blank plot. Well... not quite blank: we have labeled axes, corresponding to our definitions inside the `ggplot()` function. And we have a gray background—don't worry, it is easy to change the background if you don't like it.

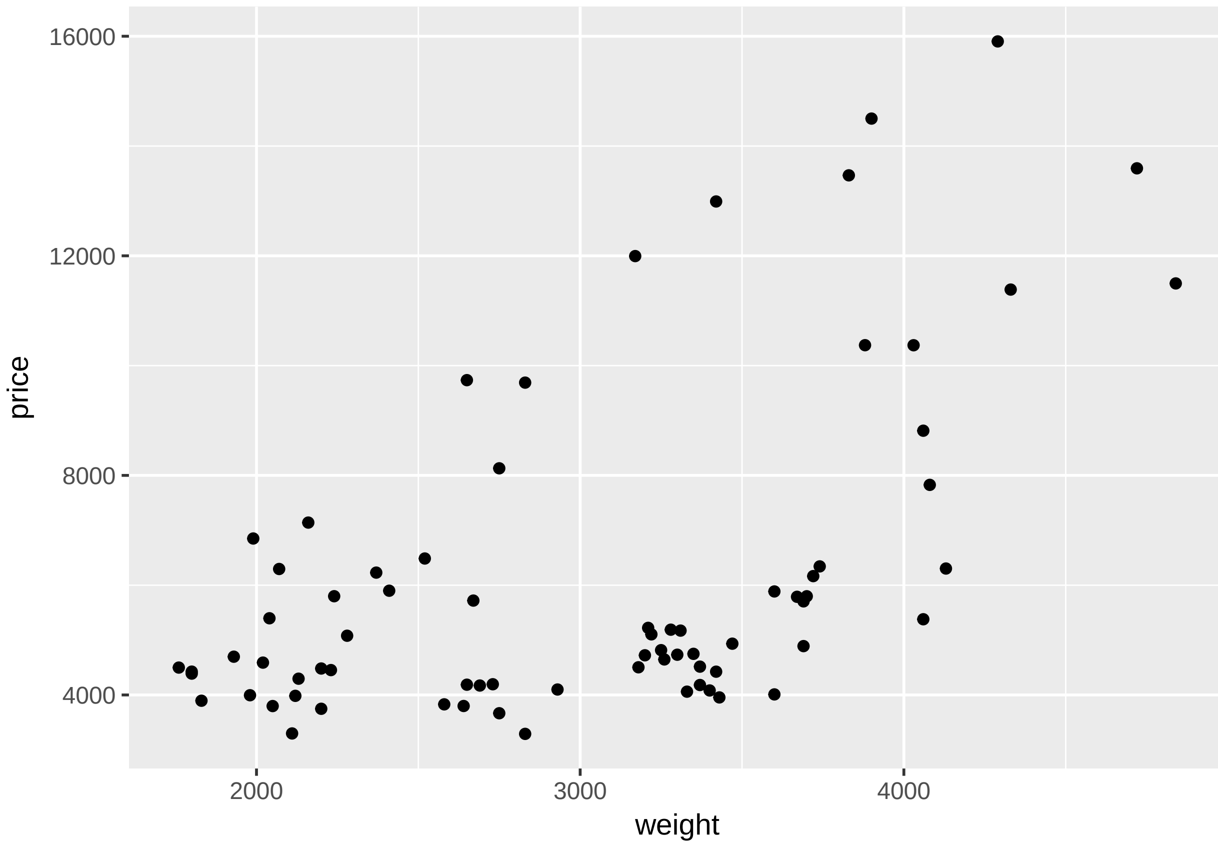
Also, notice that we defined the axes inside of a function called `aes()`, which is inside of the `ggplot()` function. We use the `aes()` function to "construct aesthetic mappings"—it tells `ggplot2` which variables we want to use from the dataset and how we want to use them. In the case above, we are telling `ggplot2` that we want to use two variables (weight and price) as the axes in the plot. You can also define aesthetic mapping using `aes()` it other layers.

3.6 Adding `geom` layers

So why is the graph above blank? It is blank because we have not added a plotting layer—we have only defined the dataset and defined the axes.

Let's add a layer. In `ggplot2`, we add layers with the addition sign (+). Many of the plotting layers begin with the suffix `geom_`. For instance, if we want to create a scatter plot, we will add the `geom_point()` function to our existing plot. Let's try it.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point()
```



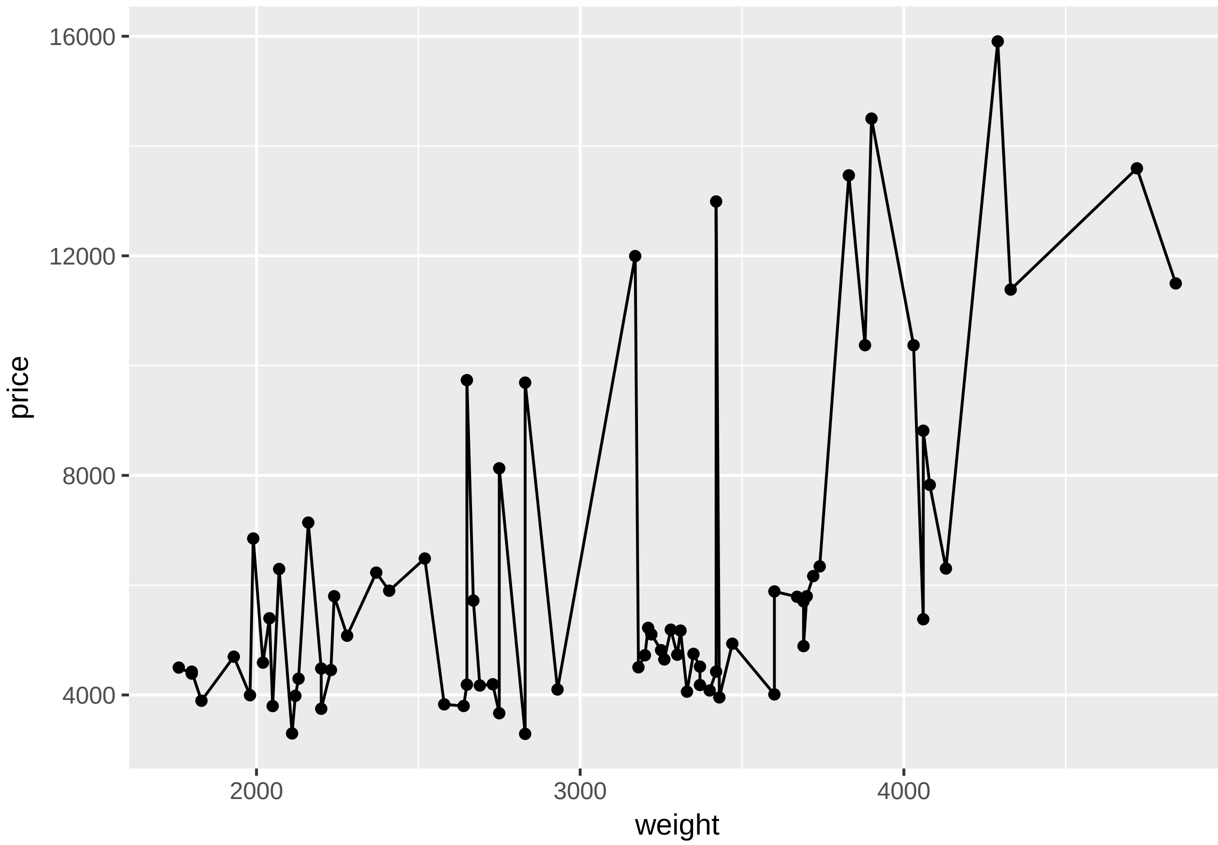
Hurray—we have something! And it is even a little interesting!

Let's read the R code, step-by-step, just as `ggplot2` reads it.

1. We create a new plot with the function `ggplot()`.
2. We define our dataset to be the data stored in the `cars` object.
3. Using the `aes()` function, we define our x-variable to be weight and our y-variable to be price.
4. We add a layer that plots points for each observation in our dataset.

What if we want to connect points with a line? We simply add a new layer using `geom_line()`:

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point() +
  geom_line()
```



That was easy.

Hopefully you are beginning to see how `ggplot2`'s syntax allows a lot of flexibility and customization. By defining the dataset with `ggplot()` and mapping the axes with `aes()` inside of `ggplot()`, the layers that create the points and lines know exactly what to do without any further specification.[5]

On thes other hand, this graph doesn't really make any sense. It actually seems less informative than our previous graph. We don't care about connecting dots.

3.7 `stat_function()`

While we don't care about connecting dots, we *do* care about fitting a line through our points. Let's find the line the best fits through these points using our old friend `ols()`. For now, we only care about the coefficients, so we will save them as `b`.

```
# Regress price on weight (with an intercept)
b <- ols(data = cars, y_var = "price", X_vars = "weight") %$% coef
```

Now we will write a function that gives the predicted value of price for a given value of weight. This function will use the coefficients stored in `b`.

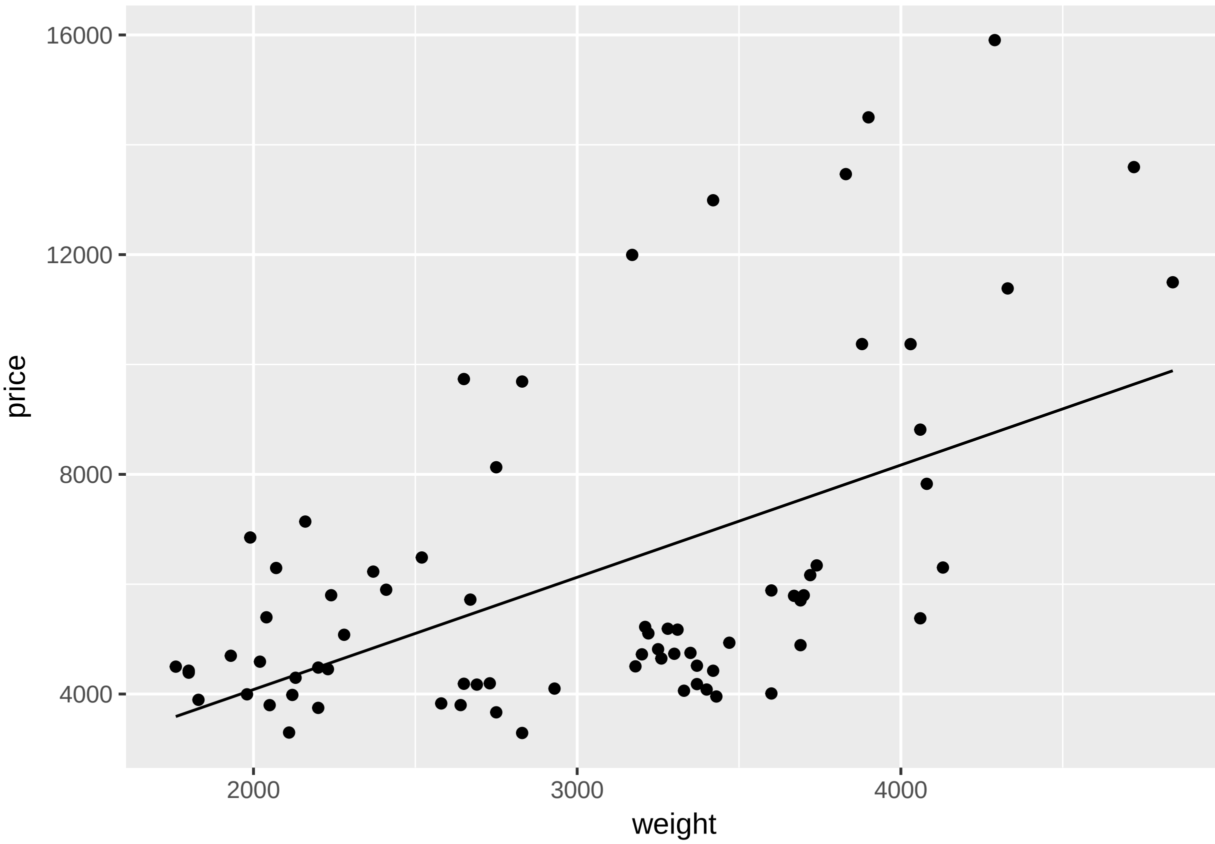
```
price_hat <- function(weight) b[1] + b[2] * weight
```

Next, we will replace the `geom_line()` layer in the plot above with a layer using the function `stat_function()`. The function `stat_function()` allows you to plot an arbitrary function. In our case, we have already defined

[5]Note that you need to use the parentheses even if you are not going to put anything in them, *e.g.*, `geom_line()`.

the x-axis, so ggplot2 will evaluate our function over the domain of the variable we defined as x (weight).

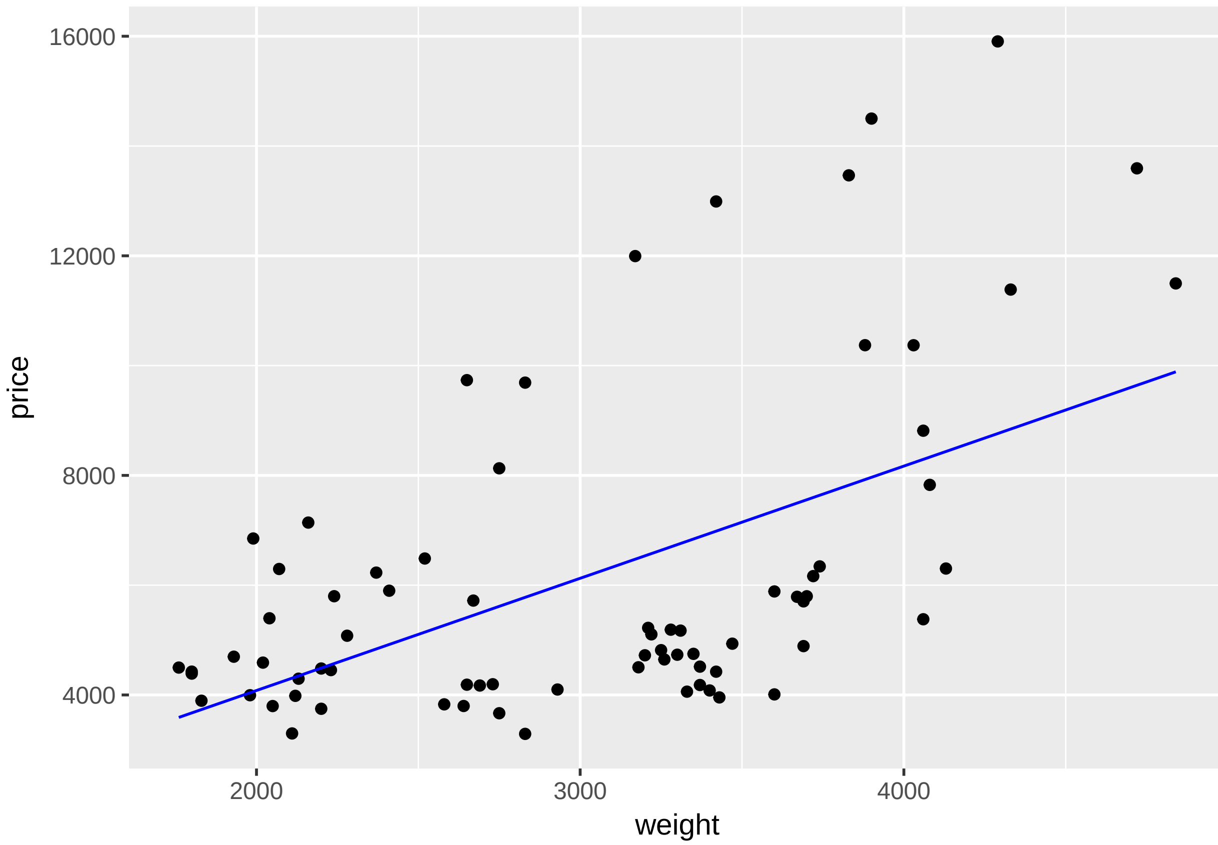
```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point() +
  stat_function(fun = price_hat)
```



What if we want to change the color of the line to blue? Easy: inside of the layer that creates the line (stat_function()), we simply add the argument color = "blue".[6]

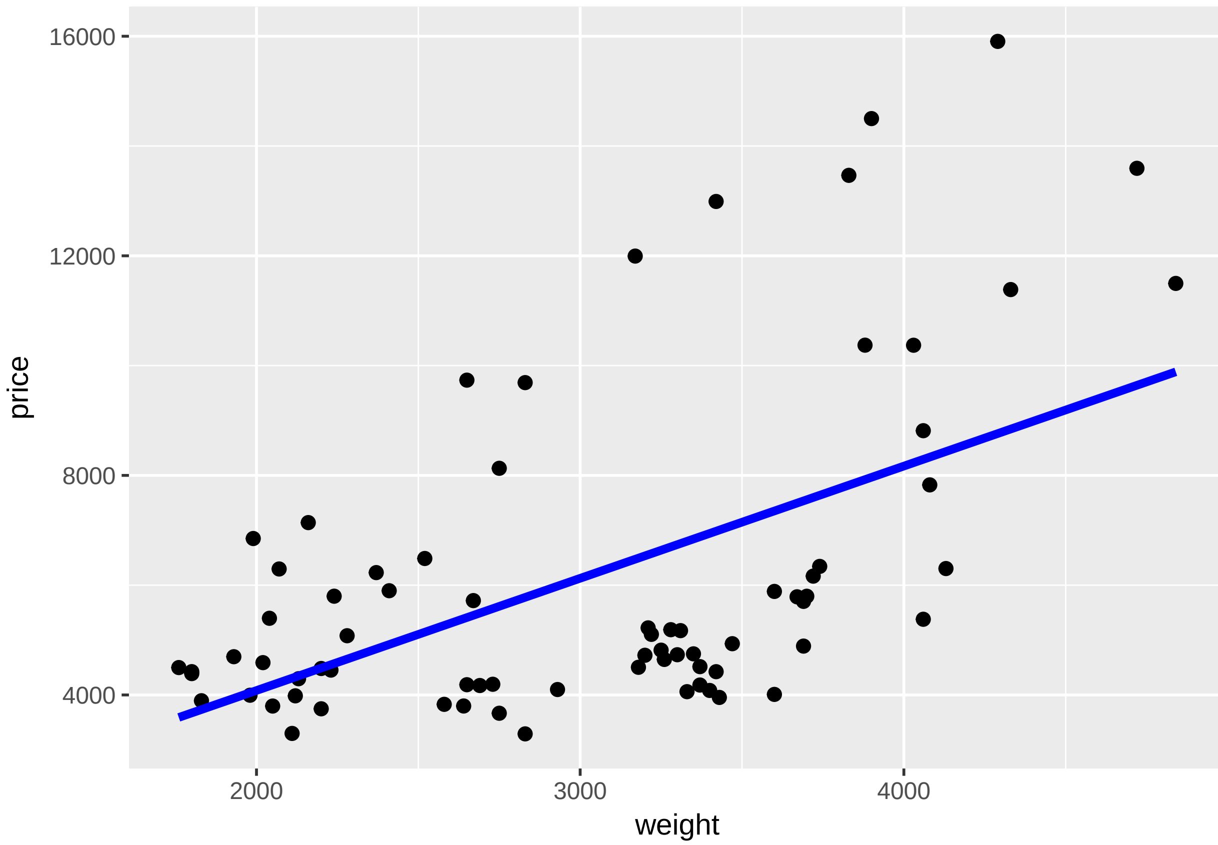
```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point() +
  stat_function(fun = price_hat, color = "blue")
```

[6]Check out this resource for recognized color names in R.



To make the line thicker, we can use `size`. `size` will also make the points bigger in `geom_point`:

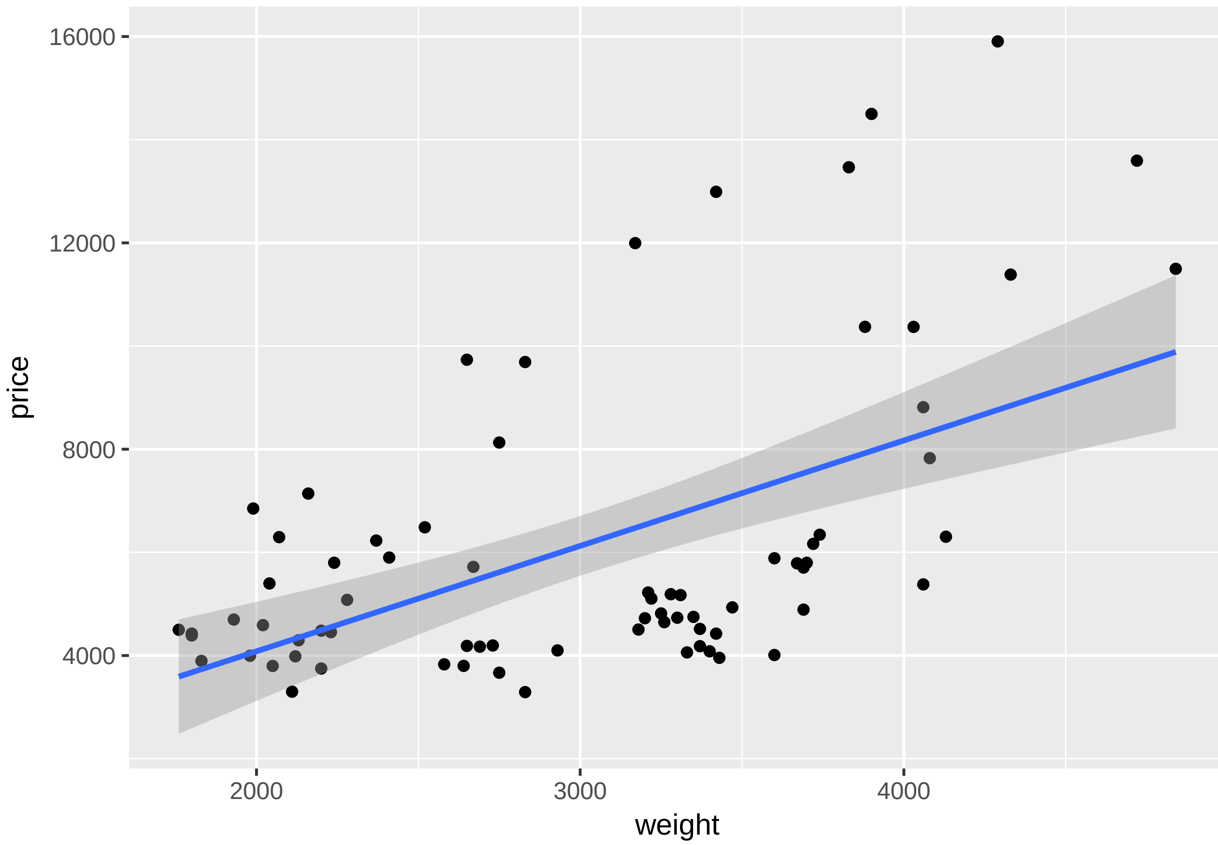
```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(size = 2) +
  stat_function(fun = price_hat, color = "blue", size = 1.5)
```



3.8 geom_smooth()

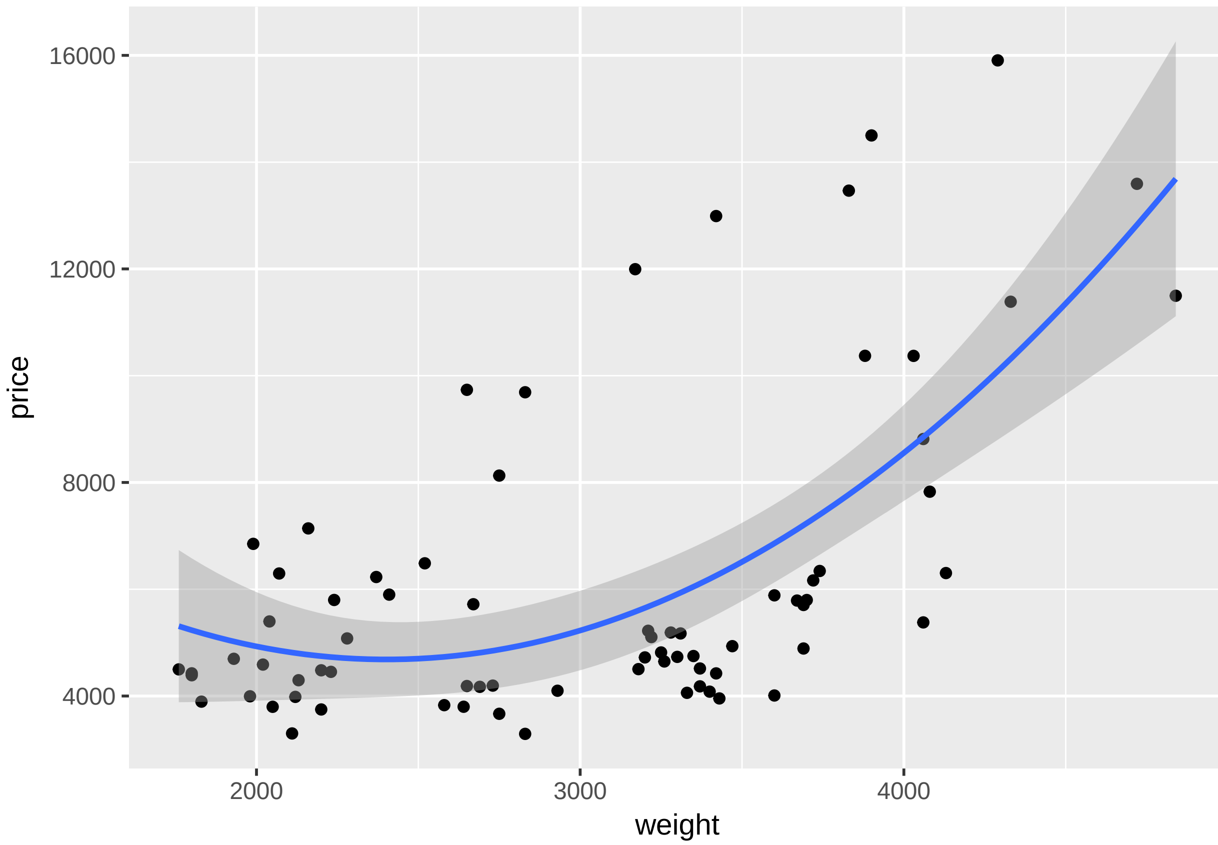
Alternatively, we could add the best-fit regression line to a plot using the `geom_smooth()` geometry. We just need to make sure the define the method to be `lm` (linear model) or `geom_smooth()` will default to a different smoother. Again, because we have already defined the axes, we do not need to define a formula for the regression that `geom_smooth()` runs.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point() +
  geom_smooth(method = "lm")
```



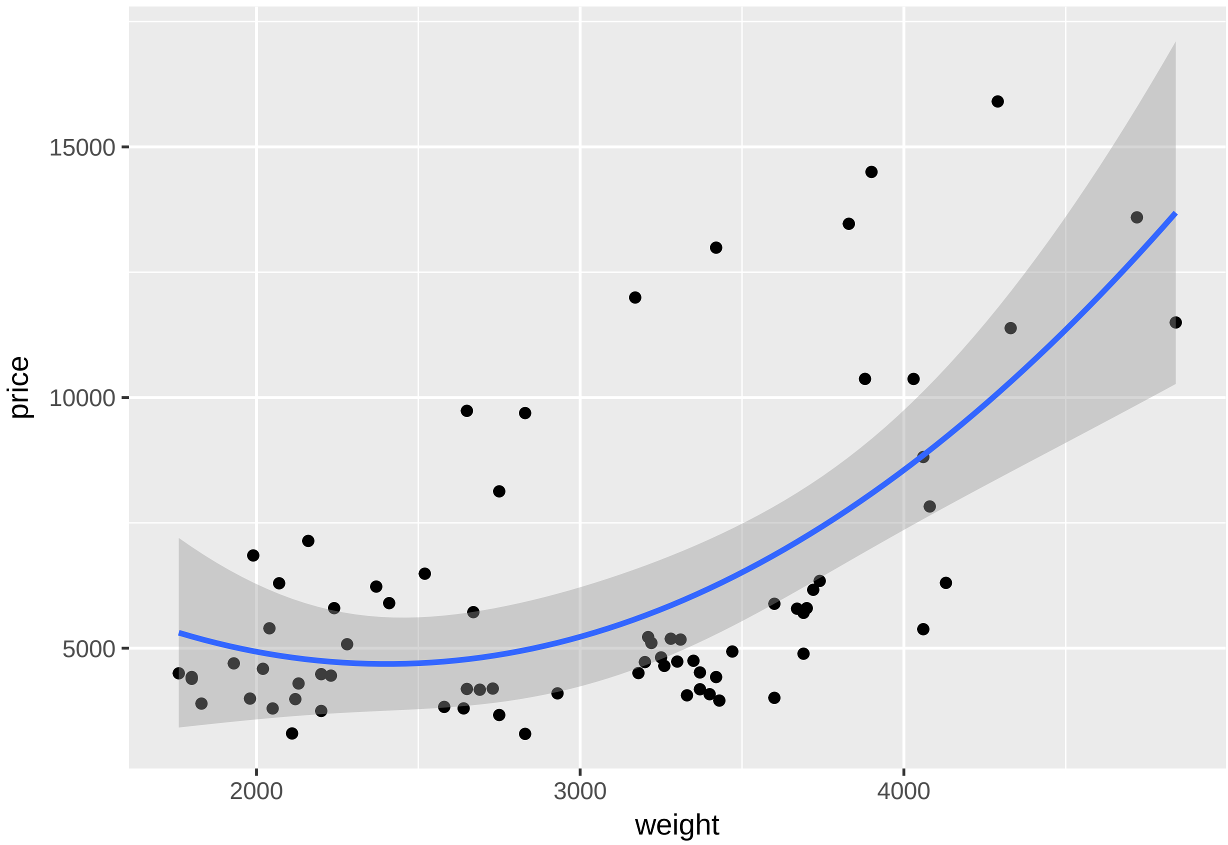
If we want to add a quadratic term to the best-fit line using `geom_smooth()`, we add a formula argument like we would use in `lm()` or `felm()`:

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point() +
  geom_smooth(method = "lm", formula = y ~ x + I(x^2))
```



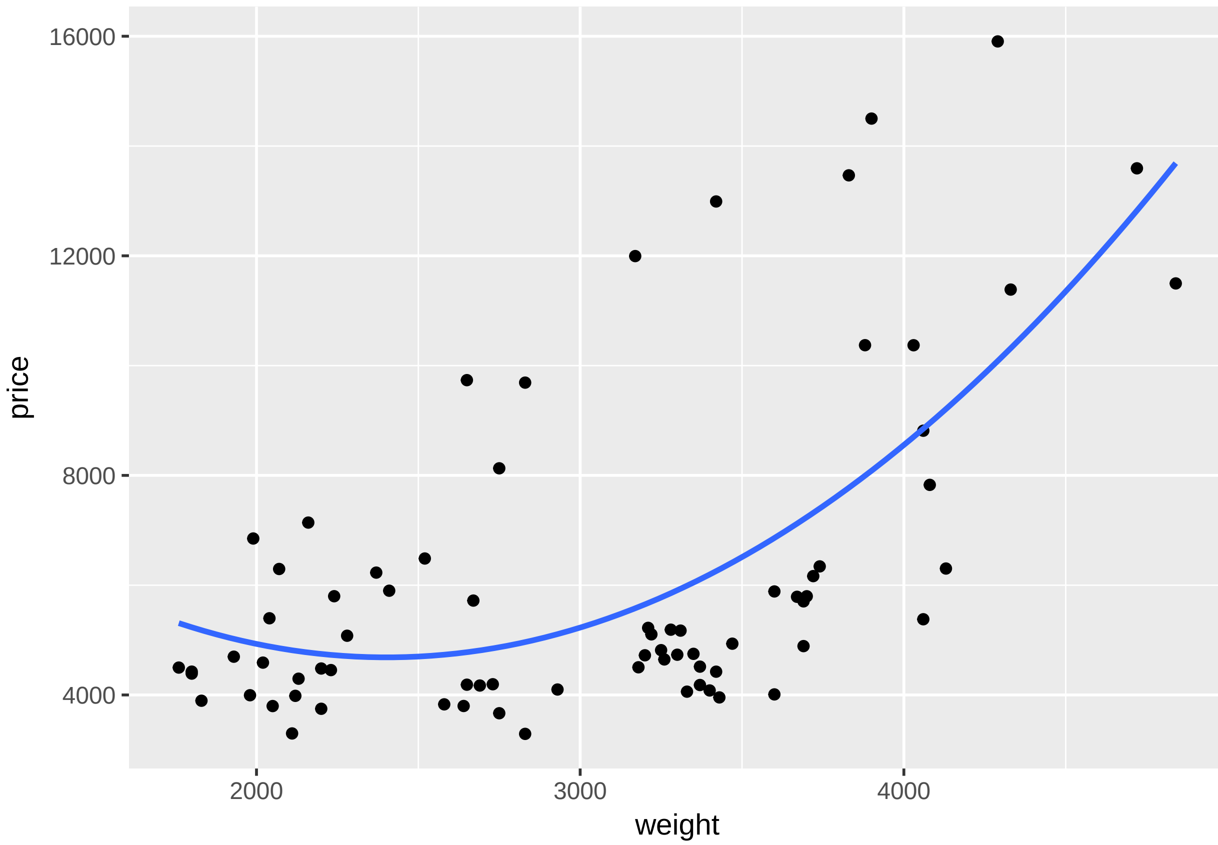
As with many function in R—and especially in `ggplot2`—we can take advantage of additional options to tweak our graphs. For instance `geom_smooth()` automatically spits out 95-percent confidence interval. We can use the `level` argument to change the level of the confidence interval

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point() +
  geom_smooth(method = "lm", formula = y ~ x + I(x^2),
    level = 0.99)
```



Or we can remove the confidence interval by specifying `se = F`.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point() +
  geom_smooth(method = "lm", formula = y ~ x + I(x^2), se = F)
```



3.9 More aesthetics

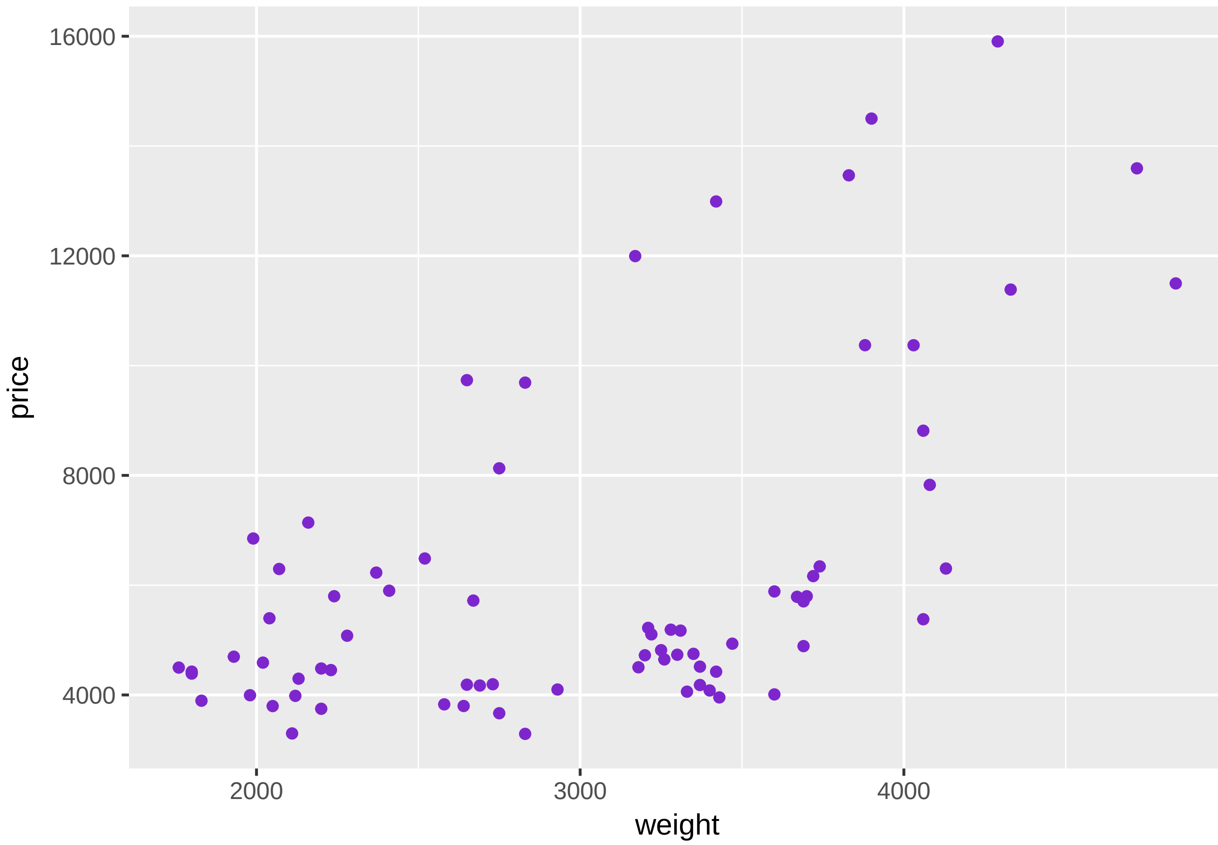
So far we've discussed two aesthetics: `x` and `y`, which define the two axes (if you only want to define one axis, just use `x`). There are a lot of other options for aesthetic mappings: color, size, shape, group, line type (`linetype`), *etc.*

In general, less is more when it comes to plotting: if your data only vary along two dimensions (*e.g.* price and weight), you probably only need to plot them using those two dimensions (as we did above with `geom_point()`). When you have a third dimension, you can use a third aesthetic/dimension to differentiate your two-dimensional plot. One option is to use color to distinguish this third dimension.

3.9.1 Color

As we discussed above, you can use `color` inside a layer to change the color of the layer. For instance, if we want to plot price and weight with purple points:

```
ggplot(data = cars, aes(x = weight, y = price, group = foreign)) +
  geom_point(color = "purple3")
```

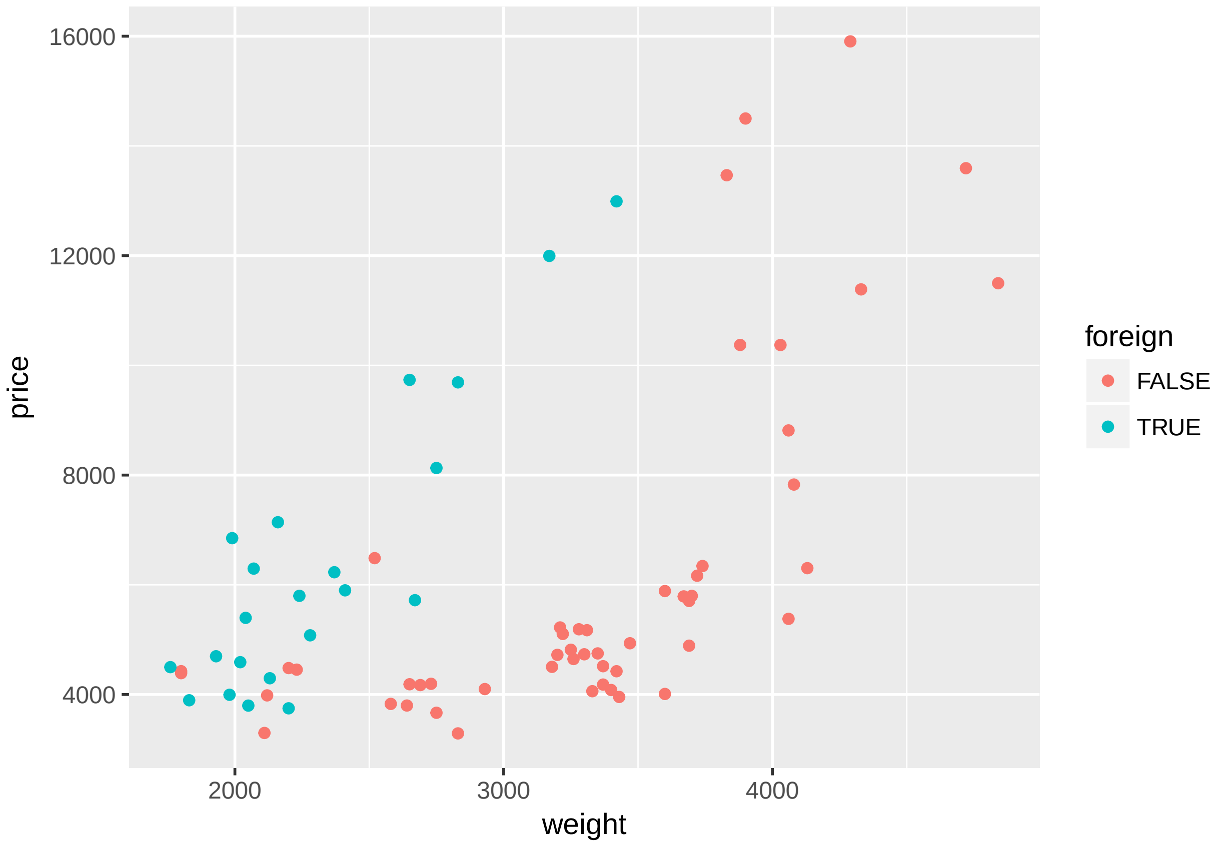


While the use of color above can make a plot marginally prettier, the real power of color in `ggplot2` is combining it with other dimensions of the data. For instance, we have a variable in our `cars` dataset (named `foreign`) that denotes whether a car is foreign or domestic. Currently the variable is an integer; let's change it to logical (`T` if foreign).

```
cars %<>% mutate(foreign = foreign == 1)
```

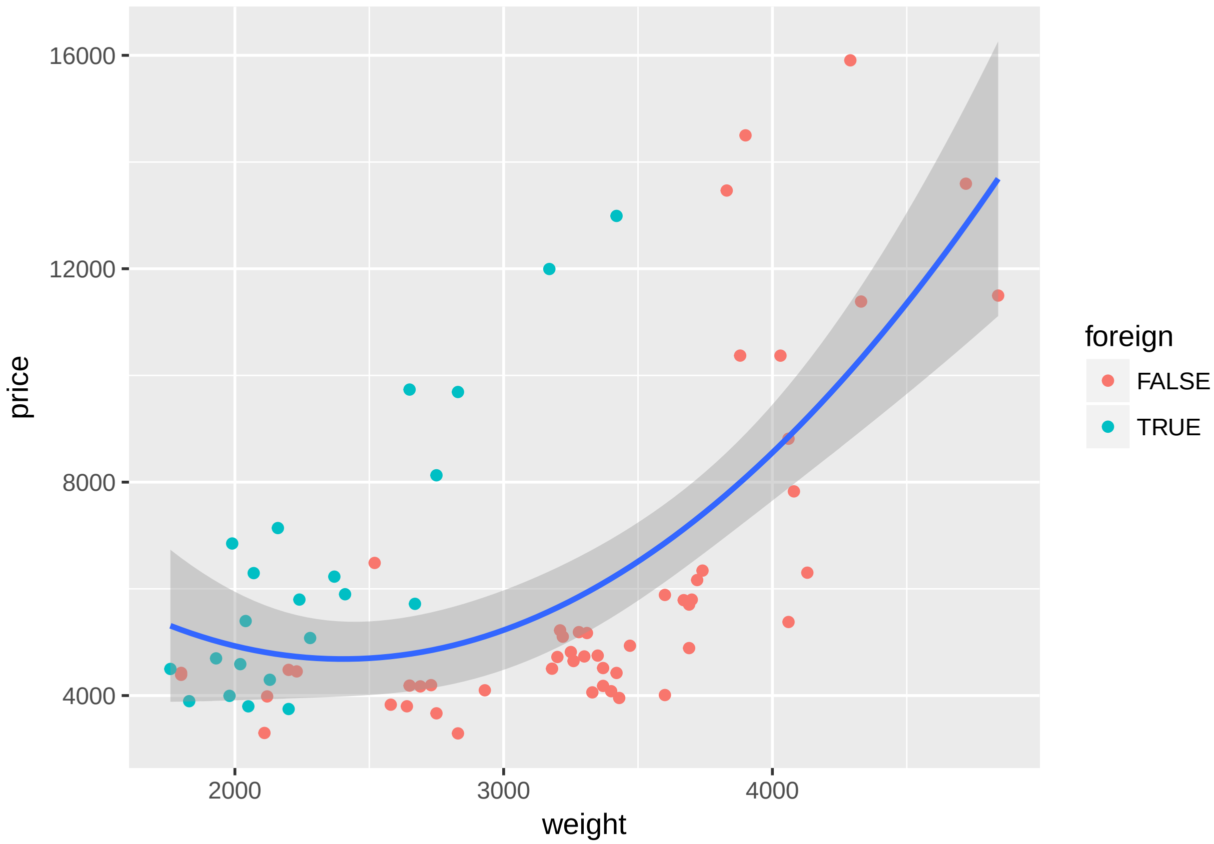
Instead of telling R we want to change the color of the points to purple, let's tell R to change the color of the point based upon the observation's value of the variable `foreign`. Because we now want to map a variable to a graphical parameter (`color`), we need to imbed this call of `color = foreign` inside the `aes()` function, *i.e.*, `aes(color = foreign)`. We can place this mapping in the initial call to `ggplot()` or into a specific layer.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign))
```



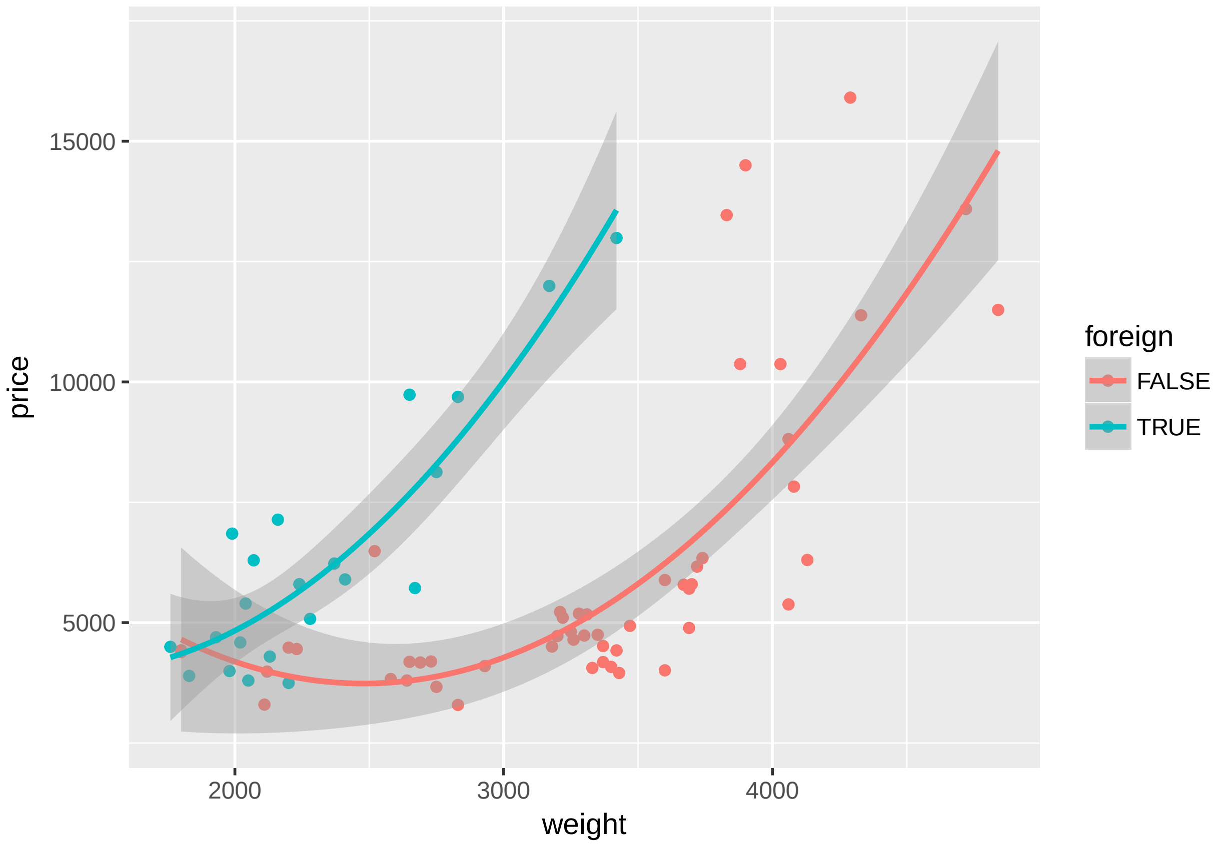
Interesting. It looks like the relationship between weight and price might differ depending upon whether the car comes from a domestic or foreign company. Let's add a quadratic regression line for each type of car.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign)) +
  geom_smooth(method = "lm", formula = y ~ x + I(x^2))
```



Nope—not quite what we want. We wanted separate lines for foreign and domestic cars, but we only got one line. What happened? Our mapping of `color` to the variable `foreign` is inside of a single layer (the layer created by `geom_point()`). If we want this mapping to apply to other layers, we should move the mapping to the original `ggplot()` instance:

```
ggplot(data = cars, aes(x = weight, y = price, color = foreign)) +
  geom_point() +
  geom_smooth(method = "lm", formula = y ~ x + I(x^2))
```

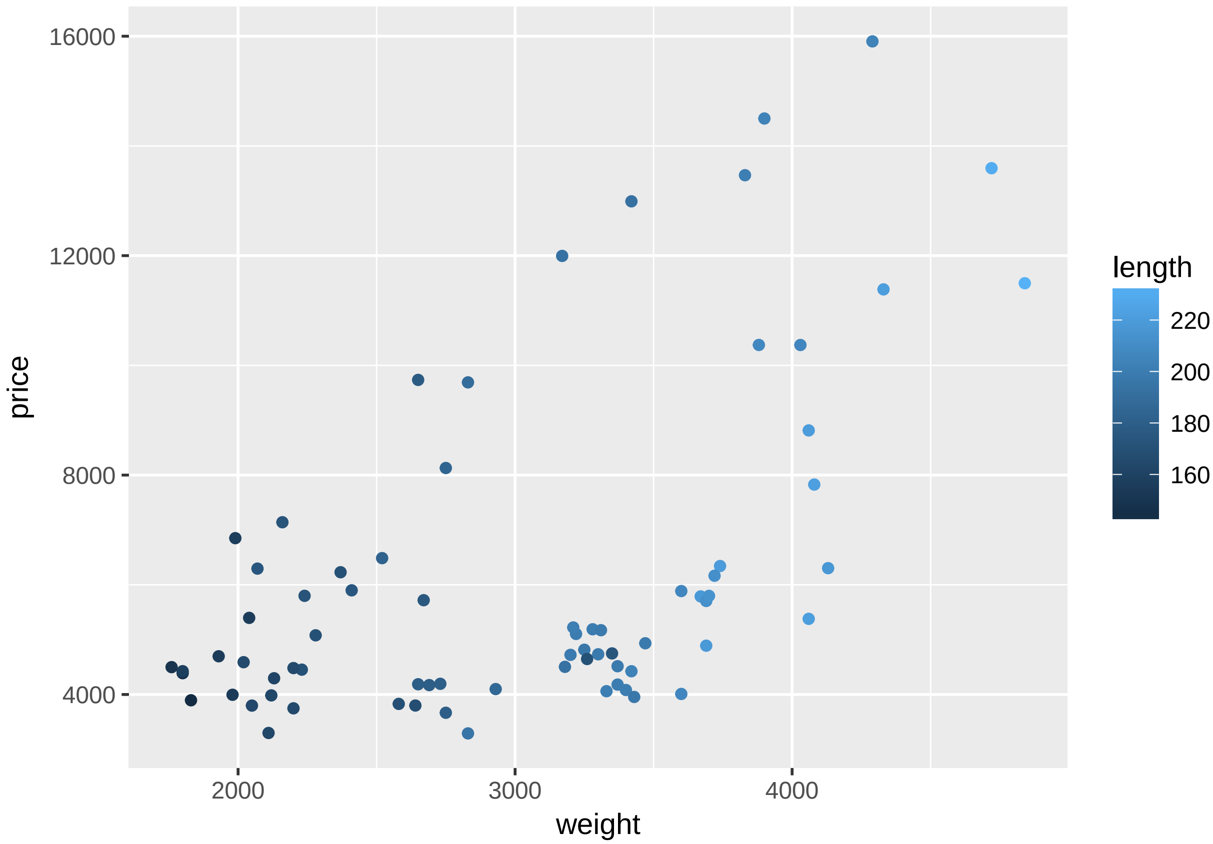


Because the variable `foreign` is either `TRUE` or `FALSE`, `ggplot2` treats it as a factor/categorical variable. `ggplot2` treats both logical and character variables as categorical variables.[7]

When you map a continuous variable to `color`, instead of plotting discrete colors, `ggplot2` will give you a color scale. For example, let's map the mileage variable `length` to color (instead of `foreign`).

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = length))
```

[7] I'm not crazy about the default colors that `ggplot2` provides—they are not colorblind friendly and just leave a bit to be desired. We will discuss how you can change them later.



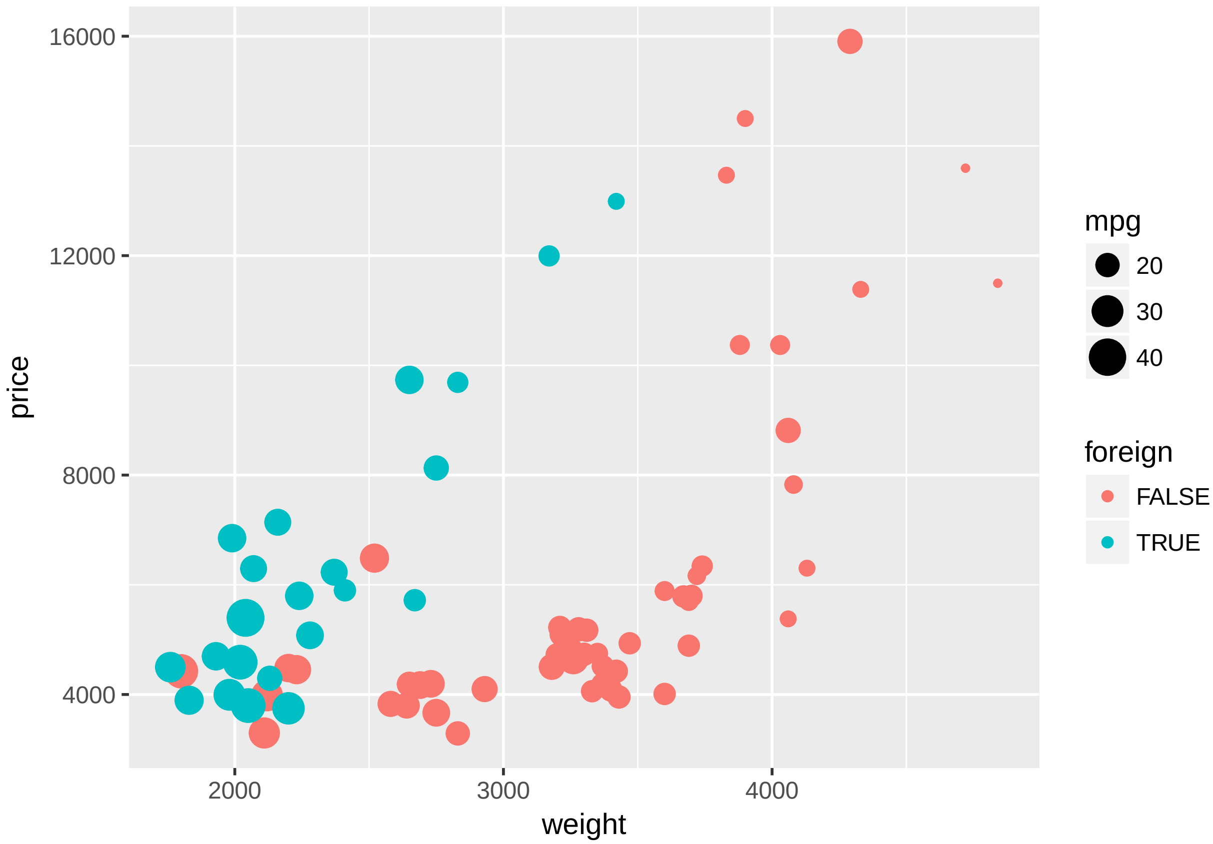
Interesting.

Once again, `ggplot2`'s default color theme is not great, but we will soon cover how you can change the colors.

3.9.2 Size

As we saw above, `size` can increase (or decrease) the plotting size of points and lines. As with `color`, you can use this aesthetic to tweak your plots, and you can also use it to depict another dimension of your data. To illustrate this idea, let's again plot weight and price. Let's return to mapping the foreign/domestic split to the color of the point. And now let's map the mileage (`mpg`) of the car to the size of the point (*i.e.*, `size = mpg`).

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg))
```



We are now showing four dimensions of the data with a single plot on two axes. Pretty impressive.

3.9.3 Other aesthetics

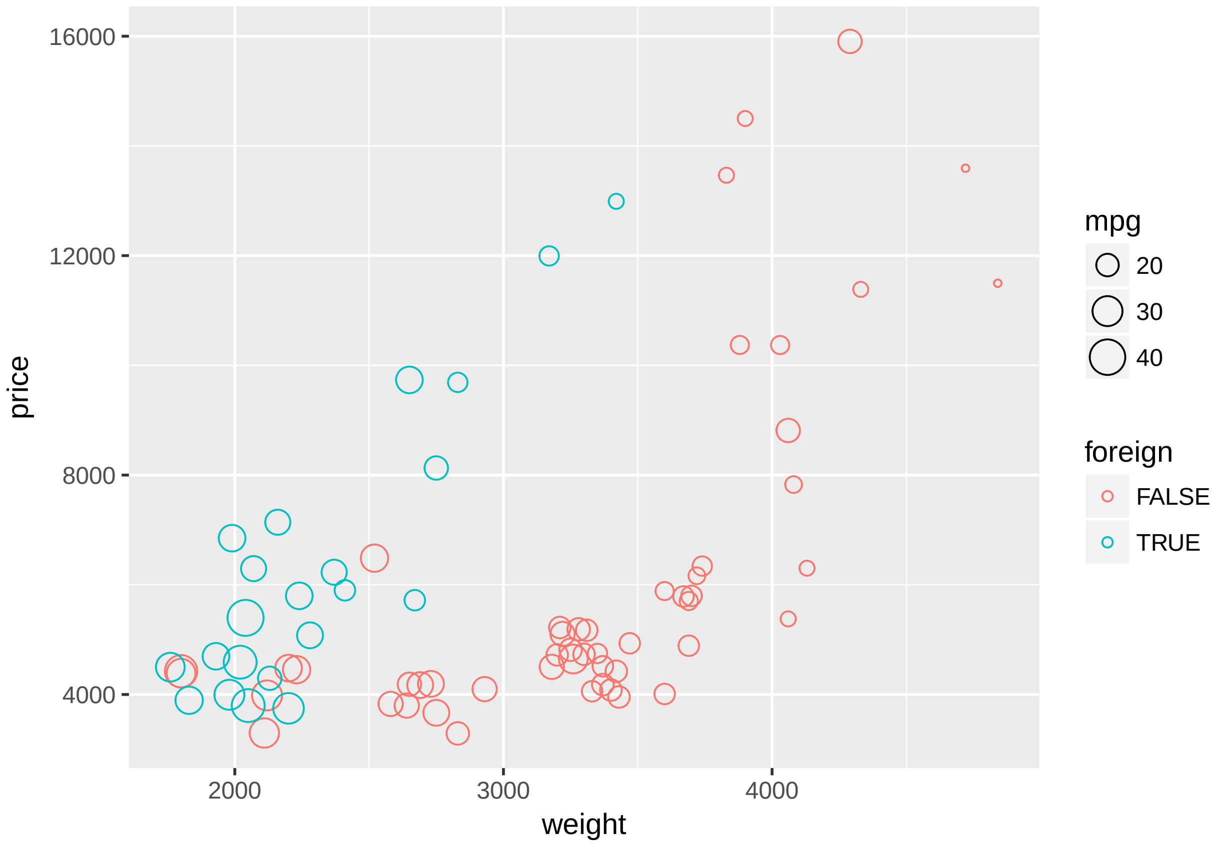
You have a bunch of other options aesthetics that work in similar ways—you can use them to adjust graphical parameters of your plot and/or to create additional dimensions of your figure:

- shape (`shape`): changes the shape of the points
- fill (`fill`): very similar to `color`; some geometries have color, others have fills, and still others have both colors and fills
- group (`group`): creates groups of objects for plotting—especially helpful for grouping series of lines
- line type (`linetype`): changes the type of line
- alpha (`alpha`): adjusts the opacity of the elements in your plot

If you think that the points are beginning to overlap a little too much but you don't want to change the size, you could try adjusting either `shape` or `alpha`.

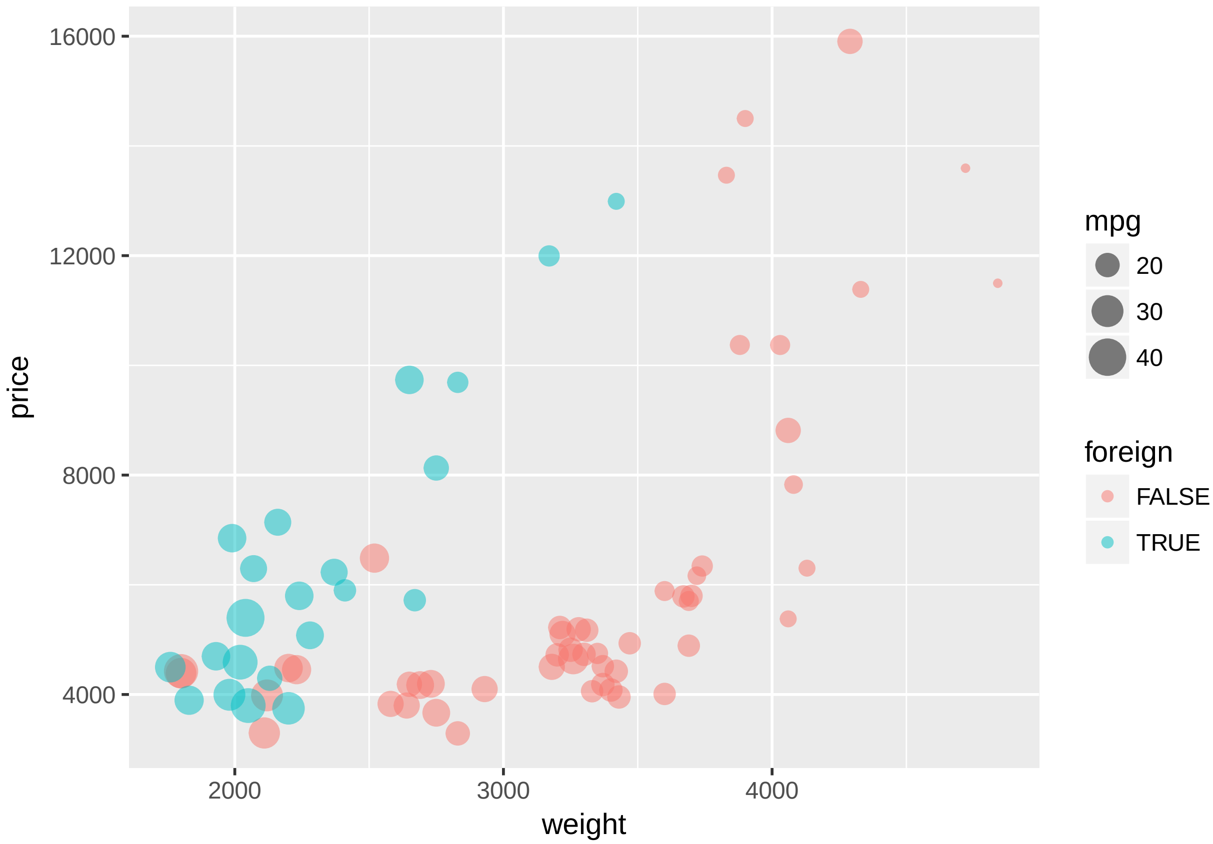
First, let's change the shape to `shape = 1`. Because we adjusting `shape` and not mapping it to a specific variable, we need to place the `shape = 1` argument **outside** of the `aes()` function.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), shape = 1)
```



Now let's try using the default shape and instead set `alpha = 0.5`. This setting of `alpha` will make the plotted characters semi-transparent. Again, because we adjusting `alpha` and not mapping it to a specific variable, we need to place the `alpha = 0.5` argument **outside** of the `aes()` function.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5)
```



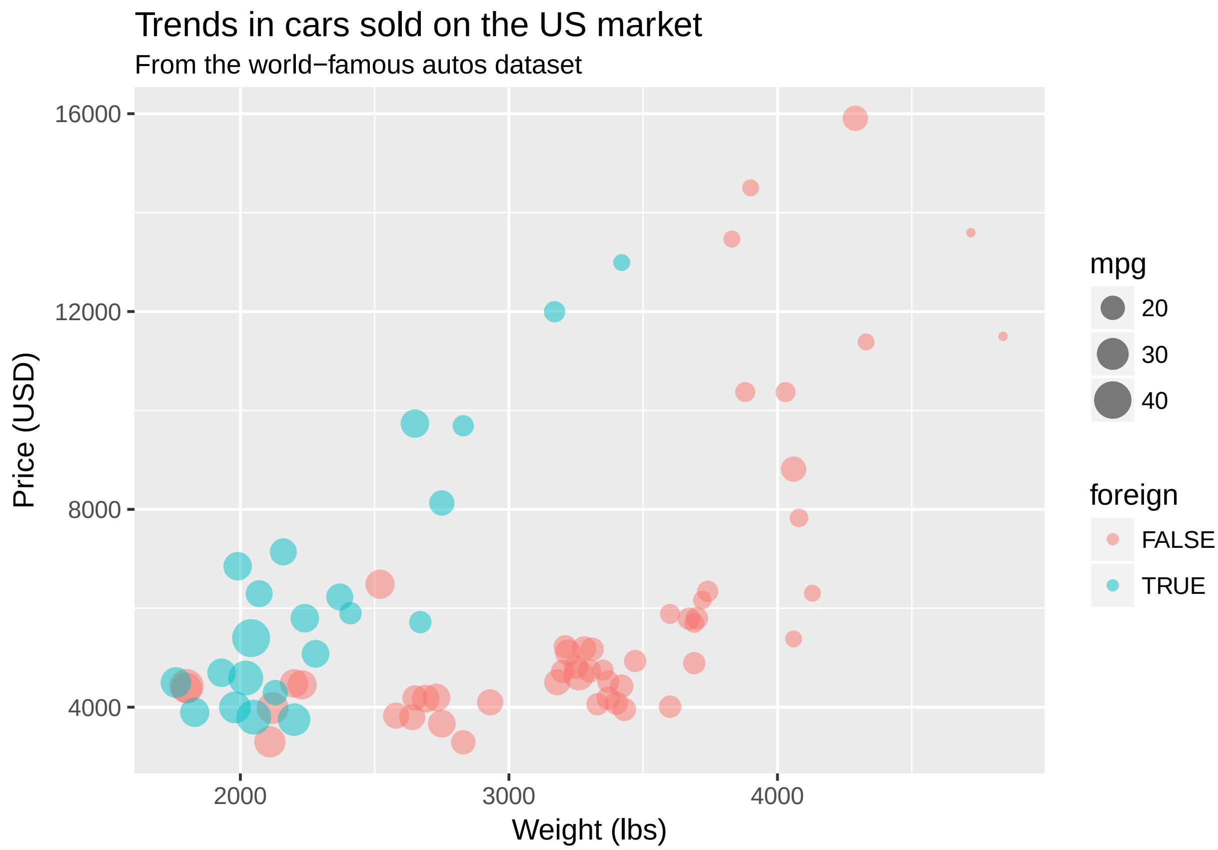
I'm not sure which way is better for showing overlapping points, but I think both of these methods help show the overlapping points better than using default values.

3.10 Labels

Clear and coherent labels and titles are an extremely important element of informative figures. To label the x- and y-axis, add the layers with the functions `xlab()` and `ylab()`. To add a title to your plot, add a layer with `ggtitle()`. `ggtitle()` also takes a second optional argument `subtitle`.

Let's label our plot.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset")
```



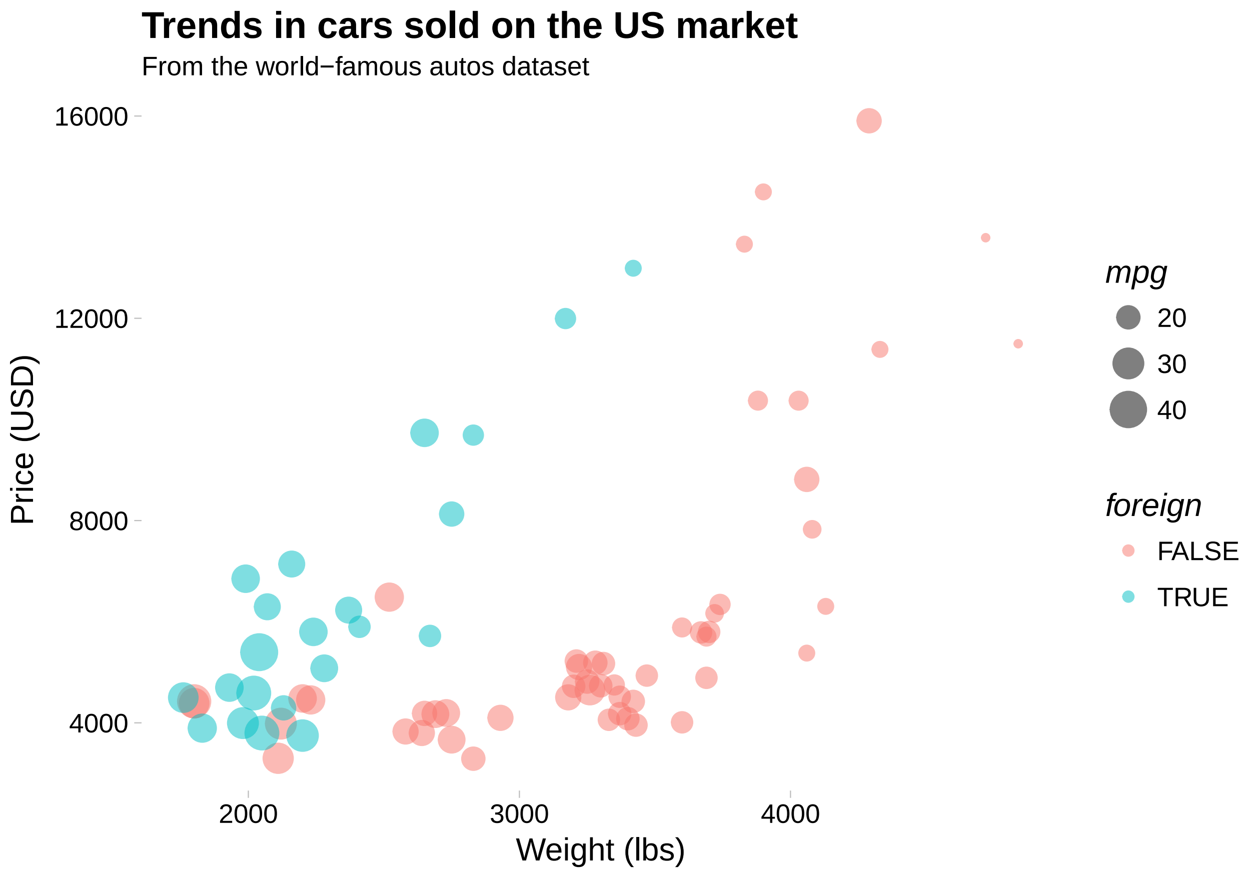
3.11 Themes

If you want to change facets of your figure like the background, the size of the labels on the axis, or the position of the legend, you can add adjust elements inside `ggplot2`'s theme. Or you can use a pre-built theme. `ggplot2` offers a few alternative themes (*e.g.*, `theme_bw()` or `theme_minimal()`). In addition, the package `ggthemes` (unsurprisingly) offers a number of ready-to-use themes (many are inspired by news websites' themes—*e.g.*, *The Economist*, 538, and the WSJ).[8]

One very simple theme from `ggthemes` is called `theme_pander()`. To use a theme (or any other theme), just add it to the end of your figure after you've created all of the layers:

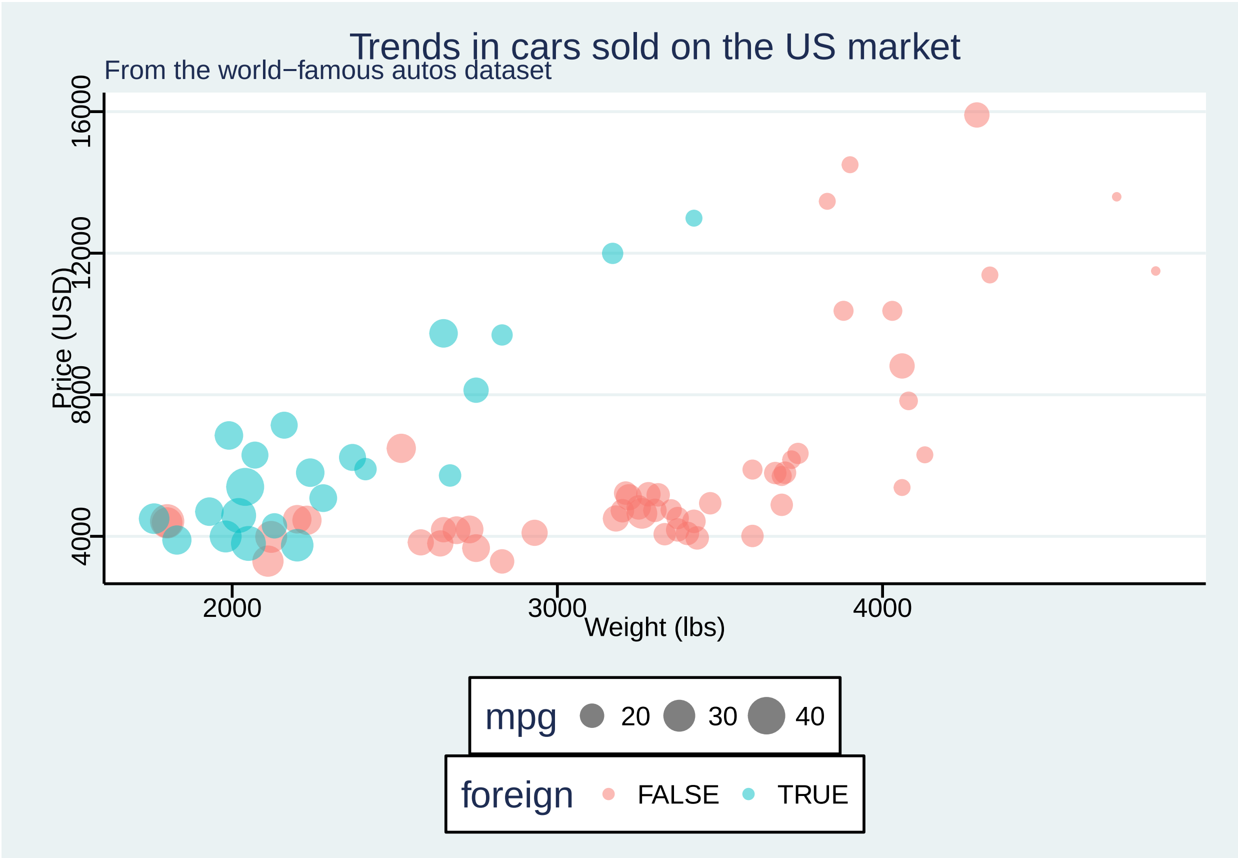
```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  theme_pander()
```

[8] See the `ggthemes` vignette for a list and examples of the available themes.



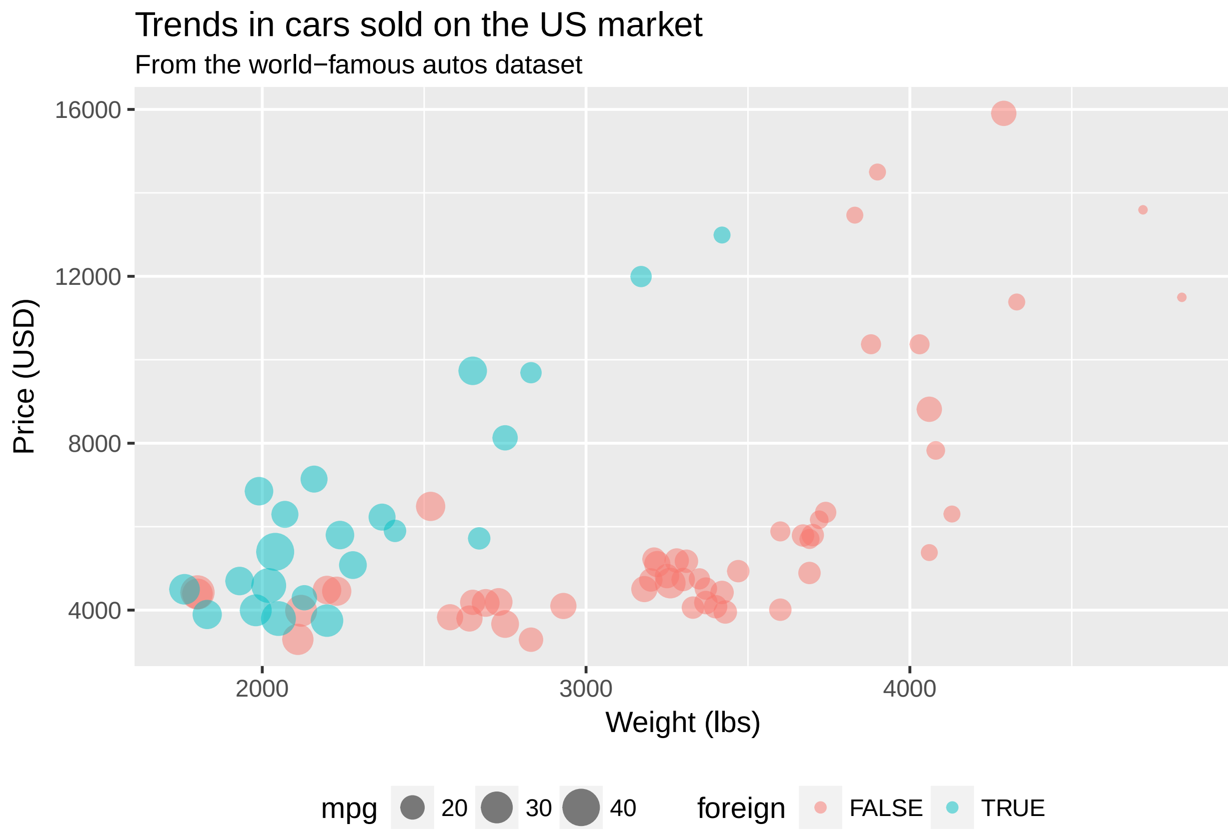
If, for some reason, you want to make people think you used Stata to make this figure, you can use the `theme_stata()` theme.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  theme_stata()
```



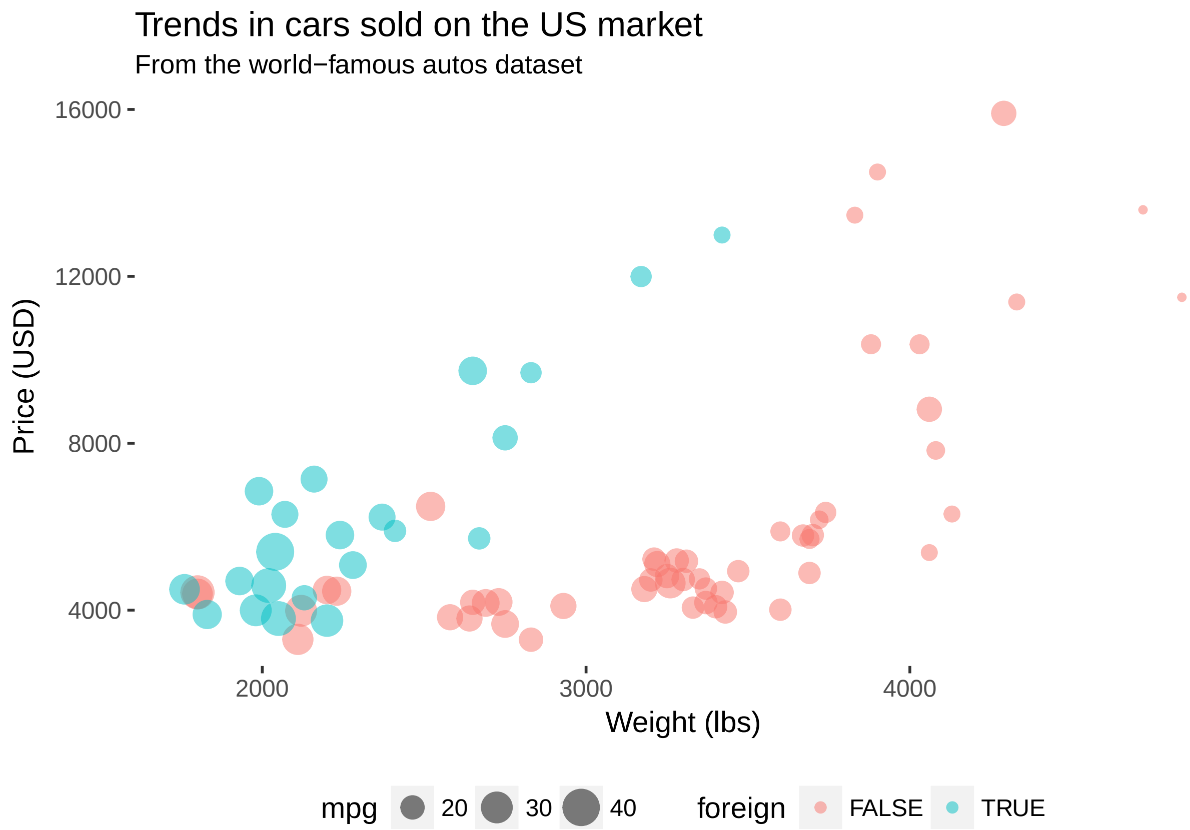
If you want even more freedom in changing the elements of your `ggplot2` theme, you can directly change them inside of `theme()`. Type `?theme` into your R console, and you will see all of the possible elements of `ggplot2`'s theme that you can edit. To change an element of the `ggplot2` theme, you need to define a new value for that element inside of `theme()` and add the `theme()` to the end of your plot. For example, to move your legend to the bottom of your figure, place `legend.position = "bottom"` inside of `theme()` and add it to your plot.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  theme(legend.position = "bottom")
```



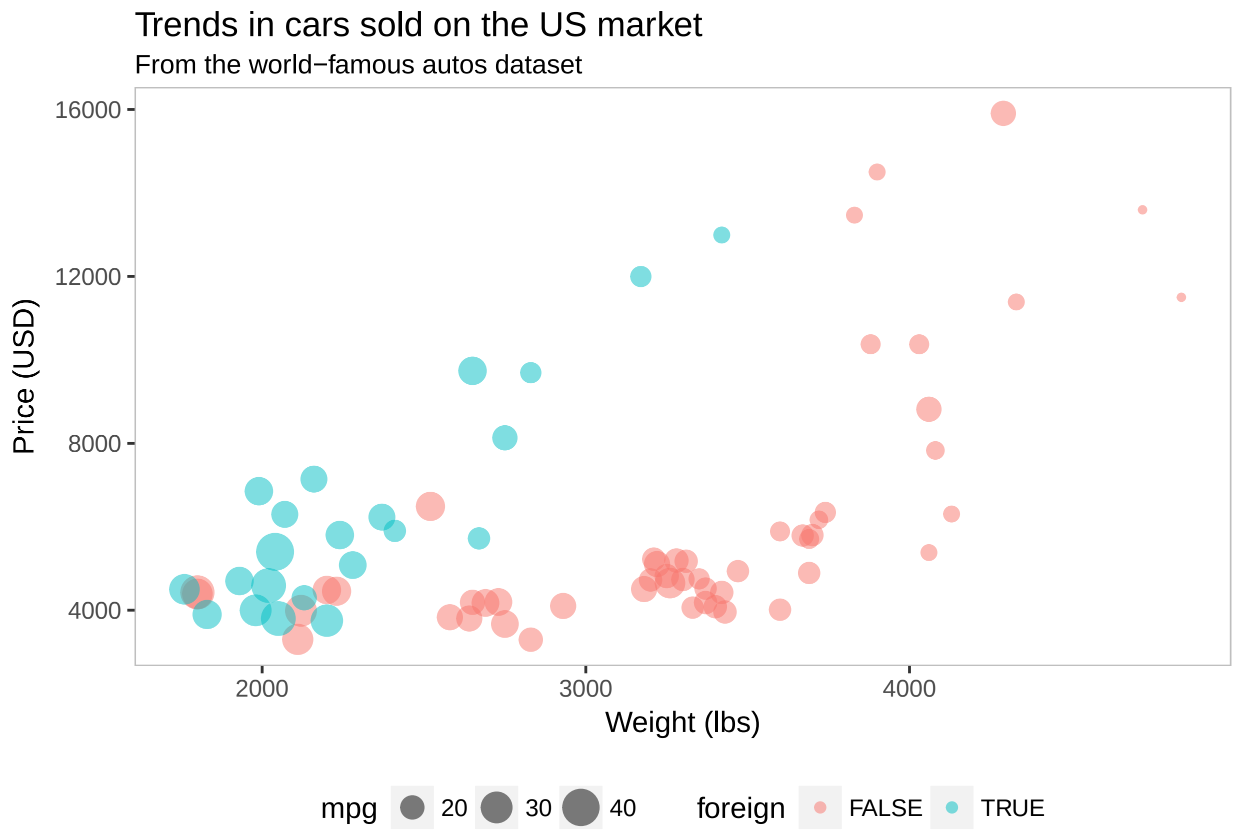
You can remove the grey background of the figure using `panel.background = element_rect(fill = NA)` inside `theme()`.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  theme(
    legend.position = "bottom",
    panel.background = element_rect(fill = NA))
```



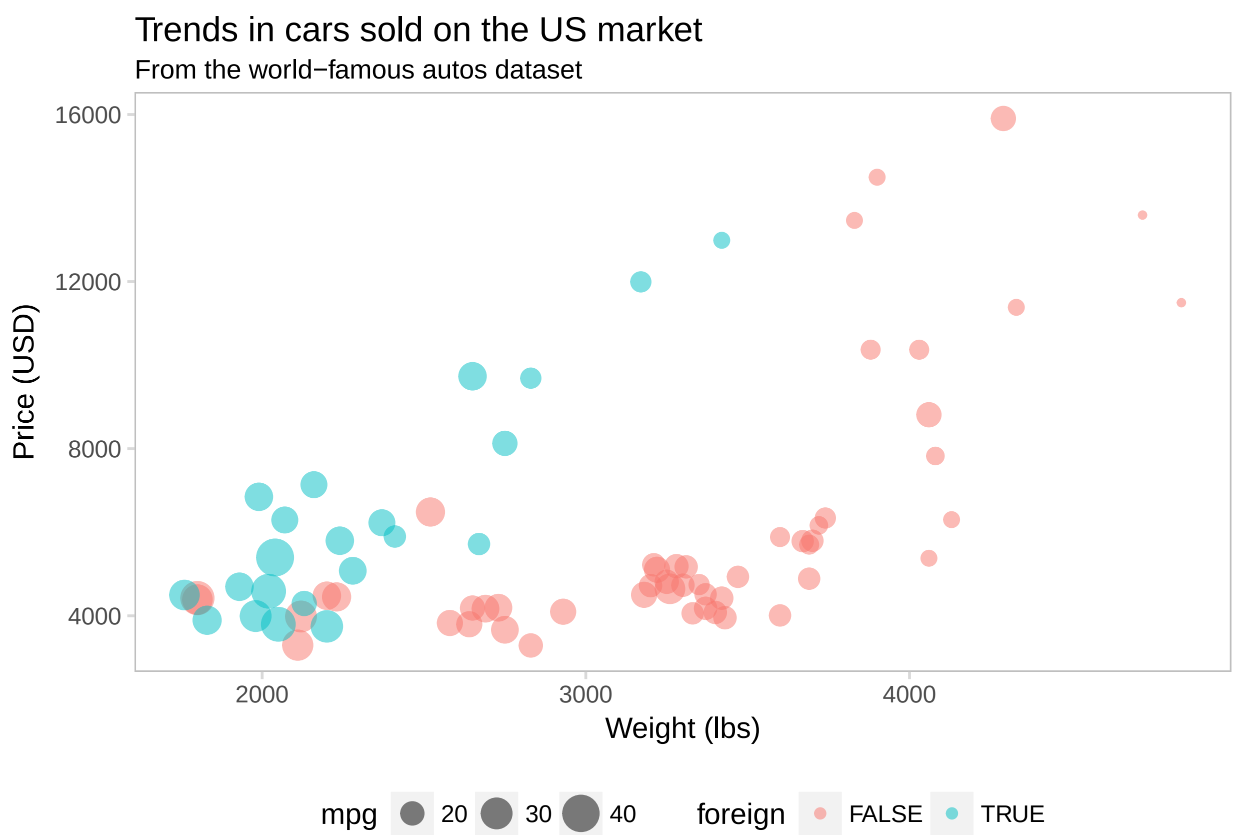
Pretty nice. But what if your advisor wants a box around the plot? We can use `panel.border` to add the border back into the theme. Let's make it grey—specificaly `grey75`, which is a fairly light grey. Note that `ggplot2` accepts values of grey starting at `grey00` (a.k.a "black") through `grey100` (a.k.a. "white").

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  theme(
    legend.position = "bottom",
    panel.background = element_rect(fill = NA),
    panel.border = element_rect(fill = NA, color = "grey75"))
```



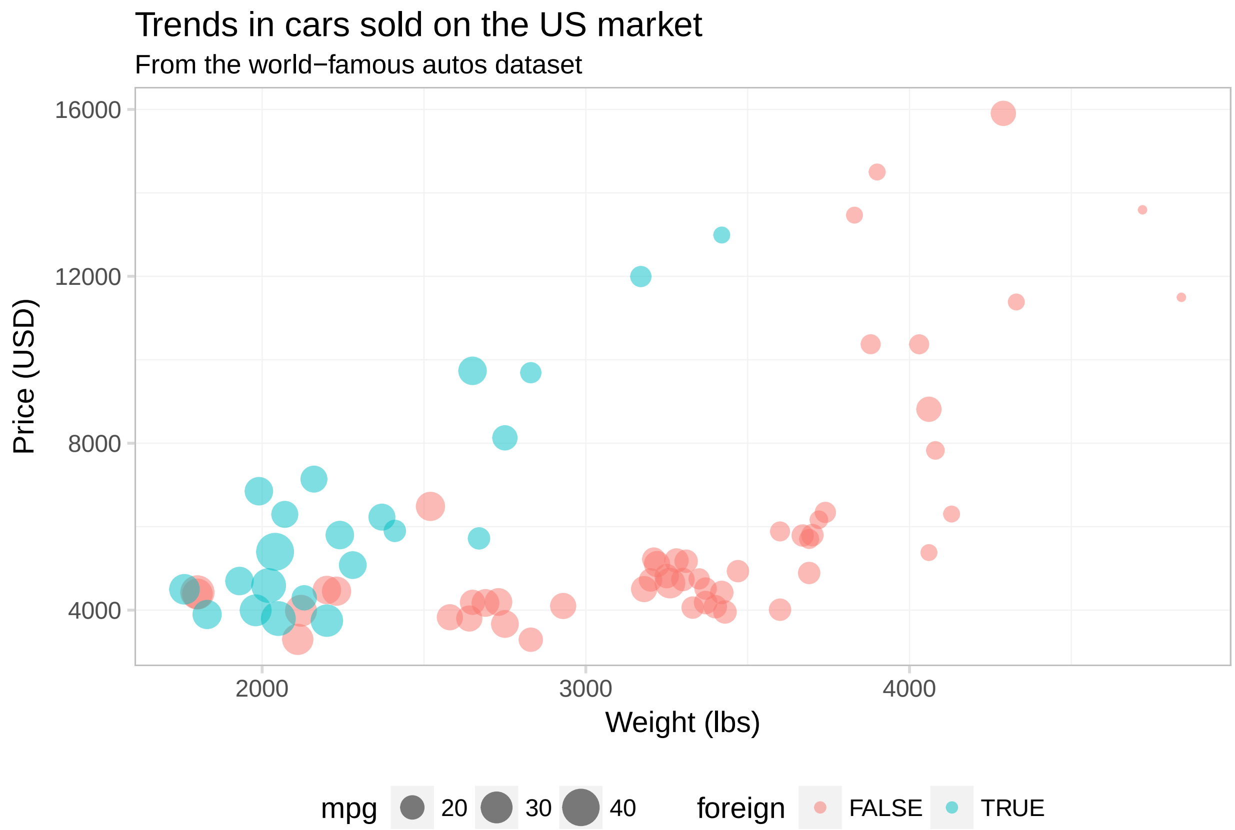
I like the lighter box, but now the ticks on the axes don't match. We should probably change their color so they are a bit lighter than the border. For this task, we will edit the color in `axis.ticks`.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  theme(
    legend.position = "bottom",
    panel.background = element_rect(fill = NA),
    panel.border = element_rect(fill = NA, color = "grey75"),
    axis.ticks = element_line(color = "grey85"))
```



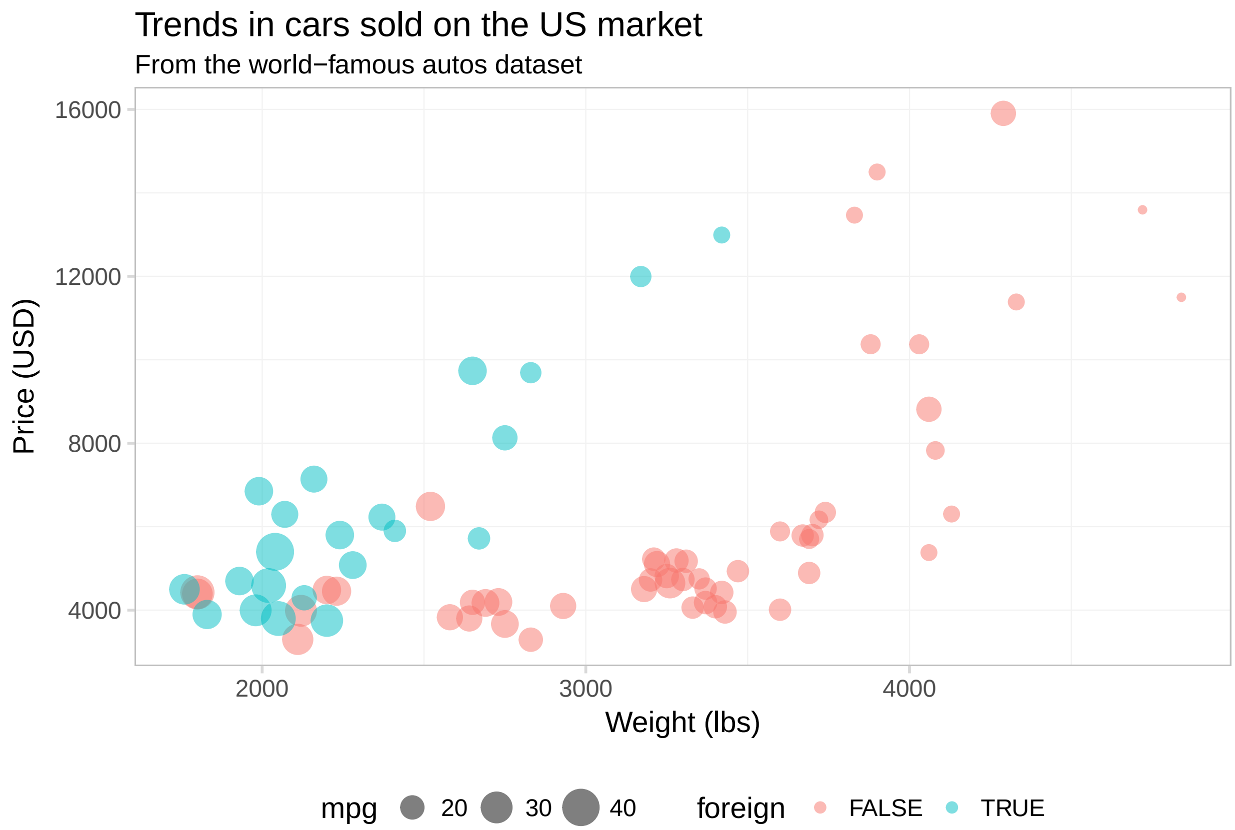
We can also add a light grid to the background of the plot.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  theme(
    legend.position = "bottom",
    panel.background = element_rect(fill = NA),
    panel.border = element_rect(fill = NA, color = "grey75"),
    axis.ticks = element_line(color = "grey85"),
    panel.grid.major = element_line(color = "grey95", size = 0.2),
    panel.grid.minor = element_line(color = "grey95", size = 0.2))
```



Finally, I am going to remove the little grey boxes around the legend elements by setting `legend.key` to `element_blank()`.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  theme(
    legend.position = "bottom",
    panel.background = element_rect(fill = NA),
    panel.border = element_rect(fill = NA, color = "grey75"),
    axis.ticks = element_line(color = "grey85"),
    panel.grid.major = element_line(color = "grey95", size = 0.2),
    panel.grid.minor = element_line(color = "grey95", size = 0.2),
    legend.key = element_blank())
```



Okay. I think the figure is looking better.

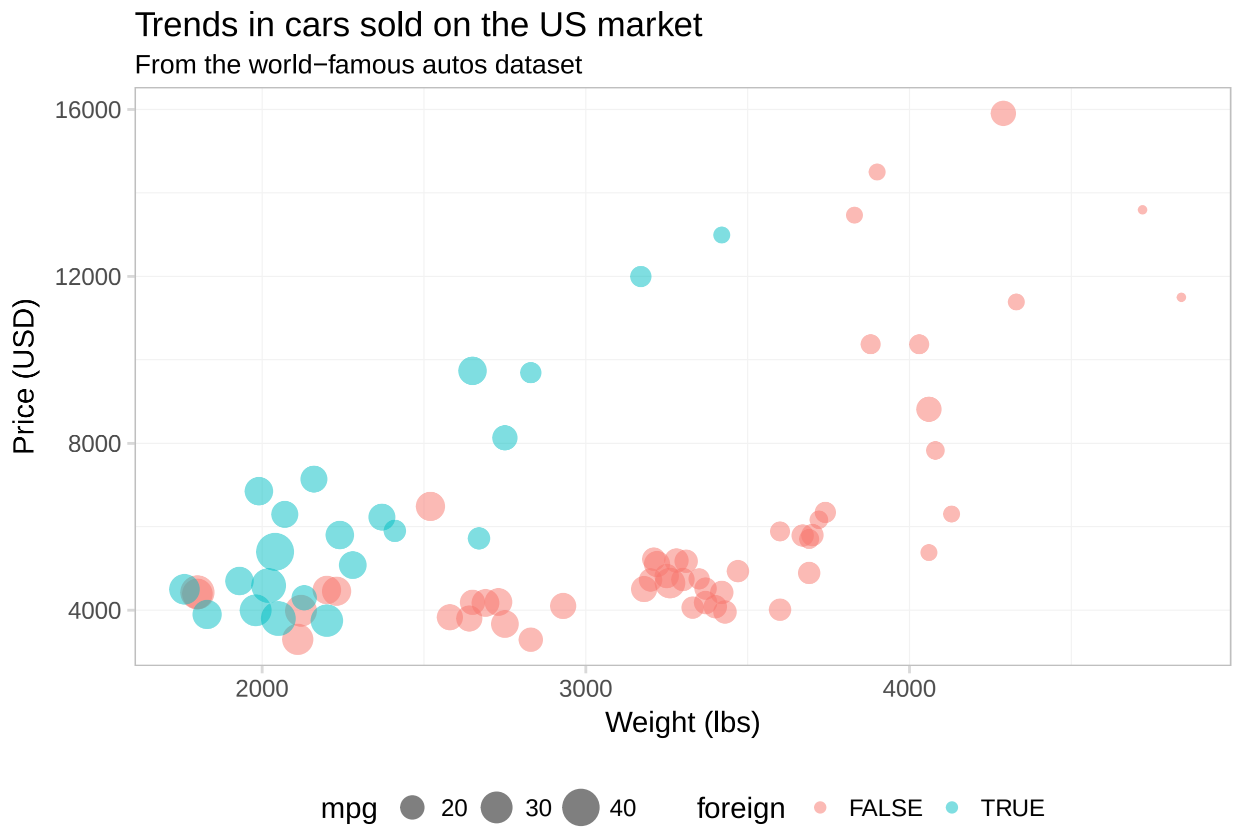
If you figure out a set of settings for the `theme` that you really like, you can create your own `theme` object to apply to your figures, just like you would write a function to avoid typing the same thing repeatedly. Creating your own theme also ensures your figures will match each other.

Let's create our own theme based upon the values in the `theme()` above:

```
theme_ed <- theme(
  legend.position = "bottom",
  panel.background = element_rect(fill = NA),
  panel.border = element_rect(fill = NA, color = "grey75"),
  axis.ticks = element_line(color = "grey85"),
  panel.grid.major = element_line(color = "grey95", size = 0.2),
  panel.grid.minor = element_line(color = "grey95", size = 0.2),
  legend.key = element_blank())
```

That's it! Now all we need to do is add `theme_ed` to the end of a figure.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  theme_ed
```



3.12 More control

Our figure is looking pretty good right at this point, but there are a few things I do not love: (1) the colors and (2) the legend labels. To change elements in the legend (colors, titles, labels, *etc.*), you will typically add a layer to your plot using a function that begins with `scale_`. Examples of these `scale_` functions include—but are not limited to—`scale_color_gradientn()`, `scale_fill_manual()`, `scale_size_continuous()`.

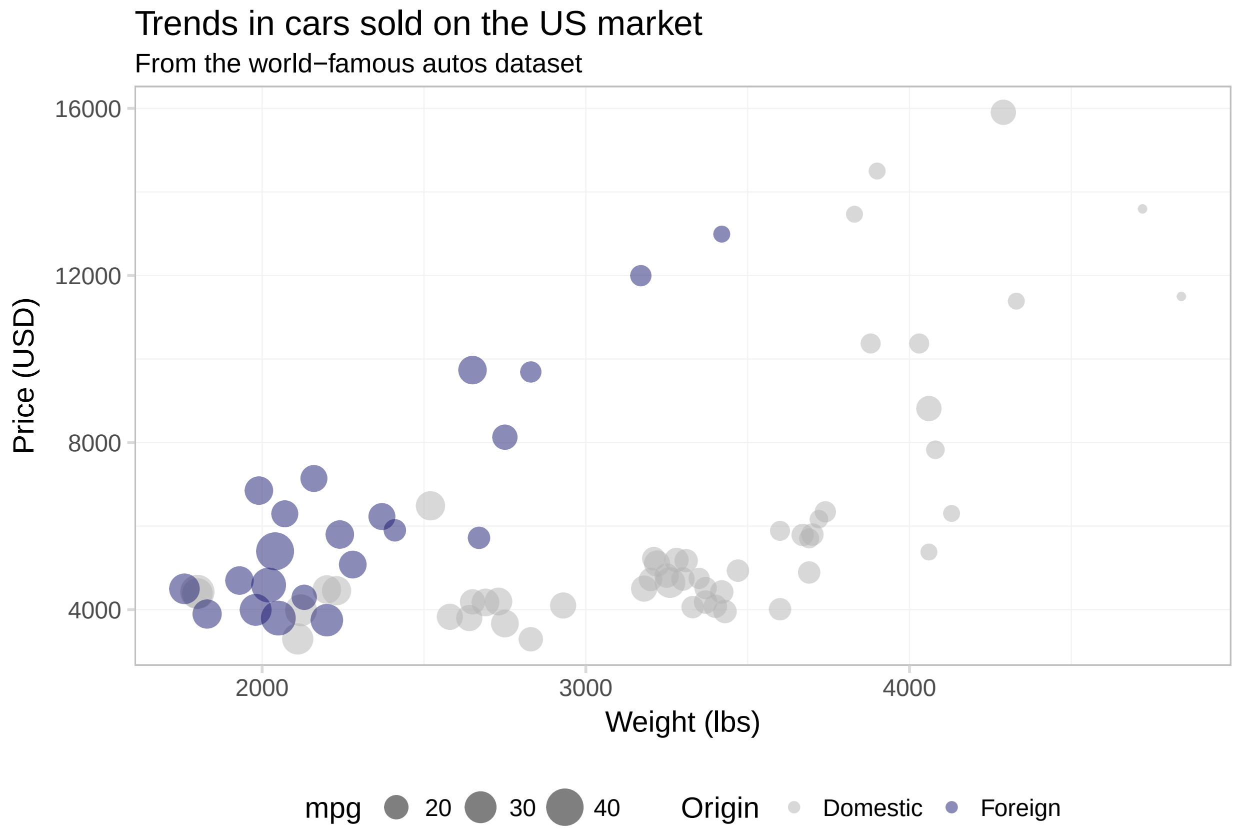
The general idea of these `scale_` functions is that the middle word is the mapped aesthetic (`size`, `color`, `shape`, *etc.*) and the last word determines how to create the scale (*e.g.*, is the scale discrete or continuous).

To customize our discrete colorscale created by mapping the variable `foreign` to `color`, we will use `scale_color_manual()`. The `manual()` suffix is for discrete color scales; if we had mapped a continuous variable to `color`, we would use one of the `scale_` functions that end with `gradient`. The `scale_color_manual()` function needs three arguments:

1. the title of the scale for the legend
2. a character vector of `values` that give the desired colors
3. a character vector of `labels` that give the labels for the legend

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.5) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
```

```
  scale_color_manual("Origin",
    values = c("grey70", "midnightblue"),
    labels = c("Domestic", "Foreign")) +
  theme_ed
```



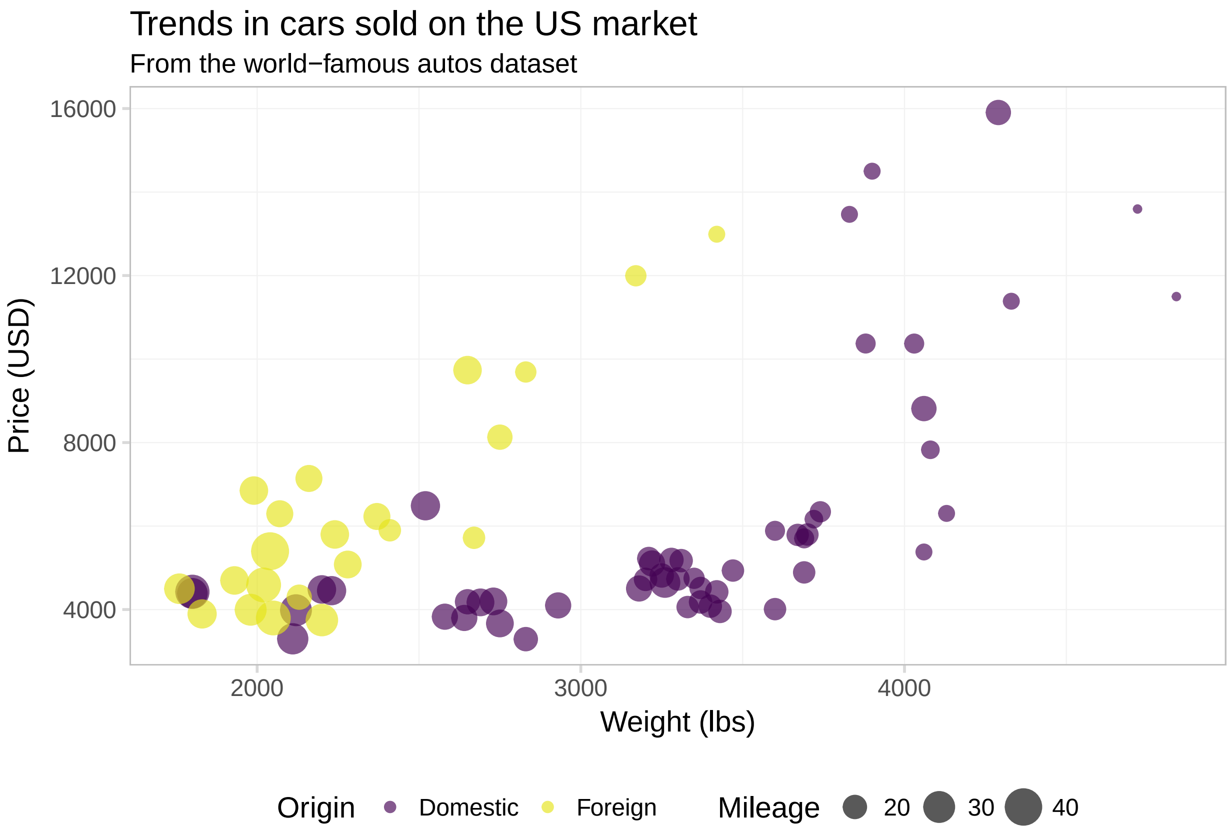
It is important to keep in mind that R defaults to alpha-numeric ordering. Our `foreign` variable takes on the values `TRUE` and `FALSE`, which means that R will place `FALSE` as the first item in the legend and `TRUE` as the second. So if we want to change the label associated with domestic cars, we need to consider how R has ordered the levels of `foreign` in the legend.

If you are having problems deciding which colors to use, there are many pre-defined color themes (palettes) in R. One example in the base installation of R is `rainbow()`. If you give `rainbow()` an integer n, it will return n colors from the rainbow palette. There are also packages written exclusively for creating color palettes. One popular option is the package `RColorBrewer`. I'm a fan of the package `viridis` because it is color-blind friendly, honest, and pretty. To learn more about it, check out the vignette on CRAN. Let's use the `viridis()` function (from the `viridis` package) to pick two colors for our figure.[9] I am also going to increase the `alpha` value a bit to make the colors a little brighter.

```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.65) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
```

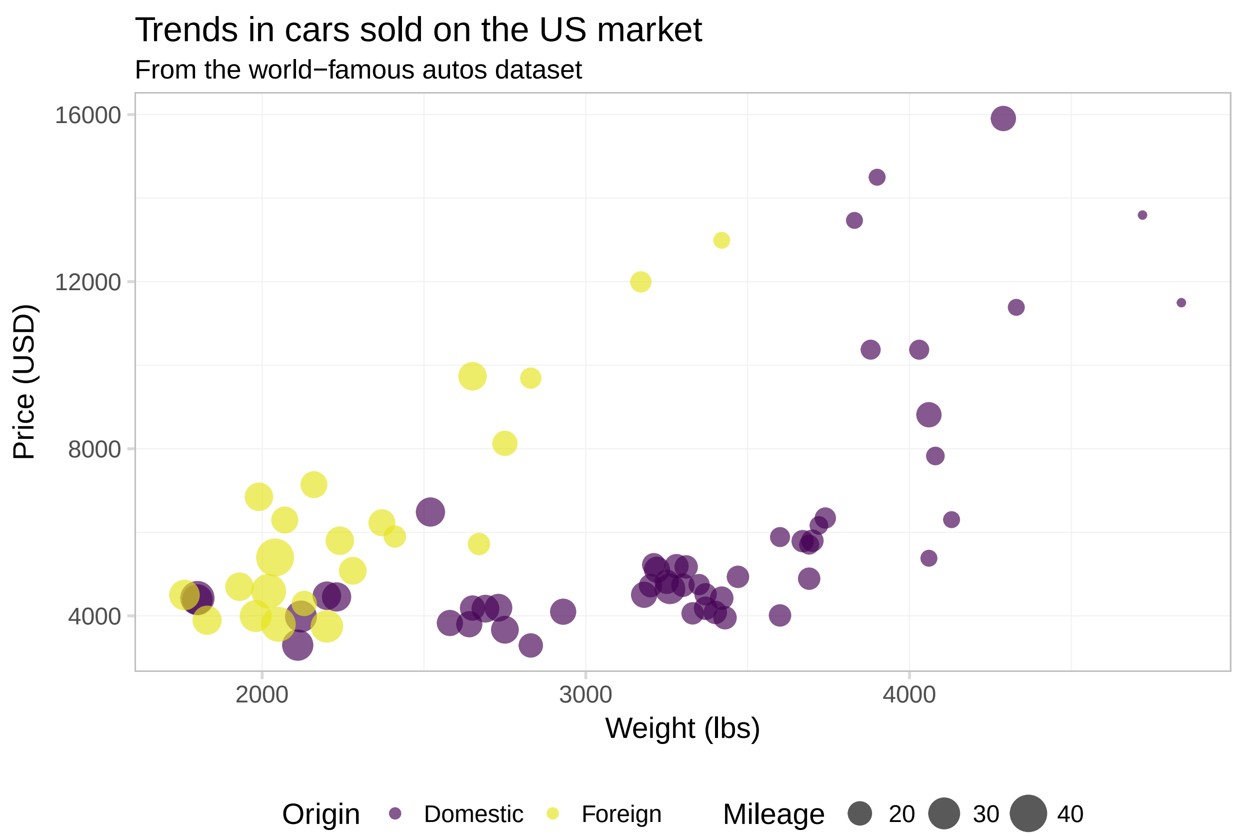
[9] The `end = 0.96` argument in `viridis()` tells the function to choose the second color slightly before the end of the colors cale. The end of the color scale is a pretty bright yellow that does not always show up well on projectors.

```
    subtitle = "From the world-famous autos dataset") +
  scale_color_manual("Origin",
    values = viridis(2, end = 0.96),
    labels = c("Domestic", "Foreign")) +
  scale_size_continuous("Mileage") +
  theme_ed
```



Now, let's change the title of the `mpg` variable in our legend. Because we've mapped `mpg` to `size`, and because `mpg` is a continuous variable, we will use the function `scale_size_continuous()`.

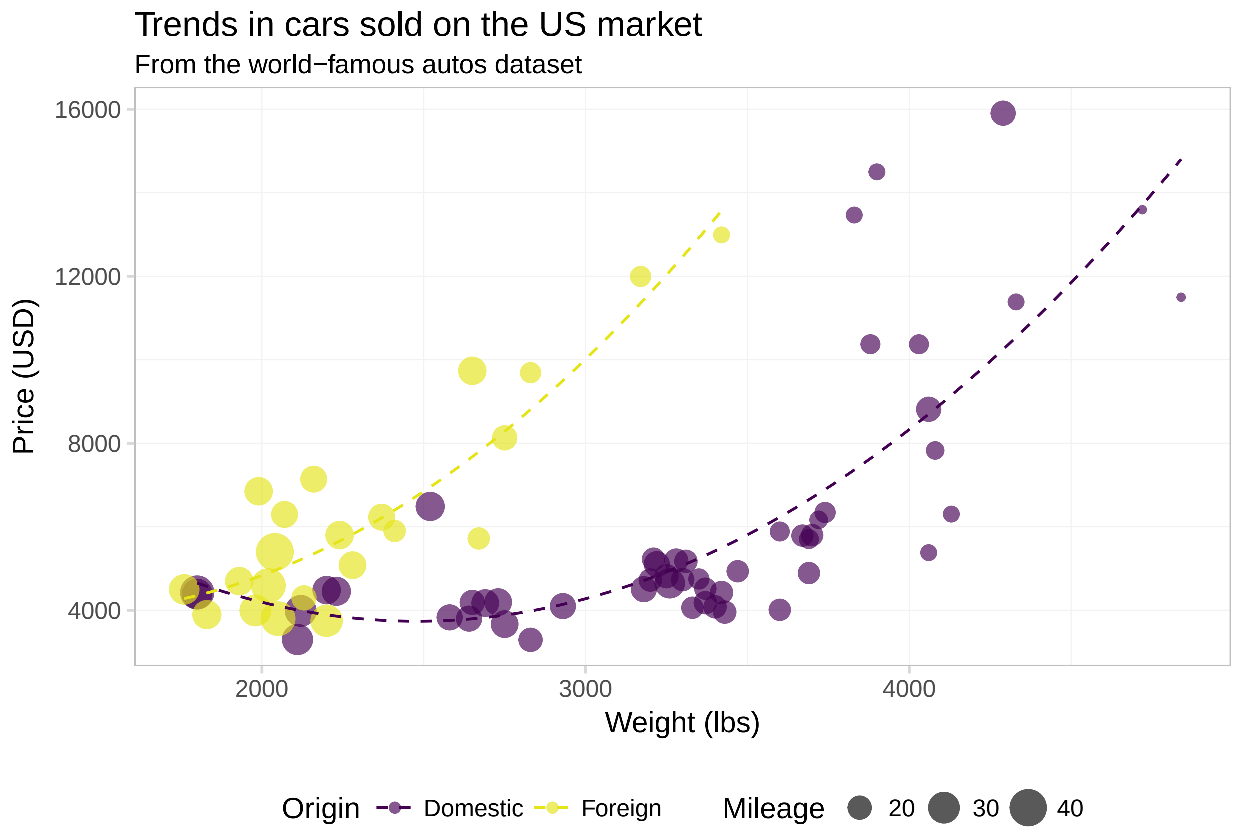
```
ggplot(data = cars, aes(x = weight, y = price)) +
  geom_point(aes(color = foreign, size = mpg), alpha = 0.65) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  scale_color_manual("Origin",
    values = viridis(2, end = 0.96),
    labels = c("Domestic", "Foreign")) +
  scale_size_continuous("Mileage") +
  theme_ed
```



Notice that order of the layers matters: because we changed `scale_size_continuous()` last, it now prints second in the legend (after `scale_color_manual()`).

Finally, let's add the quadratic regression lines without confidence intervals. I am going to move `color = foreign` from the `aes()` inside of `geom_point()` to the `aes()` inside `ggplot()` to force `ggplot2` to calculate the regression for domestic and foreign cars separately. We will also make the lines a bit thinner (`size = 0.5`) and dashed (`linetype = 2`).

```
ggplot(data = cars,
  aes(x = weight, y = price, color = foreign)) +
  geom_point(alpha = 0.65, aes(size = mpg)) +
  geom_smooth(method = "lm", formula = y ~ x + I(x^2),
    se = F, size = 0.5, linetype = 2) +
  xlab("Weight (lbs)") +
  ylab("Price (USD)") +
  ggtitle("Trends in cars sold on the US market",
    subtitle = "From the world-famous autos dataset") +
  scale_color_manual("Origin",
    values = viridis(2, end = 0.96),
    labels = c("Domestic", "Foreign")) +
  scale_size_continuous("Mileage") +
  theme_ed
```



Alright. I think we've done enough with this one figure. Let's talk about a few other geometries in the `ggplot2` library.

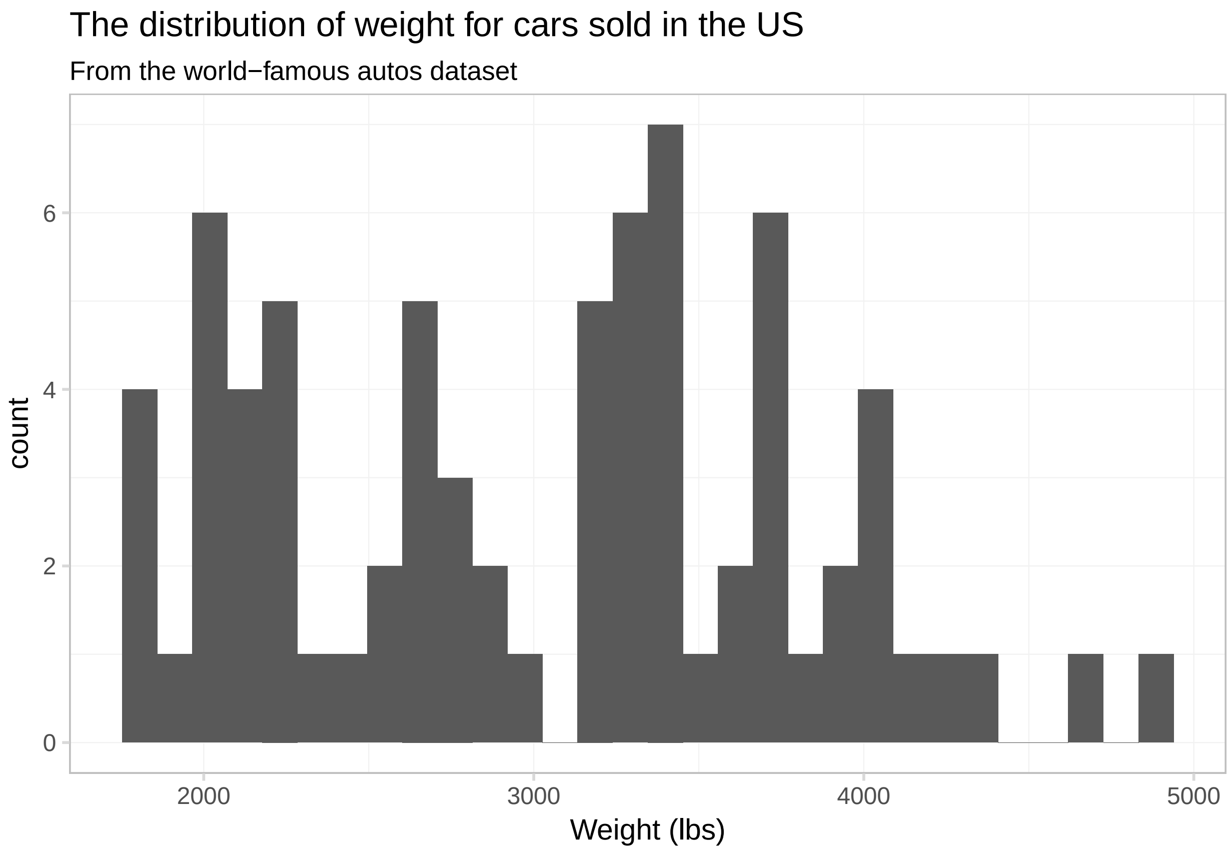
3.13 Histograms and density plots

Two common and related geometries are `geom_histogram()` and `geom_density()`. As you might guess, `geom_histogram()` creates histograms, and `geom_density()` creates smoothed density estimates. Let's check out the histogram of weights from our `cars` data. The big differences here—compared to our figures above—are

1. We need to use `geom_histogram()` rather than `geom_point()`
2. We will only map the `x` to `weight` (no mapping for `y`).

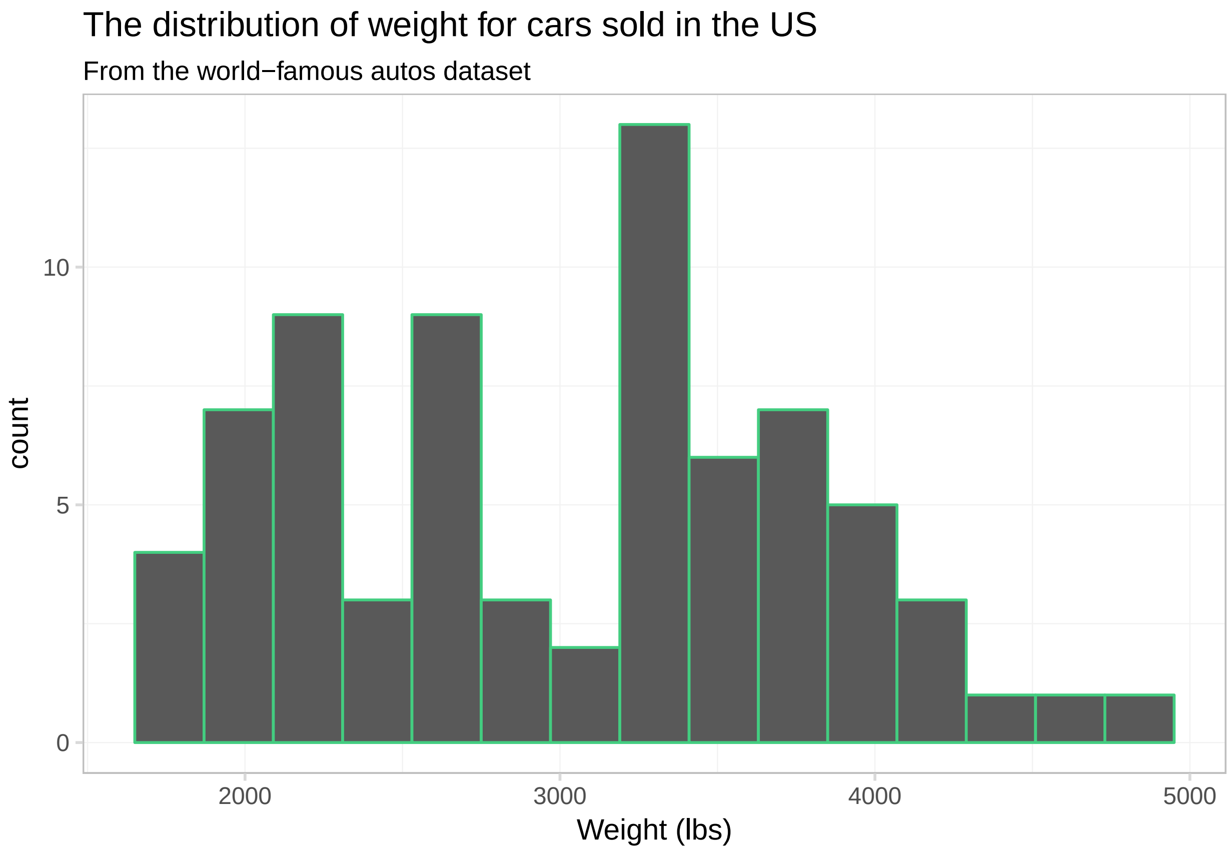
```
ggplot(data = cars, aes(x = weight)) +
  geom_histogram() +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  theme_ed
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



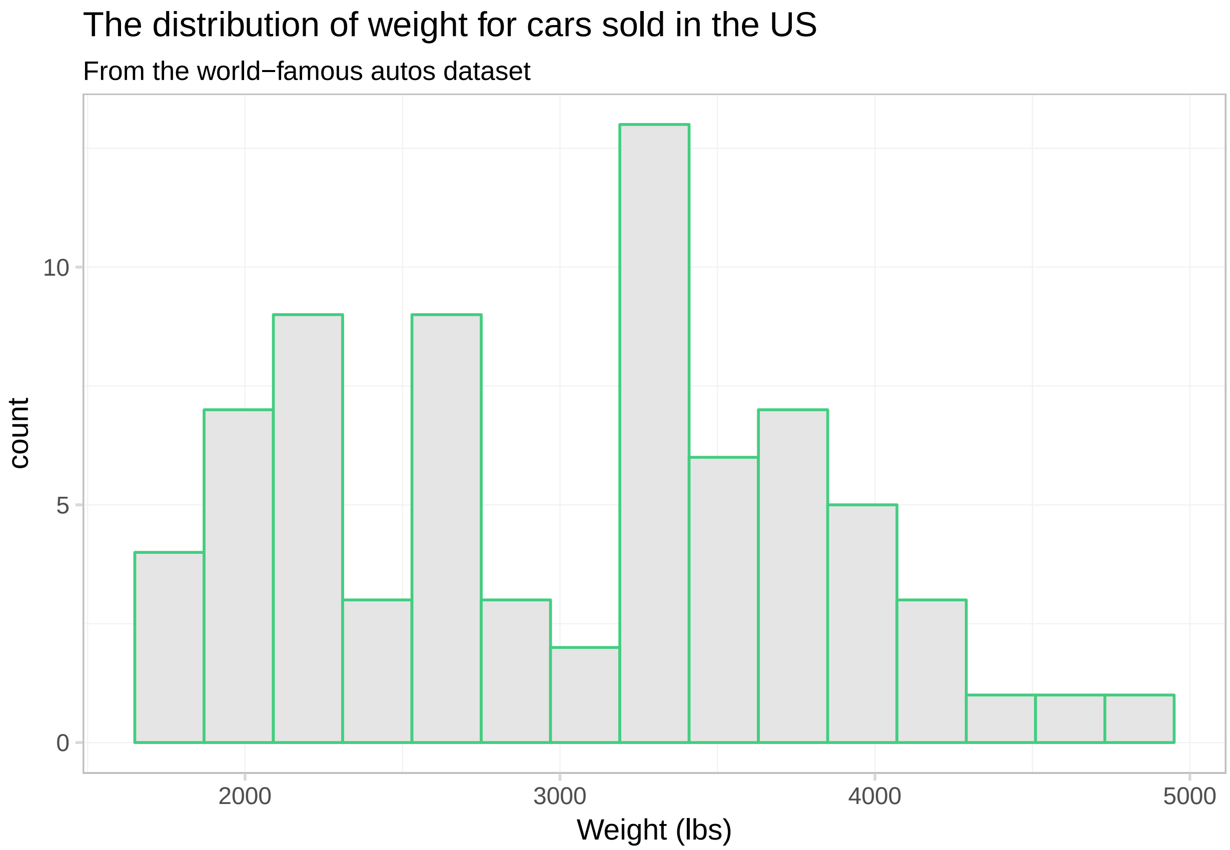
Not terrible, but I think we have too many bins. Let's tell `ggplot2` that we only want 15 bins. To change the number of bins, we can give `geom_histogram()` an optional argument of `bins`. Let's also see what happens when we give `geom_histogram()` a color, *i.e.*, `color = "seagreen3"`.

```
ggplot(data = cars, aes(x = weight)) +
  geom_histogram(bins = 15, color = "seagreen3") +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  theme_ed
```



We now have 15 bins. You probably also noticed that each bin now has a sea green border. This colored border resulted from `color = "seagreen3"`. If we want to fill the histogram's bins with a color, we should use the `fill` argument, *i.e.*, `fill = "grey90"`. Let's try again.

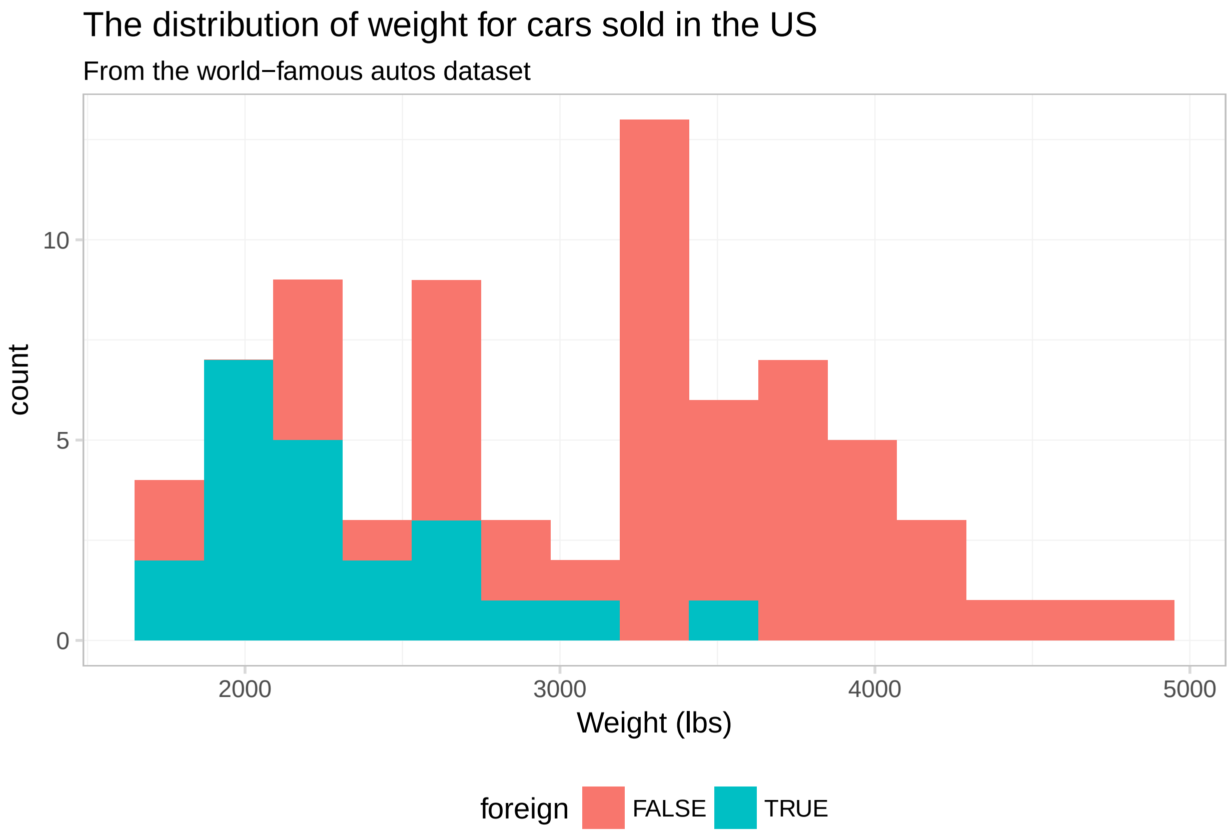
```
ggplot(data = cars, aes(x = weight)) +
  geom_histogram(bins = 15, color = "seagreen3", fill = "grey90") +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  theme_ed
```



Okay, it worked. Not necessarily the prettiest graph in the world—I'm not sure what the green borders are adding to our figure—but the point is that `color` and `fill` do different things.

What if we want to plot separate histograms for foreign and domestic cars? We need to map an aesthetic to the variable `foreign`, but which aesthetic do we want? Probably `fill`—color will only vary the border on the bins. Let's map `fill` to `foreign` and see what happens.

```
ggplot(data = cars, aes(x = weight)) +
  geom_histogram(bins = 15, aes(fill = foreign)) +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  theme_ed
```

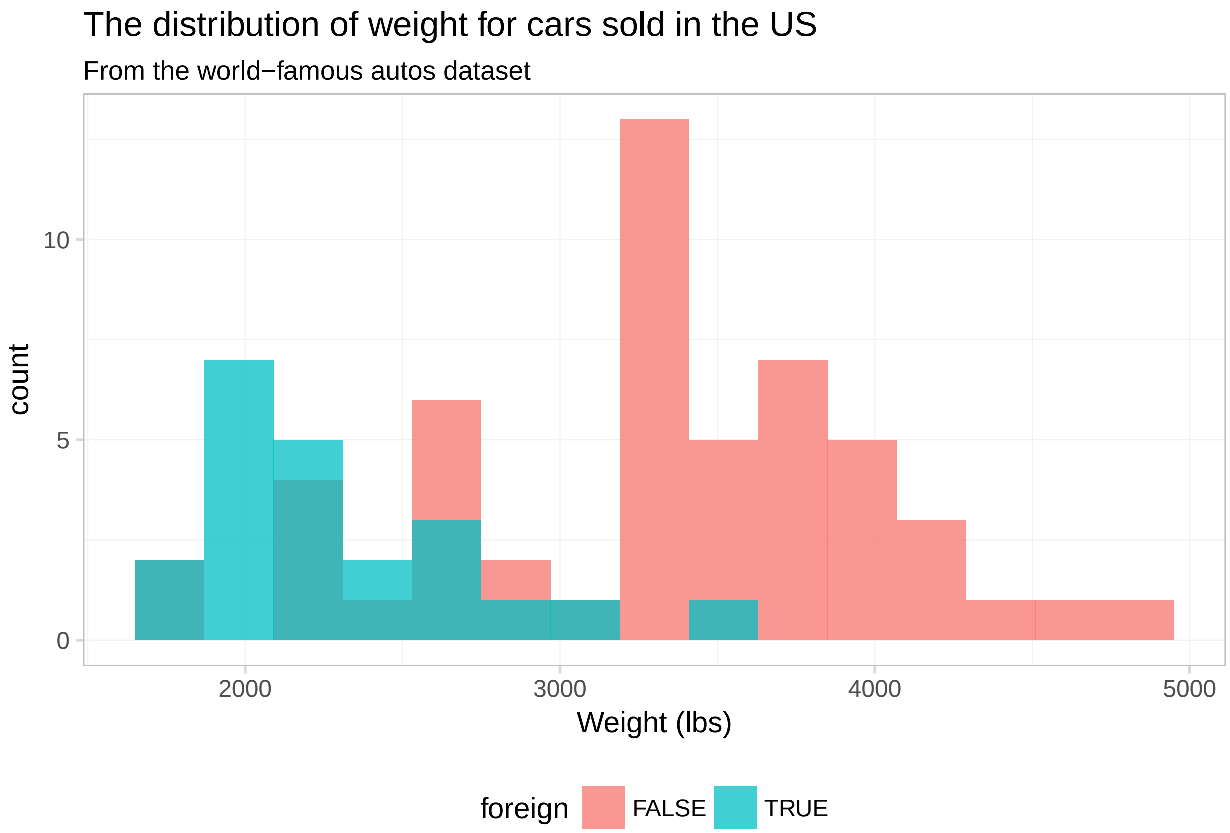


Strange. It looks like someone is about to lose at Tetris.

To see what is going on here, compare this figure to the previous figure. Notice that the two figures have the same histogram shape—`ggplot2` is not creating separate histograms. Instead, `ggplot2` is `fill`-ing the histogram based upon the variable `foreign`—essentially stacking the histograms. We can tell `ggplot2` that want to let the histograms overlap—as opposed to stacking them—using the argument `position = "identity"` inside `geom_histogram( )`:[10]

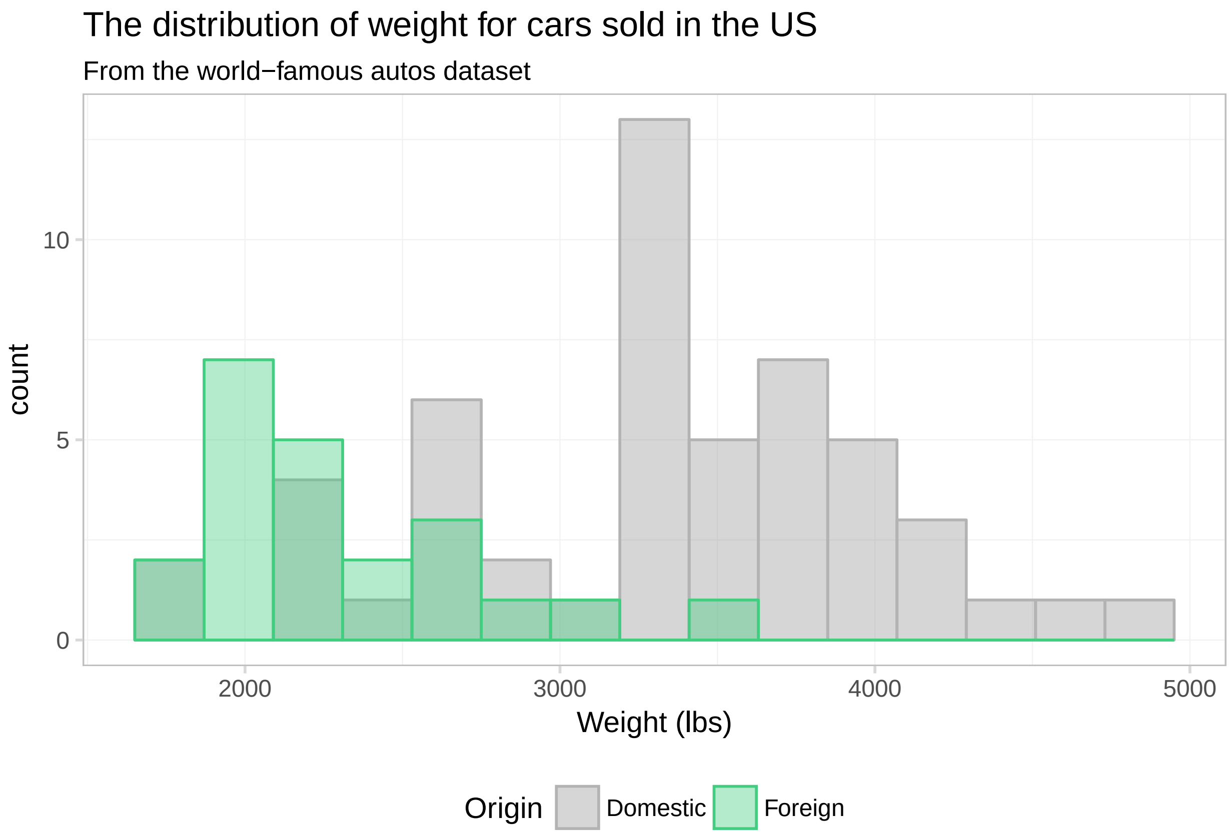
```
ggplot(data = cars, aes(x = weight)) +
  geom_histogram(aes(fill = foreign),
    bins = 15, position = "identity", alpha = 0.75) +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  theme_ed
```

[10] I also add `alpha = 0.75` so we can tell if the two histograms overlap.



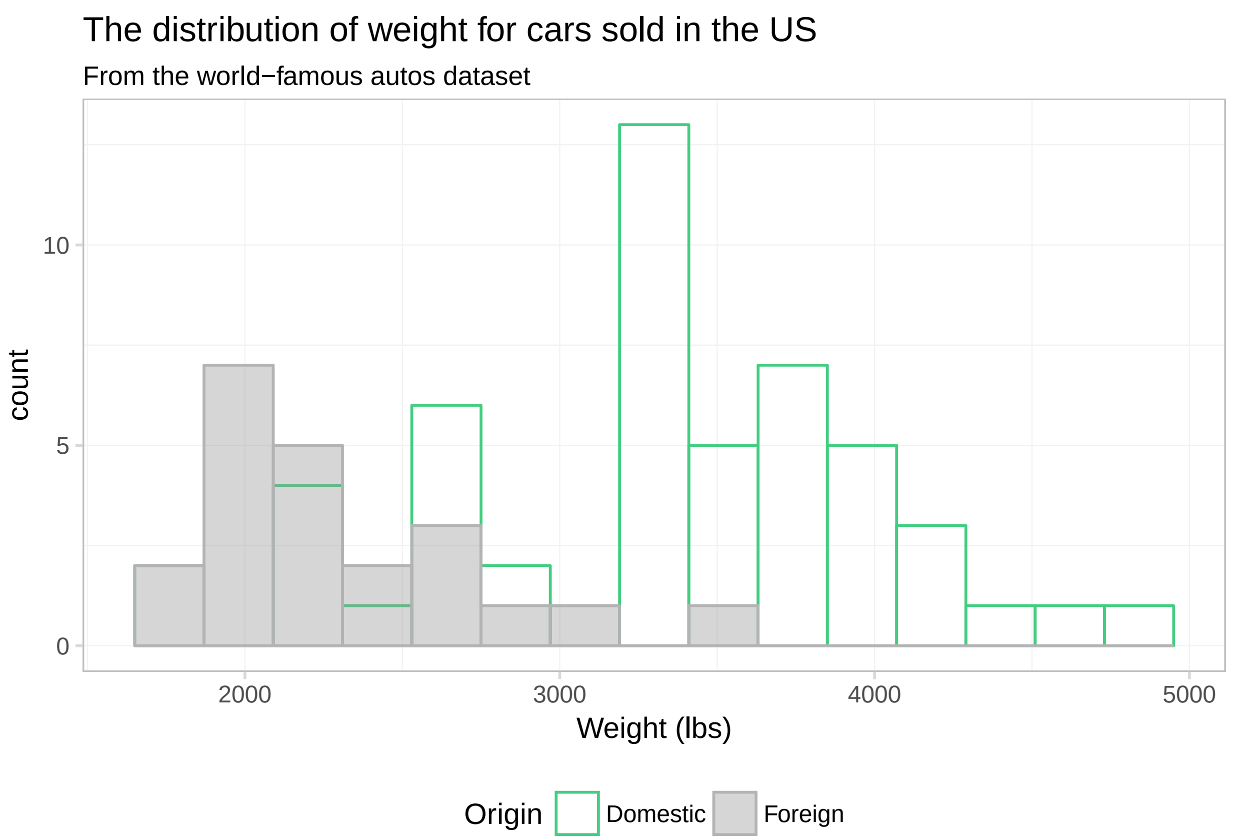
No you can see why `ggplot2` defaults to stacking—this figure does not really present a clear picture of what is going on. Let's see if we can clean this figure up a bit.

```
ggplot(data = cars, aes(x = weight)) +
  geom_histogram(aes(color = foreign, fill = foreign),
    bins = 15, position = "identity", alpha = 0.4) +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  scale_color_manual("Origin",
    values = c("grey70", "seagreen3"),
    labels = c("Domestic", "Foreign")) +
  scale_fill_manual("Origin",
    values = c("grey60", "seagreen3"),
    labels = c("Domestic", "Foreign")) +
  theme_ed
```



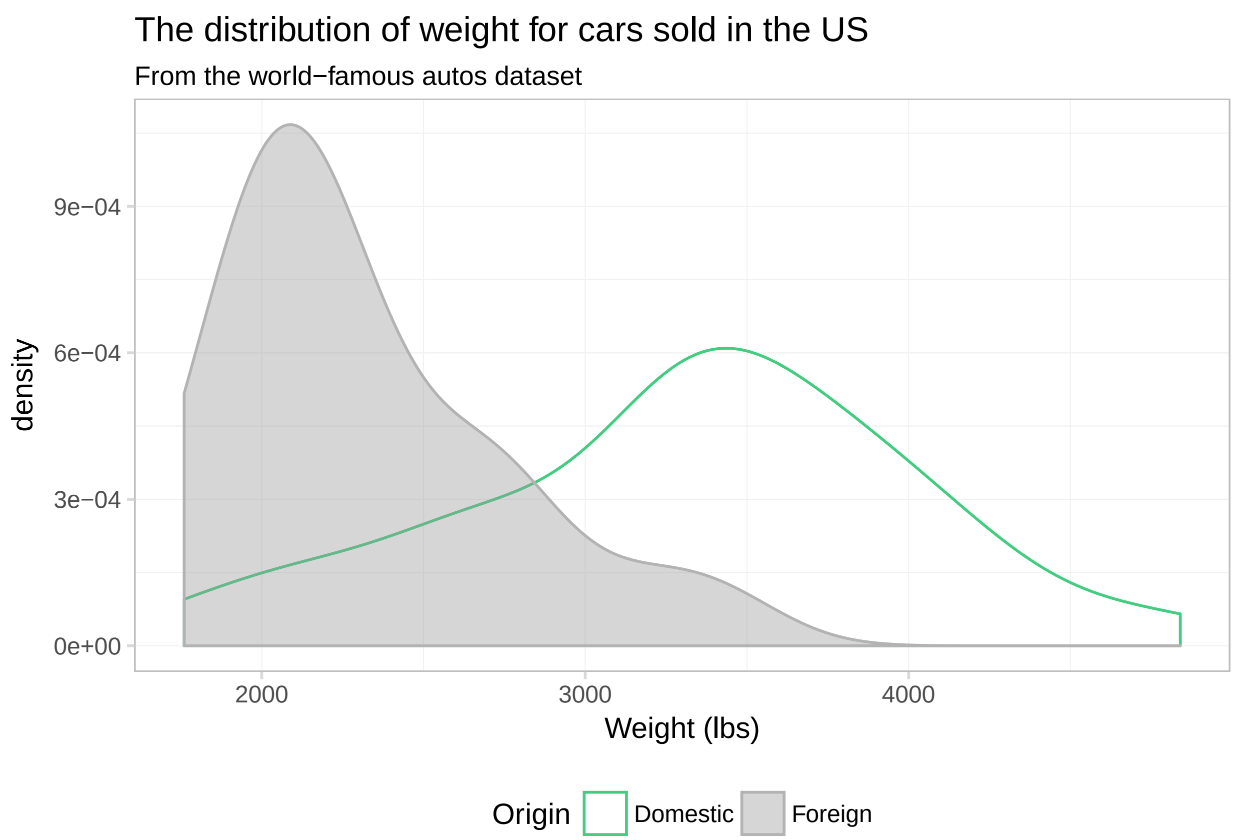
That's a bit better. What if we just drop one of the fills altogether? Instead of assigning a color in `scale_fill_manual()`, we can just assign `NA`:

```
ggplot(data = cars, aes(x = weight)) +
  geom_histogram(aes(color = foreign, fill = foreign),
    bins = 15, position = "identity", alpha = 0.4) +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  scale_color_manual("Origin",
    values = c("seagreen3", "grey70"),
    labels = c("Domestic", "Foreign")) +
  scale_fill_manual("Origin",
    values = c(NA, "grey60"),
    labels = c("Domestic", "Foreign")) +
  theme_ed
```



Maybe. I still think the overlapping bins are a little confusing. Let's try a density plot. We can essentially swap `geom_density()` for `geom_histogram()`. We just drop `bins = 15`, as the density plot does not have bins.

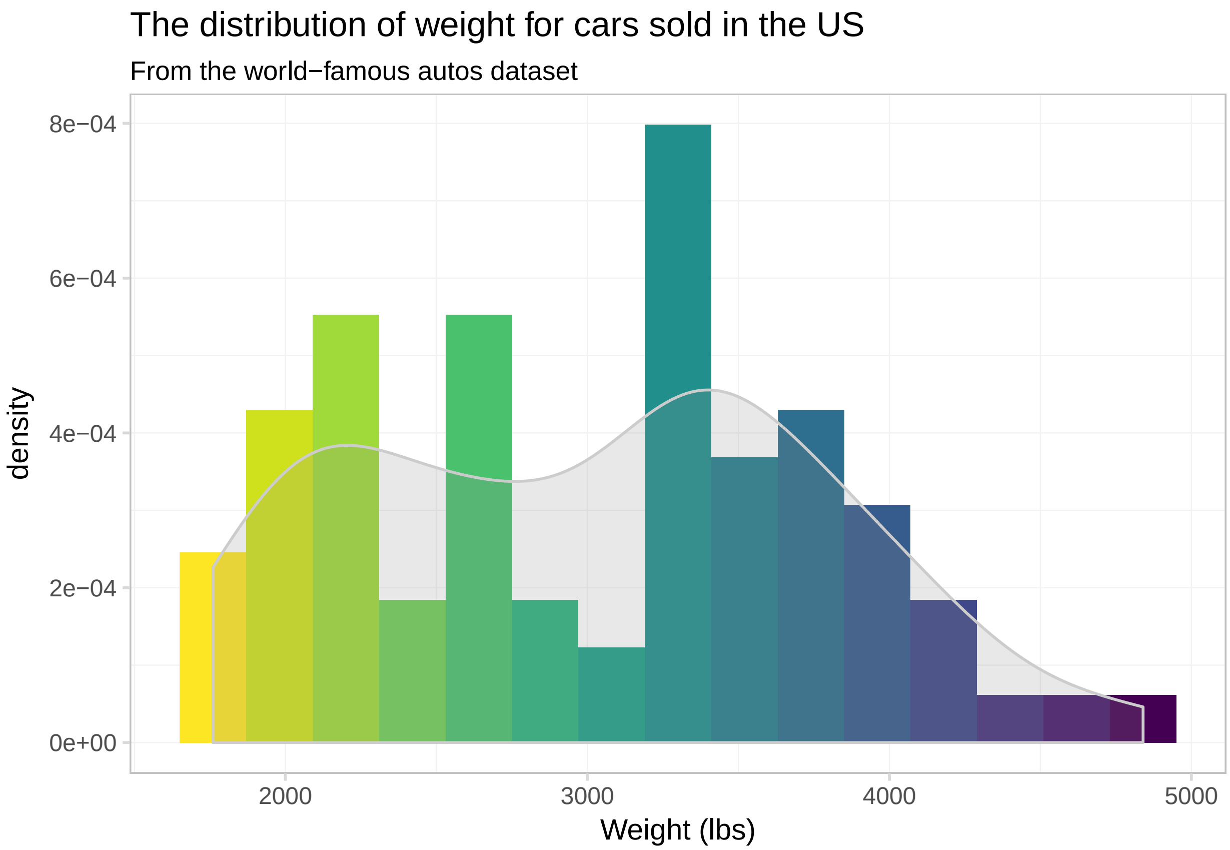
```
ggplot(data = cars, aes(x = weight)) +
  geom_density(aes(color = foreign, fill = foreign),
    alpha = 0.4) +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  scale_color_manual("Origin",
    values = c("seagreen3", "grey70"),
    labels = c("Domestic", "Foreign")) +
  scale_fill_manual("Origin",
    values = c(NA, "grey60"),
    labels = c("Domestic", "Foreign")) +
  theme_ed
```



I would say this plot provides a lot more insight than any of the histograms we produced above.

Notice that the y-axis has changed from *count* to *density*, as we are now approximating a continuous distribution. You can force `ggplot2` to give you a density-based y-axis for histograms by mapping the aesthetic `y` to `..density..`, which is a variable that `ggplot2` calculates in the process of making the plot. Using this option, we can plot a histogram and density plot in the same figure. And just for fun, let's color each bin of the histogram a different color. Because we are not mapping a variable to the `color` aesthetic, our call to `color` needs to be outside of the `aes()` in `geom_histogram()`. I'm going to using 15 colors from `viridis()`, and I am going to reverse them using the `rev()` function. Handy, right?

```
ggplot(data = cars, aes(x = weight)) +
  geom_histogram(aes(y = ..density..),
    bins = 15, color = NA, fill = rev(viridis(15))) +
  geom_density(fill = "grey55", color = "grey80", alpha = 0.2) +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  theme_ed
```



Well… it's colorful, if nothing else. I'm not sure the individually colored bins provide much information.

3.14 Saving

Saving the your `ggplot2` figures is pretty straightforward: you use the `ggsave()` function. The arguments you will typically use in `ggsave()`:

- `filename`: the name you wish to give your saved plot, including the suffix that denotes the file type (*e.g.*, `.png`, `.pdf`, or `.jpg`)
- `plot`: the name of the plot to save. If you do not specify a plot, `ggsave()` will save the last plot that `ggplot2` displayed.
- `path`: the path (dirctory) where you would like to save your figure. The default is the current working directory.
- `width` and `height`: the dimensions of the outputted figure (the default is inches).

Thus, if you want to save the last figure that `ggplot2` displayed as a PDF, we can write

```
ggsave(filename = "ourNewFigure.pdf", width = 16, height = 10)
```

This line of R code will save the plot in our current working directory as a 16-by-10 (inch) PDF.

You can also prevent a `ggplot2` figure from displaying on your screen by assigning it to a name like a normal object in R:

```
our_histogram <- ggplot(data = cars, aes(x = weight)) +
  geom_histogram(aes(y = ..density..),
```

```r
    bins = 15, color = NA, fill = rev(viridis(15))) +
  geom_density(fill = "grey55", color = "grey80", alpha = 0.2) +
  xlab("Weight (lbs)") +
  ggtitle("The distribution of weight for cars sold in the US",
    subtitle = "From the world-famous autos dataset") +
  theme_ed
```

The figure is now stored as `our_histogram` and did not print to the screen.

Now we can save `our_histogram` to my desktop (as PNG):

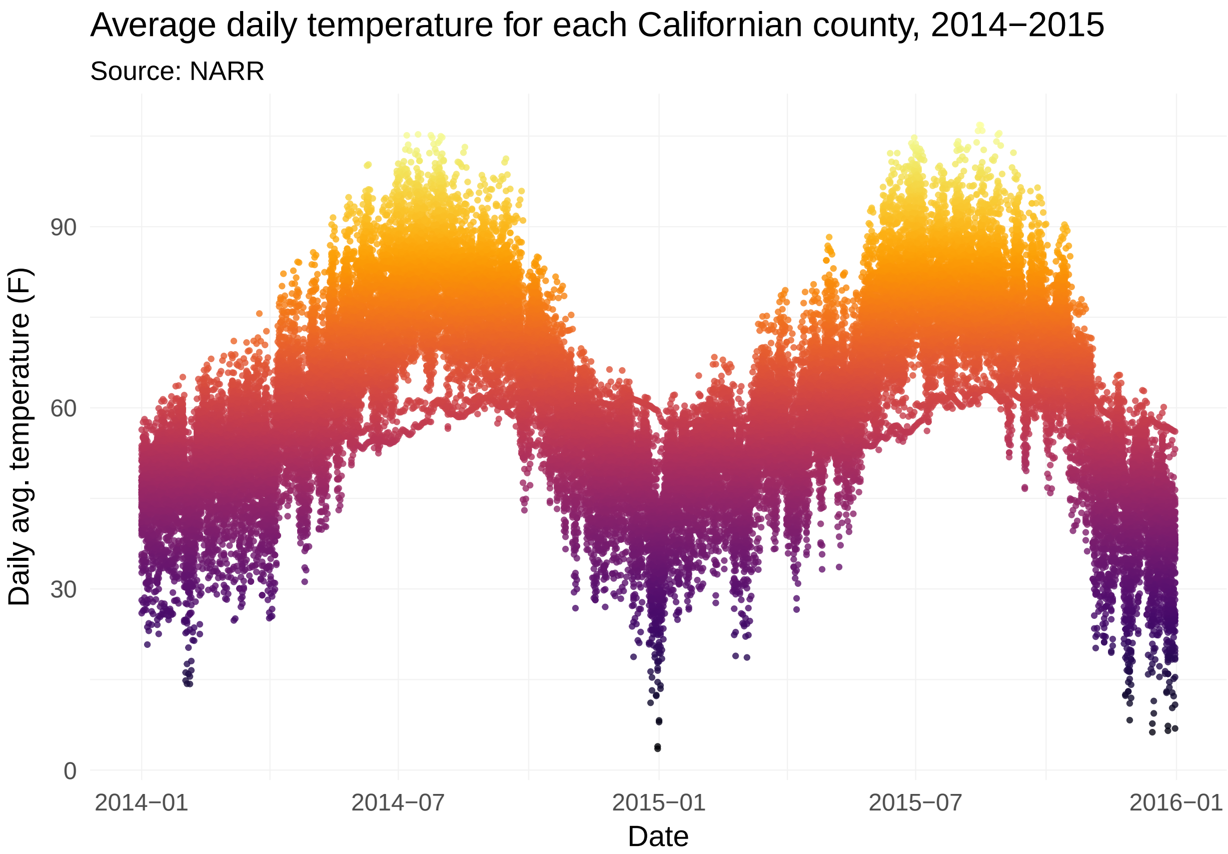
```r
ggsave(filename = "anotherHistogram.png", plot = our_histogram,
  path = "/Users/edwardarubin/Desktop", width = 10, height = 8)
```

3.15 Still more

We have only scratched the surface of `ggplot2`. Check out the documentation for `ggplot2`: there are a lot of geometries and aesthetics that we have not covered here. I'll leave you with a few examples:

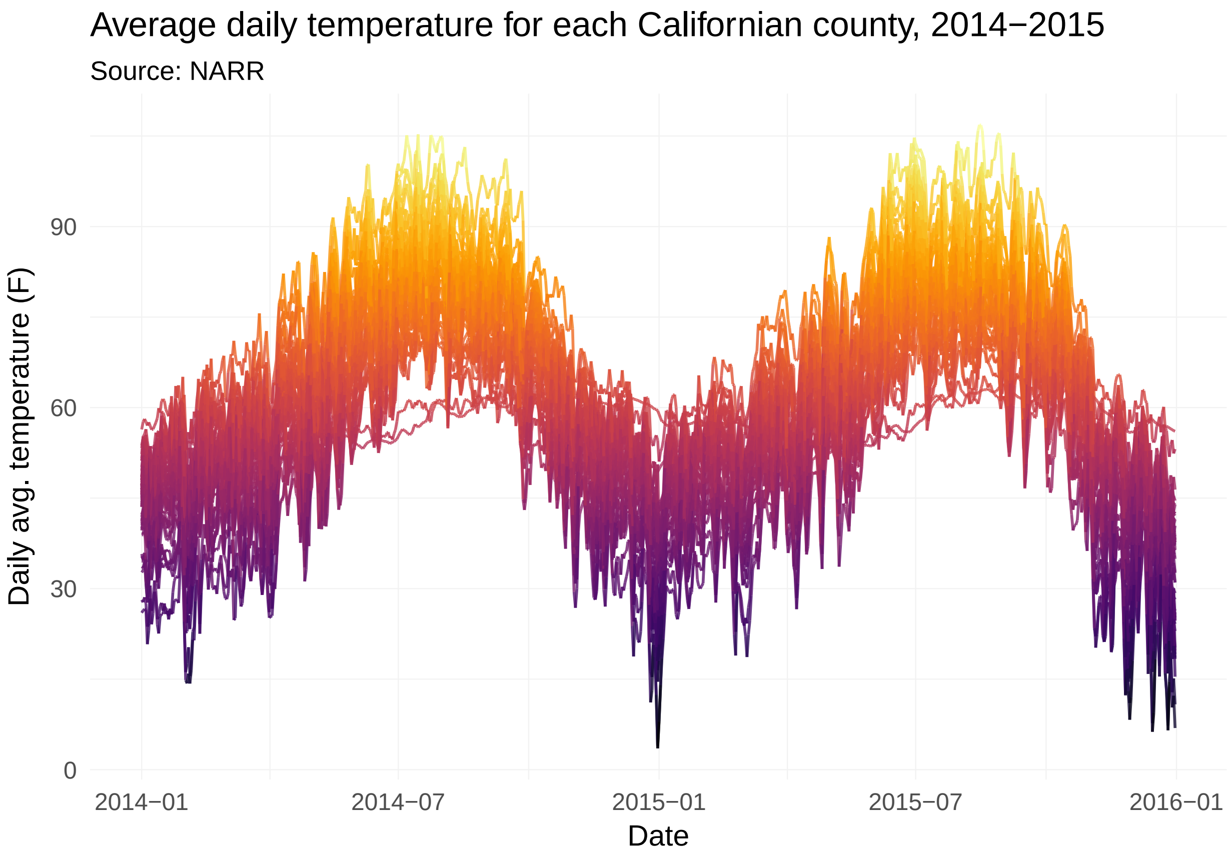
Daily average temperatures for each county in California, 2014–2015:

```r
ggplot(data = filter(weather_df, state == "06"),
  aes(x = date, y = temp)) +
  geom_point(aes(color = temp), size = 0.5, alpha = 0.8) +
  xlab("Date") +
  ylab("Daily avg. temperature (F)") +
  ggtitle(paste("Average daily temperature for",
    "each Californian county, 2014-2015"),
    subtitle = "Source: NARR") +
  scale_color_viridis(option = "B") +
  theme_ed +
  theme(
    panel.border = element_blank(),
    axis.ticks = element_blank(),
    legend.position = "none")
```



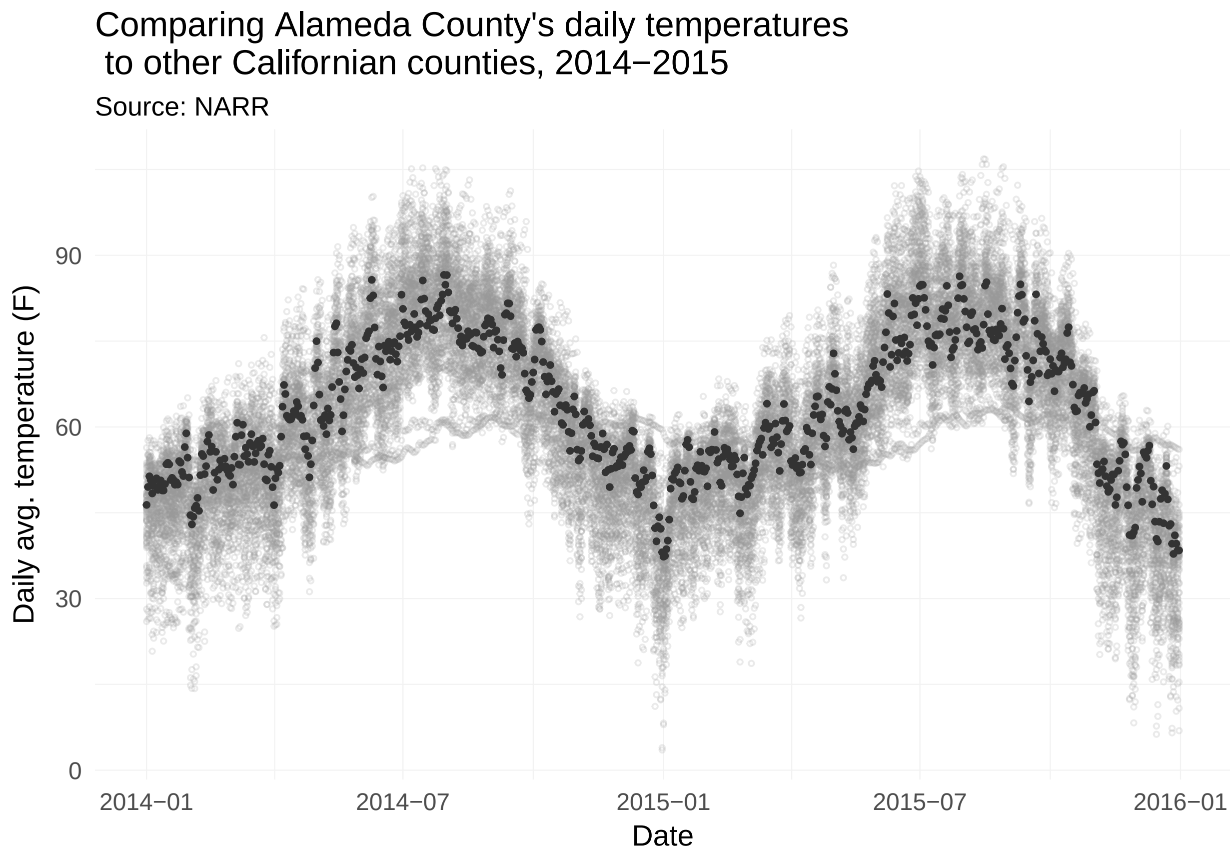
Now with lines.

```
ggplot(data = filter(weather_df, state == "06"),
  aes(x = date, y = temp, group = fips)) +
  geom_line(aes(color = temp), size = 0.5, alpha = 0.8) +
  xlab("Date") +
  ylab("Daily avg. temperature (F)") +
  ggtitle(paste("Average daily temperature for",
    "each Californian county, 2014-2015"),
    subtitle = "Source: NARR") +
  scale_color_viridis(option = "B") +
  theme_ed +
  theme(
    panel.border = element_blank(),
    axis.ticks = element_blank(),
    legend.position = "none")
```



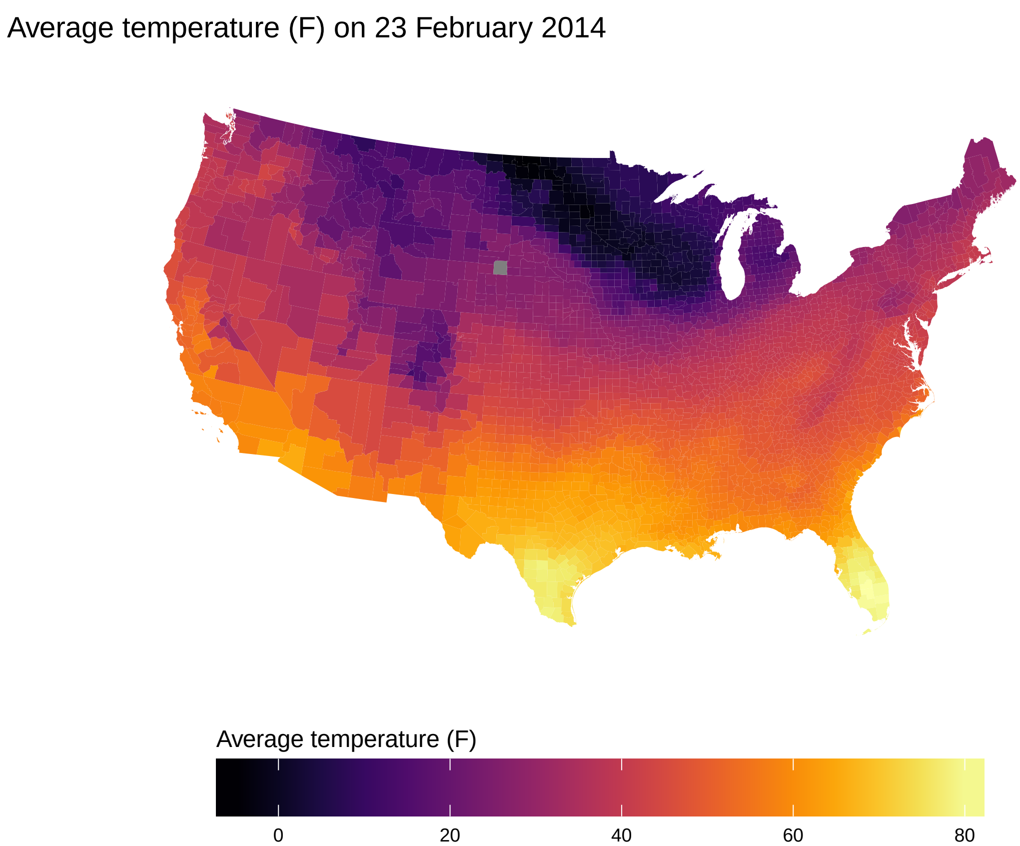
Comparing Alameda County's average daily average temperature to the rest of the counties in California.

```
ggplot() +
  geom_point(
    data = filter(weather_df, state == "06", fips != "06001"),
    aes(x = date, y = temp),
    shape = 1, alpha = 0.2, size = 0.6, color = "grey60") +
  geom_point(
    data = filter(weather_df, state == "06", fips == "06001"),
    aes(x = date, y = temp),
    color = "grey20", size = 0.7) +
  xlab("Date") +
  ylab("Daily avg. temperature (F)") +
  ggtitle(paste("Comparing Alameda County's daily temperatures\n",
    "to other Californian counties, 2014-2015"),
    subtitle = "Source: NARR") +
  scale_color_viridis(option = "B") +
  theme_ed +
  theme(
    panel.border = element_blank(),
    axis.ticks = element_blank(),
    legend.position = "none")
```



Map average temperature for each county in the US on 23 February 2014.

```
ggplot(data = us_shp,
  aes(x = long, y = lat, fill = temp, group = group)) +
  geom_polygon(color = NA) +
  ggtitle("Average temperature (F) on 23 February 2014") +
  scale_fill_viridis("Average temperature (F)", option = "B") +
  coord_map("albers", 30, 40) +
  theme_map() +
  theme(
    legend.position = "bottom",
    legend.direction = "horizontal",
    legend.justification = "center") +
  guides(fill = guide_colorbar(
    barwidth = 20,
    barheigh = 1.5,
    title.position = "top"))
```



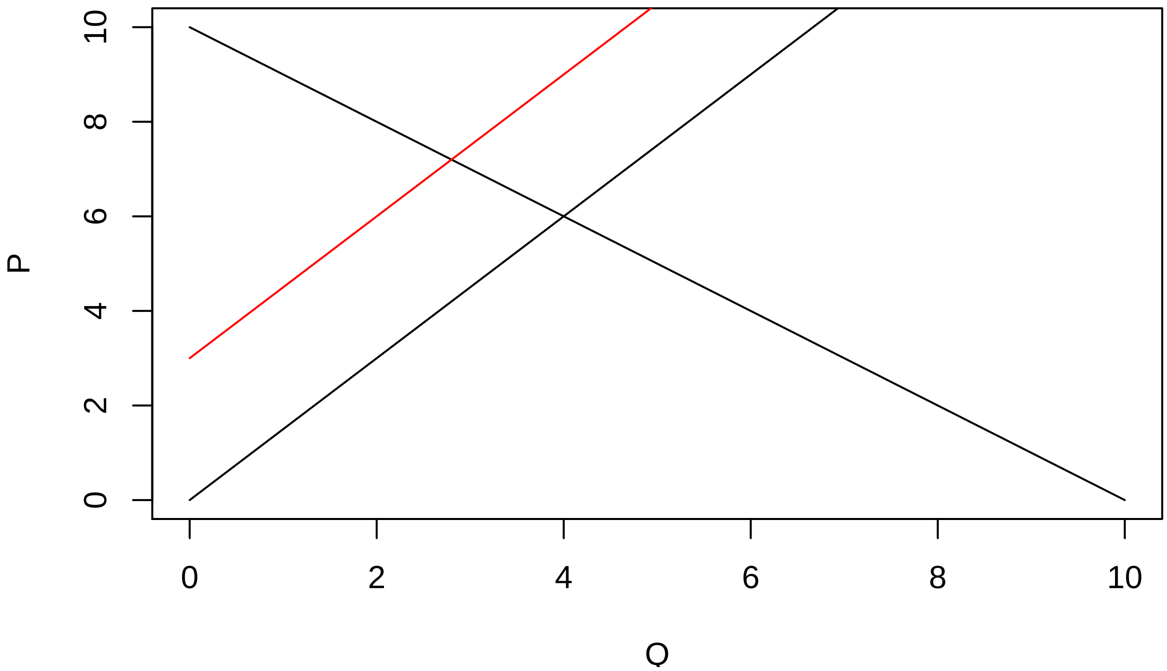
4 Plotting functions

In economics, we often want to just plot a function—for instance, a demand curve (or inverse demand curve). The easiest way to plot an arbitrary function in R is probably with the `curve()` function. Let's define inverse demand and supply functions.

```
# Define the inverse demand and supply functions
inv_demand <- function(q) 10 - q
inv_supply <- function(q) 1.5 * q
```

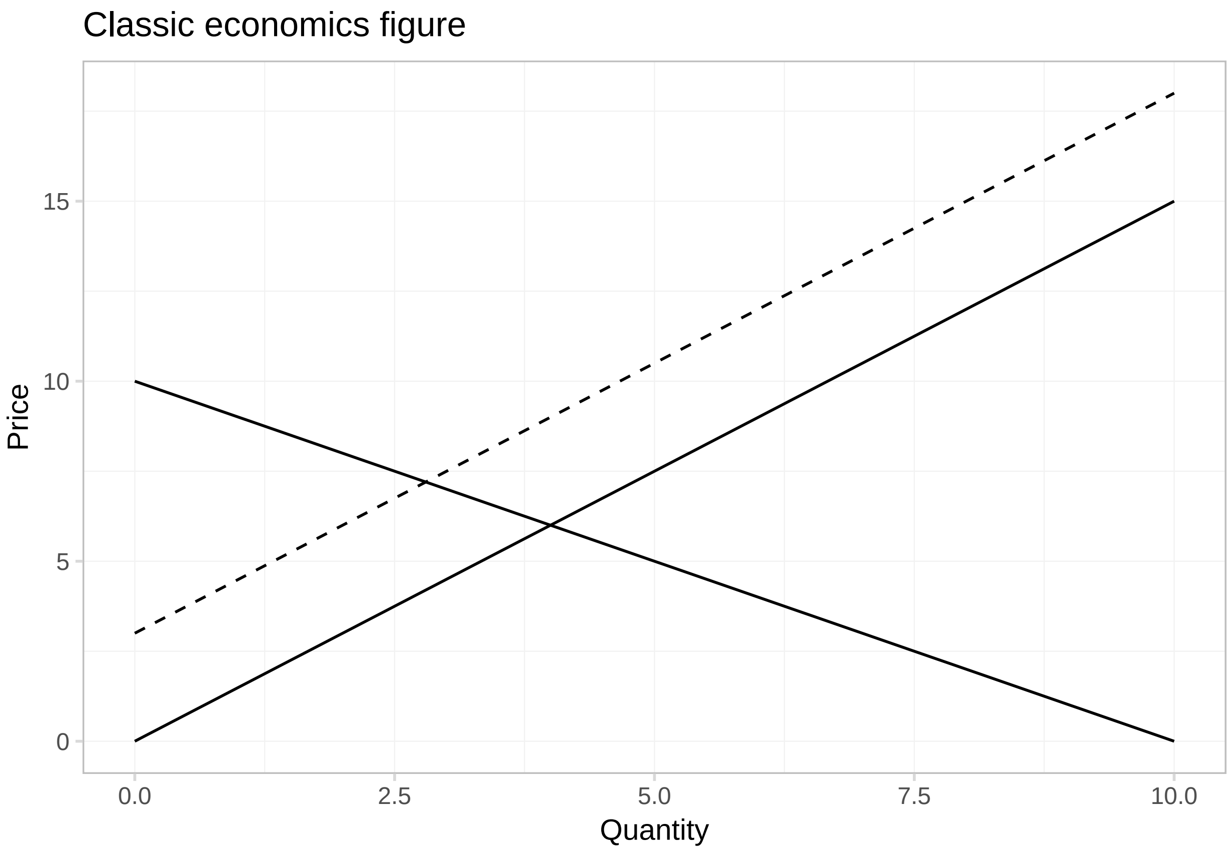
And now plot them.

```
# Plot the inverse demand and supply functions
curve(expr = inv_demand, from = 0, 10,
  xlab = "Q", ylab = "P", n = 100)
curve(expr = inv_supply,
  from = 0, 10, add = T)
# Shift the supply back
curve(expr = inv_supply(x) + 3,
  from = 0, 10, add = T, col = "red")
```



curve() is very helpful for plotting functions quickly, but we can do it in ggplot2, as well. We will define the domain of our function in the inside of a data.frame in ggplot(). Then we will create layers that trace out our functions using stat_function(). We need to tell stat_function() the name of the function we want and the geometry (geom) that we want to use.

```
ggplot(data = data.frame(x = c(0, 10)), aes(x)) +
  # The inverse demand
  stat_function(fun = inv_demand, geom = "line") +
  # The inverse supply
  stat_function(fun = inv_supply, geom = "line") +
  # The shifted inverse supply curve
  stat_function(fun = function(x) inv_supply(x) + 3, geom = "line",
    linetype = 2) +
  # Labels and themes
  xlab("Quantity") +
  ylab("Price") +
  ggtitle("Classic economics figure") +
  theme_ed
```



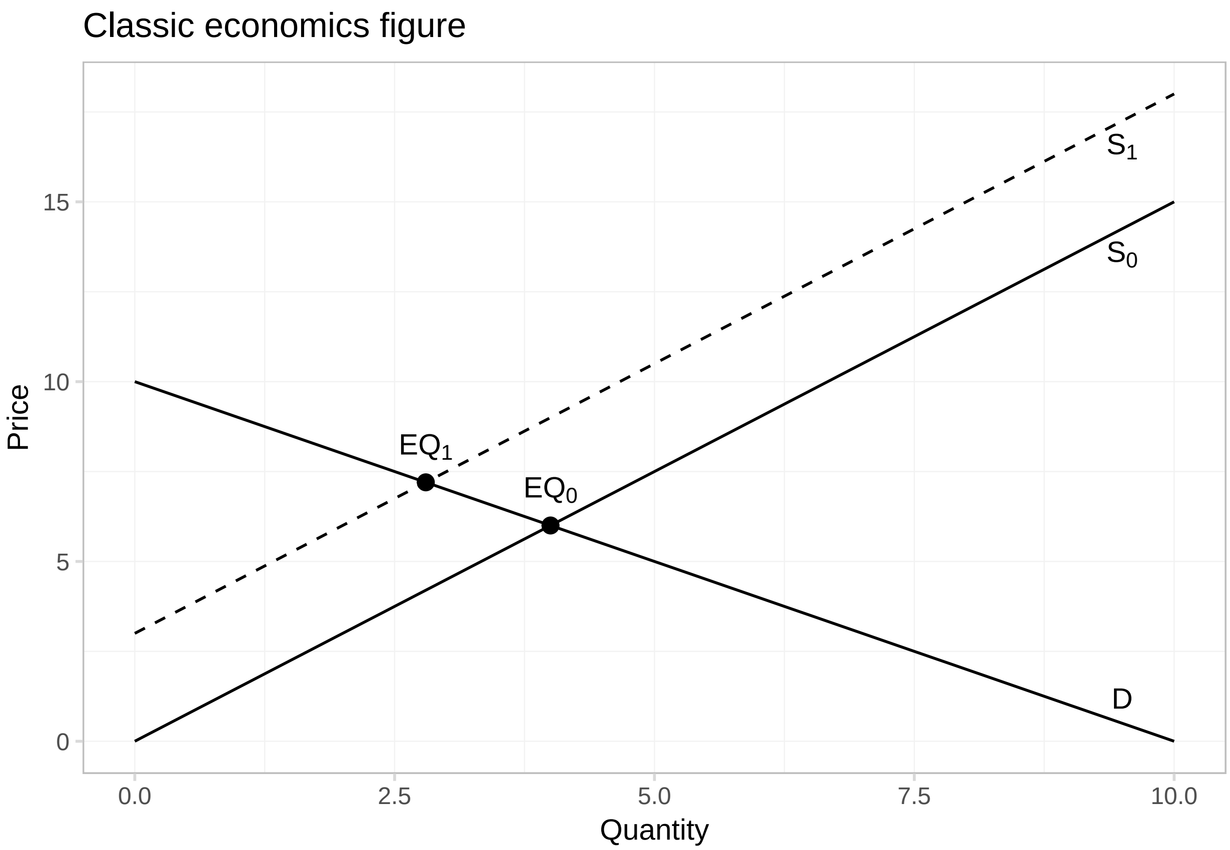
And if we want to annotate the equilibria in the picture, can we can use the `annotate()` function from `ggplot2`. First, let's solve for the equilibria. I know how to do math, but since we are doing everything in R, we can have R solve for the equilibria for us using the `uniroot()` function. We will give `uniroot()` the difference of our two functions, and it will return the point at which the difference is (approximately) zero. (Note that it will give us the equilibrium quantity; we will then have to plug the quantity into the inverse demand or supply functions to get the equilibrium price.)

```
# The first equilibrium quantity
q1 <- uniroot(
  f = function(x) inv_supply(x) - inv_demand(x),
  interval = c(0, 10))$root
p1 <- inv_demand(q1)
# The second equilibrium equantity
q2 <- uniroot(
  f = function(x) inv_supply(x) + 3 - inv_demand(x),
  interval = c(0, 10))$root
p2 <- inv_demand(q2)
```

Finally, let's annotate our figure—specifically, we will add points for each equilibrium and text to label the equilibria and lines.

```
ggplot(data = data.frame(x = c(0, 10)), aes(x)) +
  # The inverse demand
  stat_function(fun = inv_demand, geom = "line") +
  # The inverse supply
```

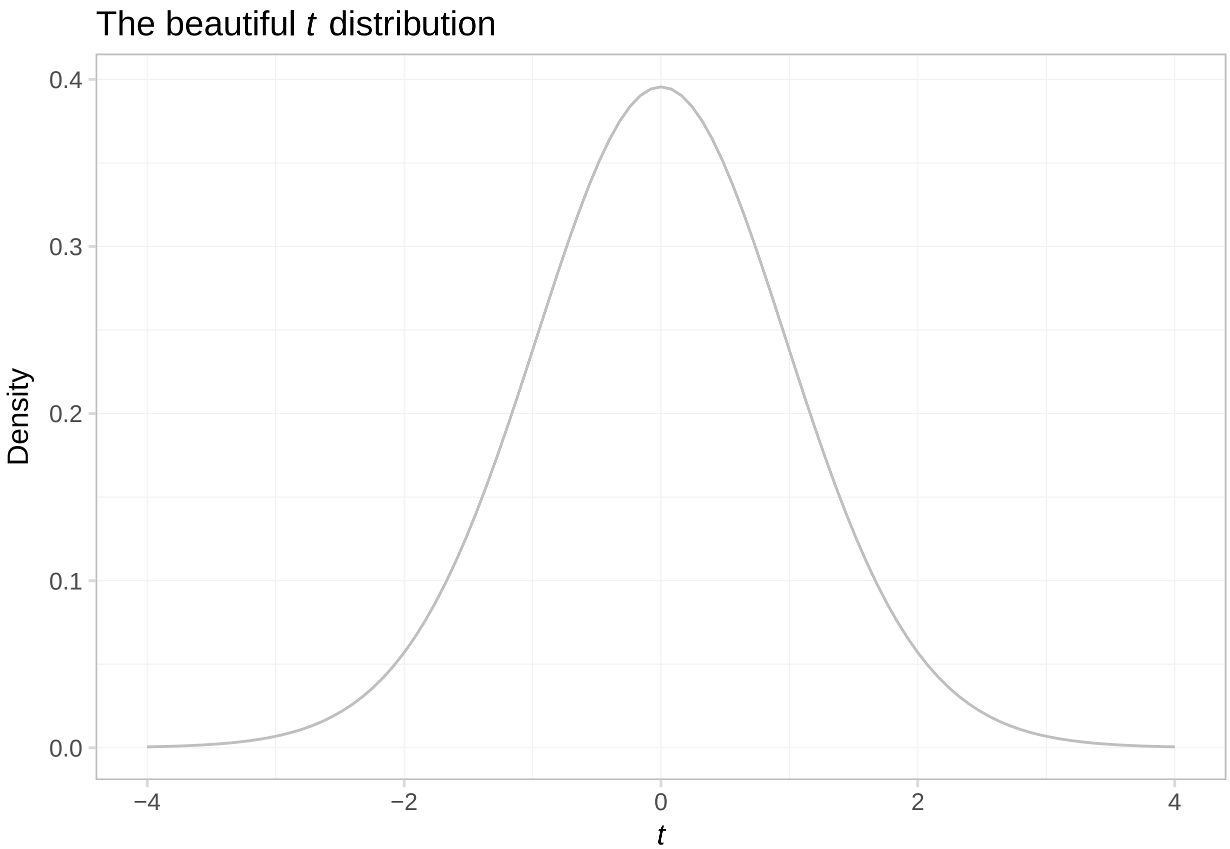
```
  stat_function(fun = inv_supply, geom = "line") +
  # The shifted inverse supply curve
  stat_function(fun = function(x) inv_supply(x) + 3, geom = "line",
    linetype = 2) +
  # Annotate!
  annotate(geom = "point", x = c(q1, q2), y = c(p1, p2), size = 2.5) +
  annotate(geom = "text", x = c(q1, q2), y = c(p1, p2) + 1,
    label = c("EQ[0]", "EQ[1]"), parse = T) +
  annotate(geom = "text", x = 9.5,
    y = c(inv_supply(9.5)-0.7, inv_supply(9.5)+3-0.7, inv_demand(9.5)+0.7),
    label = c("S[0]", "S[1]", "D"), parse = T) +
  # Labels and themes
  xlab("Quantity") +
  ylab("Price") +
  ggtitle("Classic economics figure") +
  theme_ed
```



In addition to plotting our own functions, `stat_function()` can be useful for plotting R's functions. Let's trace out the probability density function (pdf) of a random variable from a t distribution with 29 degrees of freedom.

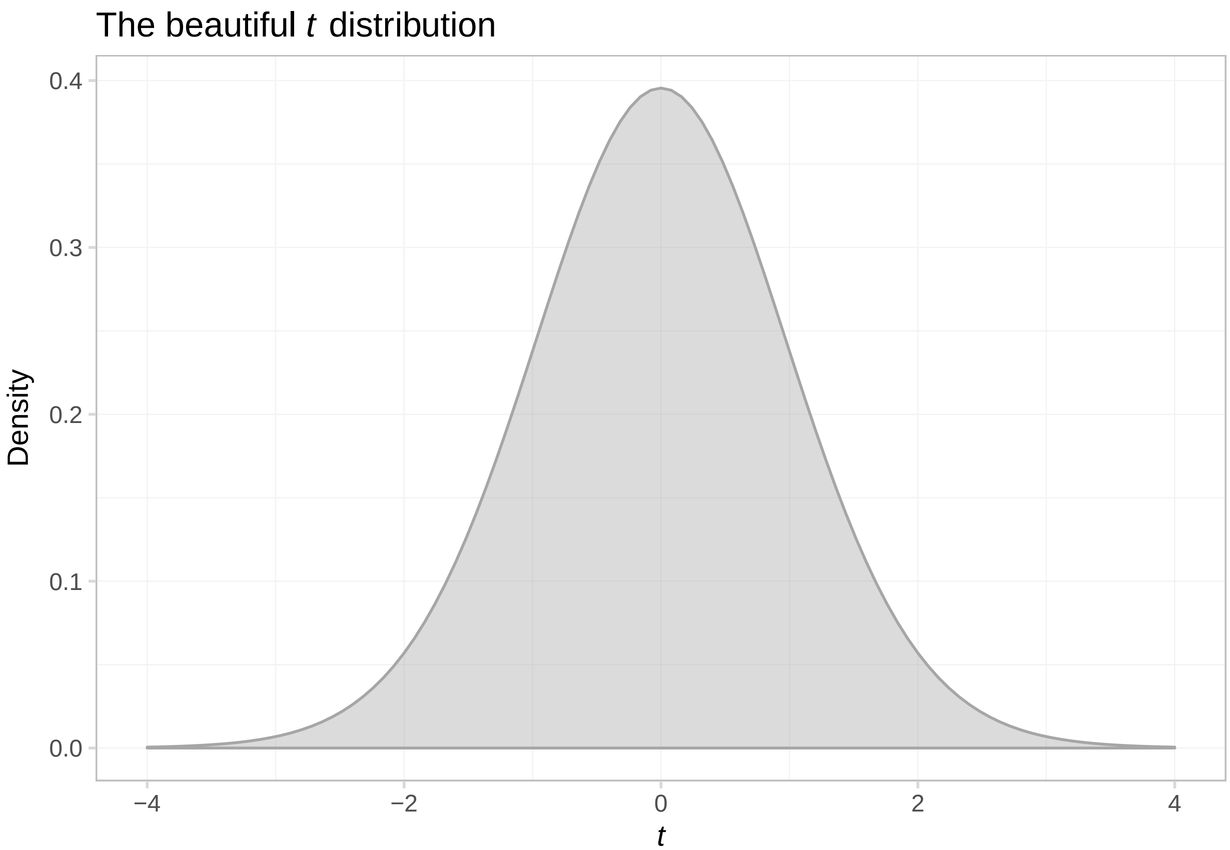
```
ggplot(data = data.frame(x = c(-4,4)), aes(x)) +
  # Plot the pdf
  stat_function(fun = function(x) dt(x, df = 29),
    color = "grey75") +
  ggtitle(expression(paste("The beautiful ", italic(t),
```

```
    " distribution"))) +
  xlab(expression(italic(t))) +
  ylab("Density") +
  theme_ed
```



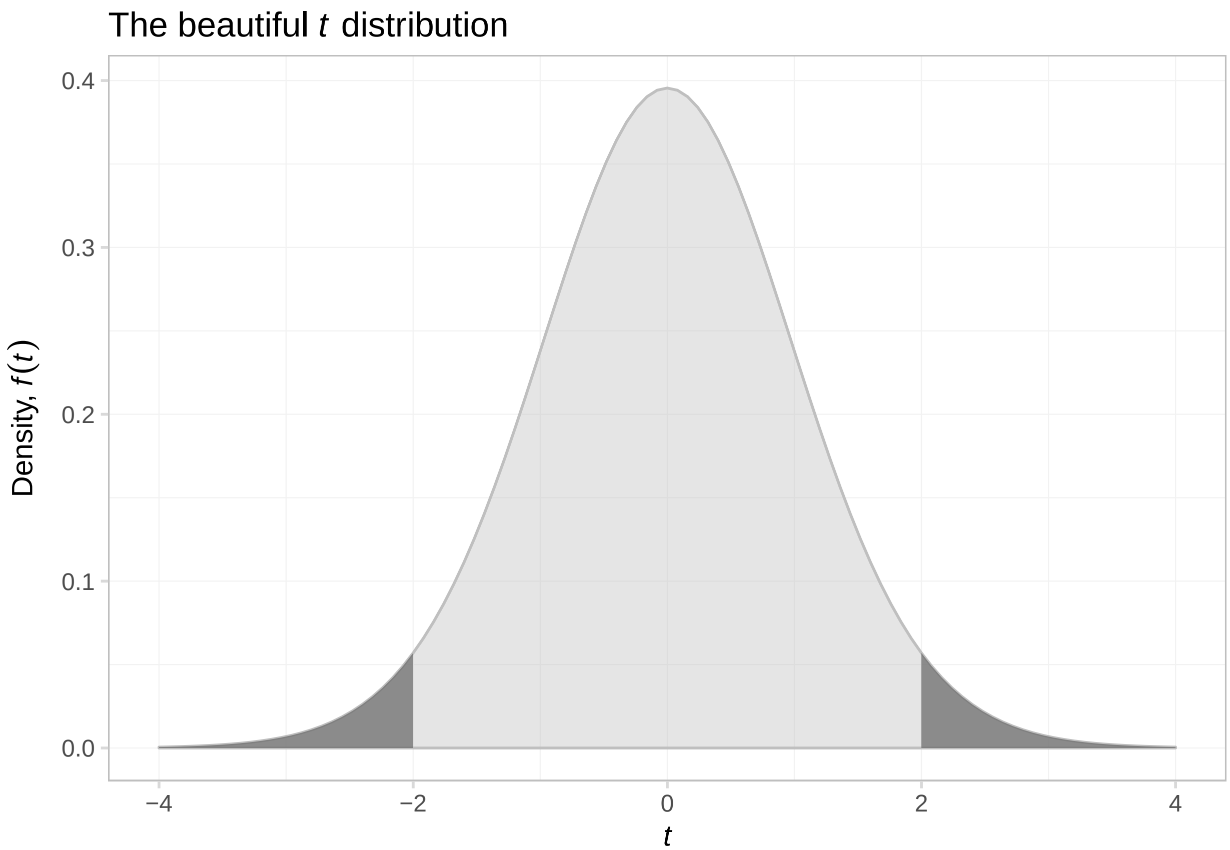
What if we want to shade the plot?

```
ggplot(data = data.frame(x = c(-4,4)), aes(x)) +
  # Plot the pdf
  stat_function(fun = function(x) dt(x, df = 29),
    geom = "area", color = "grey65", fill = "grey65", alpha = 0.4) +
  ggtitle(expression(paste("The beautiful ", italic(t),
    " distribution"))) +
  xlab(expression(italic(t))) +
  ylab("Density") +
  theme_ed
```



That was a bit trickier than expected. Anyway, let's try shading above t of 2 and below t of -2.

```
ggplot(data.frame(x = c(-4,4))) +
  # Plot the pdf
  stat_function(
    fun = function(x) dt(x, df = 29),
    aes(x),
    geom = "area", color = "grey75", fill = "grey75", alpha = 0.4) +
  # Shade below -2
  stat_function(
    fun = function(x) ifelse(x <= -2, dt(x, df = 29), NA),
    aes(x),
    geom = "area", color = NA, fill = "grey40", alpha = 0.7) +
  # Shade above 2
  stat_function(
    fun = function(x) ifelse(x >= 2, dt(x, df = 29), NA),
    aes(x),
    geom = "area", color = NA, fill = "grey40", alpha = 0.7) +
  ggtitle(expression(paste("The beautiful ", italic(t),
    " distribution"))) +
  xlab(expression(italic(t))) +
  ylab(expression(paste("Density, ", italic(f(t))))) +
  theme_ed
```



That was surprisingly difficult. I think what we are seeing here is that as we move away from figures that describe data, things become a bit more difficult. `ggplot2` can create just about any figure you can think of, but it is especially good at creating summaries of data.

5 Plotting in LaTeX

If you are interested in creating figures in LaTeX, you should check out ShareLaTeX's guide on the `tikz` and `Pgfplots` packages.