QCB 508 – Week 3

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Exploratory Data Analysis

What is EDA?

Exploratory data analysis (EDA) is the process of analzying data to uncover their key features.

John Tukey pioneered this framework, writing a seminal book on the topic (called *Exploratory Data Analysis*).

EDA involves calculating numerical summaries of data, visualizing data in a variety of ways, and considering interesting data points.

Before any model fitting is done to data, some exploratory data analysis should always be performed.

Data science seems to focus much more on EDA than traditional statistics.

Descriptive Statistics Examples

- Facebook's Visualizing Friendships (side note: a discussion)
- Hans Rosling: Debunking third-world myths with the best stats you've ever seen
- Flowing Data's A Day in the Life of Americans

Components of EDA

EDA involves calculating quantities and visualizing data for:

- Checking the n's
- Checking for missing data
- Characterizing the distributional properties of the data
- Characterizing relationships among variables and observations
- Dimension reduction
- Model formulation
- Hypothesis generation

. . . and there are possible many more activities one can do.

R4DS Workflow

Which of the following components of the *R4DS* workflow involve EDA?

1. Import
2. Tidy
3. Transform $\leftrightarrow$ Visualize $\leftrightarrow$ Model (*iterate*)
4. Communicate

Data Sets

Data `mtcars`

Load the `mtcars` data set:

```
> library("tidyverse") # why load tidyverse?
> data("mtcars", package="datasets")
> mtcars <- as_tibble(mtcars)
> head(mtcars)
# A tibble: 6 × 11
    mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear
  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1  21.0     6   160   110  3.90 2.620 16.46     0     1     4
2  21.0     6   160   110  3.90 2.875 17.02     0     1     4
3  22.8     4   108    93  3.85 2.320 18.61     1     1     4
4  21.4     6   258   110  3.08 3.215 19.44     1     0     3
5  18.7     8   360   175  3.15 3.440 17.02     0     0     3
6  18.1     6   225   105  2.76 3.460 20.22     1     0     3
# ... with 1 more variables: carb <dbl>
```

Data `mpg`

Load the `mpg` data set:

```
> data("mpg", package="ggplot2")
> head(mpg)
# A tibble: 6 × 11
  manufacturer model displ  year   cyl      trans   drv   cty
         <chr> <chr> <dbl> <int> <int>      <chr> <chr> <int>
1         audi    a4   1.8  1999     4   auto(l5)     f    18
2         audi    a4   1.8  1999     4 manual(m5)     f    21
3         audi    a4   2.0  2008     4 manual(m6)     f    20
4         audi    a4   2.0  2008     4   auto(av)     f    21
5         audi    a4   2.8  1999     6   auto(l5)     f    16
6         audi    a4   2.8  1999     6 manual(m5)     f    18
# ... with 3 more variables: hwy <int>, fl <chr>, class <chr>
```

Data `diamonds`

Load the `diamonds` data set:

```
> data("diamonds", package="ggplot2")
> head(diamonds)
# A tibble: 6 × 10
  carat       cut color clarity depth table price     x     y
  <dbl>     <ord> <ord>   <ord> <dbl> <dbl> <int> <dbl> <dbl>
1  0.23     Ideal     E     SI2  61.5    55   326  3.95  3.98
2  0.21   Premium     E     SI1  59.8    61   326  3.89  3.84
3  0.23      Good     E     VS1  56.9    65   327  4.05  4.07
4  0.29   Premium     I     VS2  62.4    58   334  4.20  4.23
5  0.31      Good     J     SI2  63.3    58   335  4.34  4.35
6  0.24 Very Good     J    VVS2  62.8    57   336  3.94  3.96
# ... with 1 more variables: z <dbl>
```

Data `gapminder`

Load the `gapminder` data set:

```
> library("gapminder")
> data("gapminder", package="gapminder")
> gapminder <- as_tibble(gapminder)
> head(gapminder)
# A tibble: 6 × 6
      country continent  year lifeExp      pop gdpPercap
       <fctr>    <fctr> <int>   <dbl>    <int>     <dbl>
1 Afghanistan      Asia  1952  28.801  8425333  779.4453
2 Afghanistan      Asia  1957  30.332  9240934  820.8530
3 Afghanistan      Asia  1962  31.997 10267083  853.1007
4 Afghanistan      Asia  1967  34.020 11537966  836.1971
5 Afghanistan      Asia  1972  36.088 13079460  739.9811
6 Afghanistan      Asia  1977  38.438 14880372  786.1134
```

Numerical Summaries of Data

Useful Summaries

- **Center**: mean, median, mode
- **Quantiles**: percentiles, five number summaries
- **Spread**: standard deviation, variance, interquartile range
- **Outliers**
- **Shape**: skewness, kurtosis
- **Concordance**: correlation, quantile-quantile plots

Measures of Center

Suppose we have data points $x_1, x_2, \ldots, x_n$.

Mean:

$$\overline{x} = \frac{x_1 + x_2 + \cdots + x_n}{n}$$

Median: Order the points $x_{(1)} \leq x_{(2)} \leq \cdots \leq x_{(n)}$. The median is the middle value:
- $x_{((n+1)/2)}$ if n is odd
- $(x_{(n/2)} + x_{(n/2+1)})/2$ if n is even

Mode: The most frequently repeated value among the data (if any). If there are ties, then there is more than one mode.

Mean, Median, and Mode in R

Let's calculate these quantities in R.

```
> mean(mtcars$mpg)
[1] 20.09062
> median(mtcars$mpg)
[1] 19.2
>
```

```
> sample_mode <- function(x) {
+   as.numeric(names(which(table(x) == max(table(x)))))
+ }
>
> sample_mode(round(mtcars$mpg))
[1] 15 21
```

It appears there is no R base function for calculating the mode.

Quantiles and Percentiles

The pth **percentile** of $x_1, x_2, \ldots, x_n$ is a number such that $p\%$ of the data are less than this number.

The 25th, 50th, and 75th percentiles are called 1st, 2nd, and 3rd "quartiles", respectively. These are sometimes denoted as Q1, Q2, and Q3. The median is the 50th percentile aka the 2nd quartile aka Q2.

In general, q-**quantiles** are cut points that divide the data into q approximately equally sized groups. The cut points are the percentiles $1/q, 2/q, \ldots, (q-1)/q$.

Five Number Summary

The "five number summary" is the minimum, the three quartiles, and the maximum. This can be calculated via `fivenum()` and `summary()`. They can produce different values. Finally, `quantile()` extracts any set of percentiles.

```
> fivenum(mtcars$mpg)
[1] 10.40 15.35 19.20 22.80 33.90
> summary(mtcars$mpg)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  10.40   15.42   19.20   20.09   22.80   33.90
>
> quantile(mtcars$mpg, prob=seq(0, 1, 0.25))
    0%    25%    50%    75%   100%
10.400 15.425 19.200 22.800 33.900
```

Measures of Spread

The variance, standard deviation (SD), and interquartile range (IQR) measure the "spread" of the data.

Variance:

$$s^2 = \frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n-1}$$

Standard Deviation: $s = \sqrt{s^2}$

Iterquartile Range: IQR = Q3 − Q1

The SD and IQR have the same units as the observed data, but the variance is in squared units.

Variance, SD, and IQR in R

Variance:

```
> var(mtcars$mpg)
[1] 36.3241
```

Standard deviation:

```
> sd(mtcars$mpg)
[1] 6.026948
```

Interquartile range:

```
> IQR(mtcars$mpg)
[1] 7.375
> diff(fivenum(mtcars$mpg)[c(2,4)])
[1] 7.45
```

Identifying Outliers

An **outlier** is an unusual data point. Outliers can be perfectly valid but they can also be due to errors (as can non-outliers).

One must define what is meant by an outlier.

One definition is a data point that less than Q1 or greater than Q3 by 1.5 $\times$ IQR or more.

Another definition is a data point whose difference from the mean is greater than 3 $\times$ SD or more. For Normal distributed data (bell curve shaped), the probability of this is less than 0.27%.

Application to `mtcars` Data

```
> sd_units <- abs(mtcars$wt - mean(mtcars$wt))/sd(mtcars$wt)
> sum(sd_units > 3)
[1] 0
> max(sd_units)
[1] 2.255336
>
> iqr_outlier_cuts <- fivenum(mtcars$wt)[c(2,4)] +
+       c(-1.5, 1.5)*diff(fivenum(mtcars$wt)[c(2,4)])
> sum(mtcars$wt < iqr_outlier_cuts[1] |
+     mtcars$wt > iqr_outlier_cuts[2])
[1] 2
```

Data Visualization Basics

Plots

- Single variables:
  - Barplot
  - Boxplot
  - Histogram
  - Density plot
- Two or more variables:
  - Side-by-Side Boxplots

  - Stacked Barplot
  - Scatterplot

R Base Graphics

- We'll first plodding through "R base graphics", which means graphics functions that come with R.

- By default they are very simple. However, they can be customized *a lot*, but it takes *a lot* of work.
- Also, the syntax varies significantly among plot types and some think the syntax is not user-friendly.
- We will consider a very highly used graphics package next week, called `ggplot2` that provides a "grammar of graphics". It hits a sweet spot of "flexibility vs. complexity" for many data scientists.

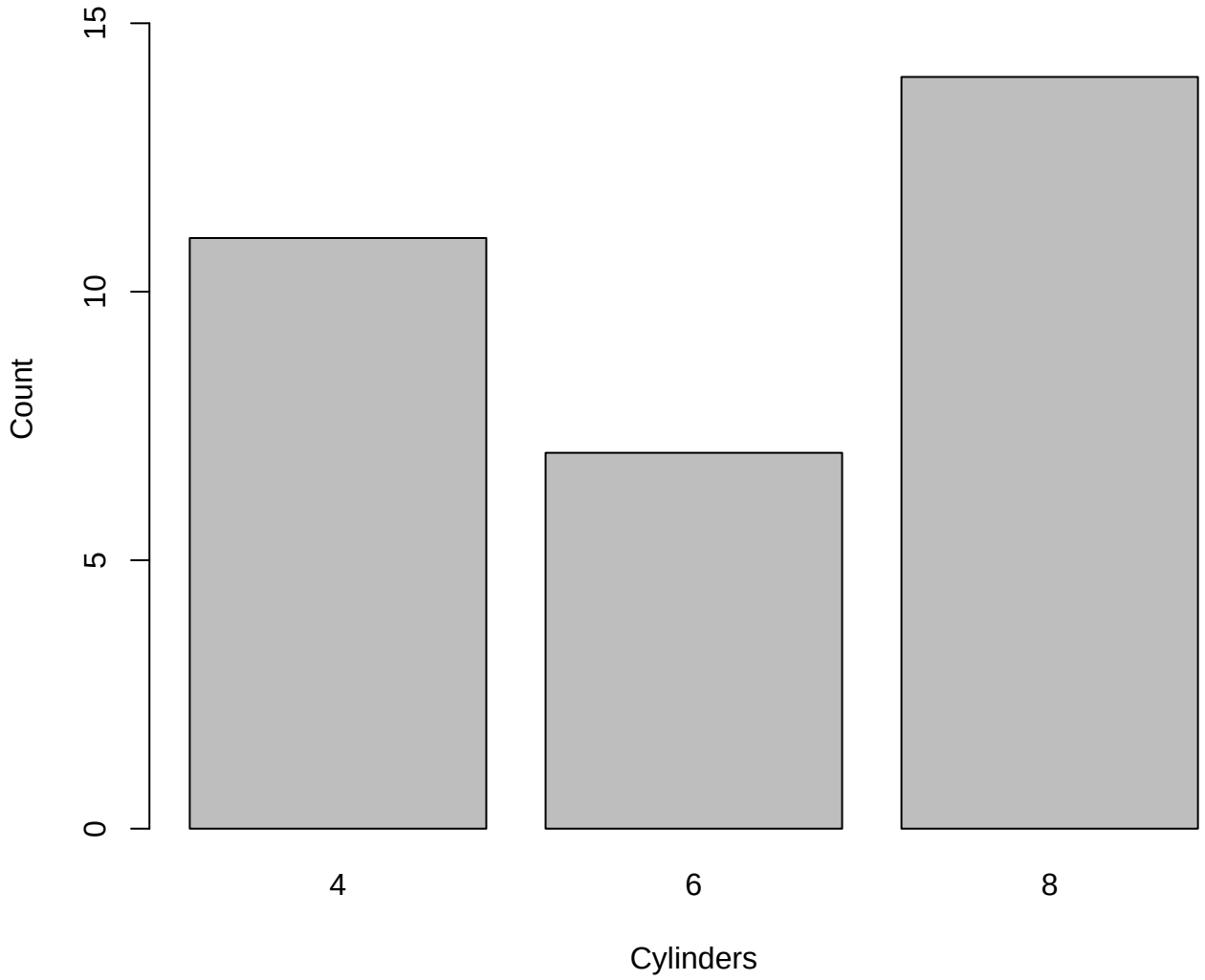
Read the Documentation

For all of the plotting functions covered below, read the help files.

```
> ?barplot
> ?boxplot
> ?hist
> ?density
> ?plot
> ?legend
```

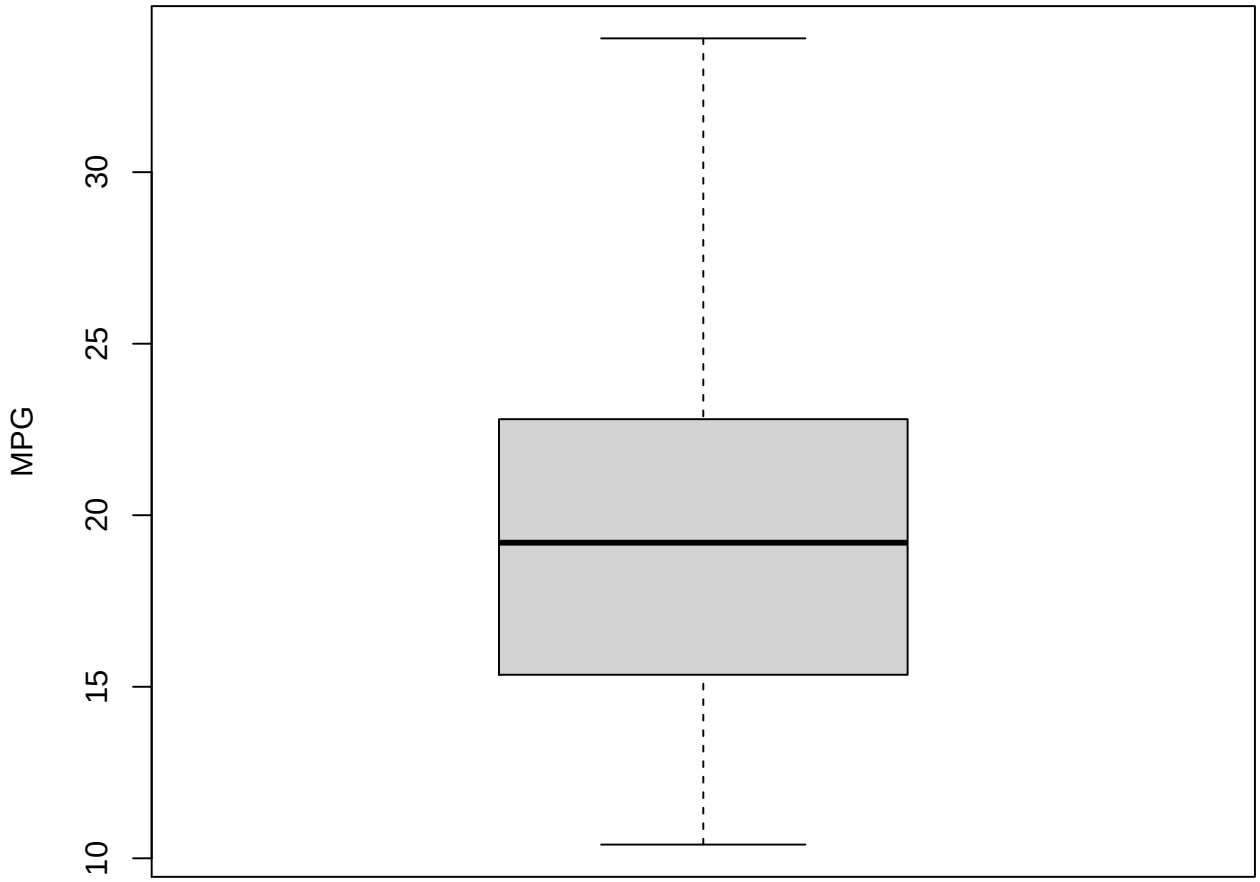
Barplot

```
> cyl_tbl <- table(mtcars$cyl)
> barplot(cyl_tbl, xlab="Cylinders", ylab="Count")
```



Boxplot

```
> boxplot(mtcars$mpg, ylab="MPG", col="lightgray")
```

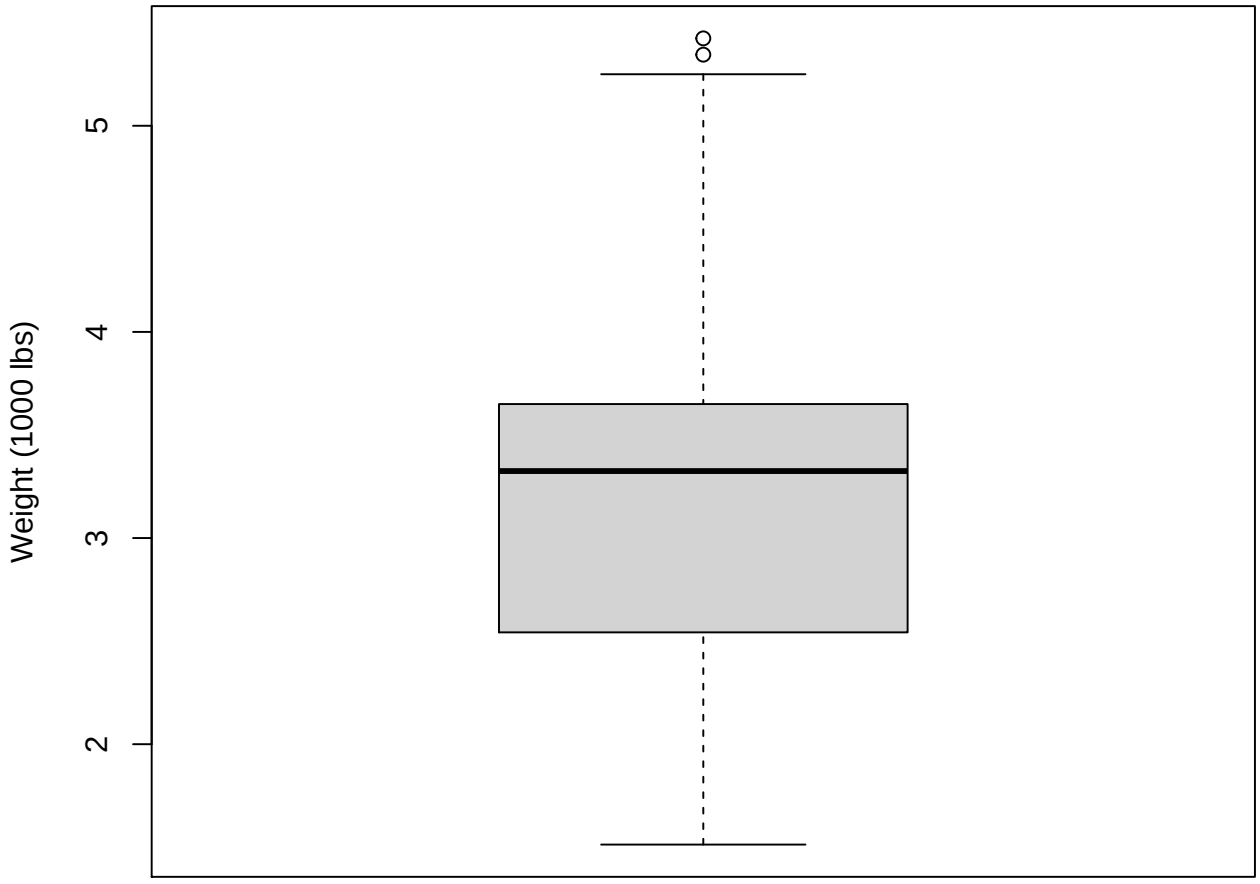


Constructing Boxplots

- The top of the box is Q3
- The line through the middle of the box is the median
- The bottom of the box is Q1
- The top whisker is the minimum of Q3 + 1.5 × IQR or the largest data point
- The bottom whisker is the maximum of Q1 - 1.5 × IQR or the smallest data point
- Outliers lie outside of (Q1 - 1.5 × IQR) or (Q3 + 1.5 × IQR), and they are shown as points
- Outliers are calculated using the `fivenum()` function

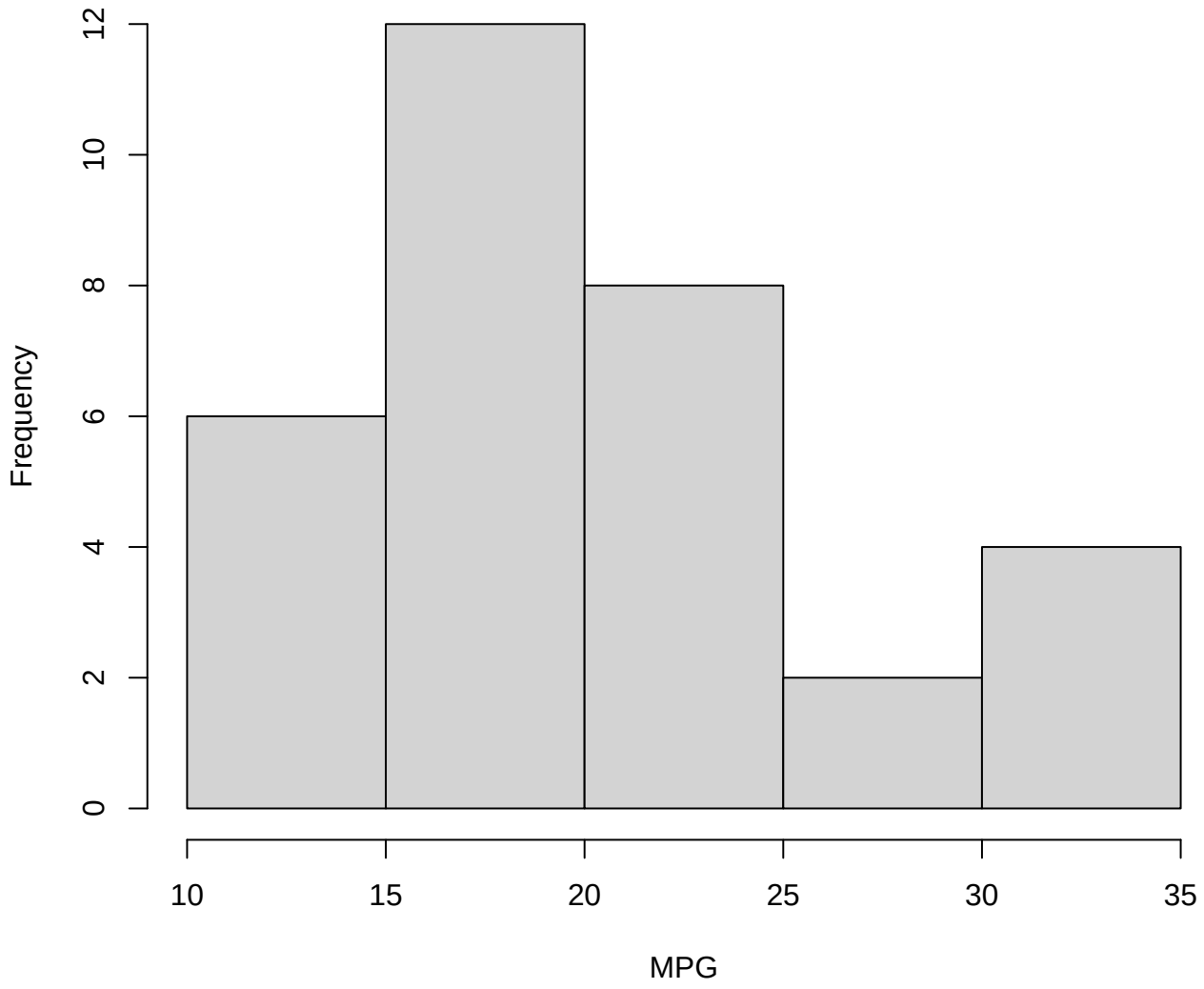
Boxplot with Outliers

```
> boxplot(mtcars$wt, ylab="Weight (1000 lbs)",
+         col="lightgray")
```



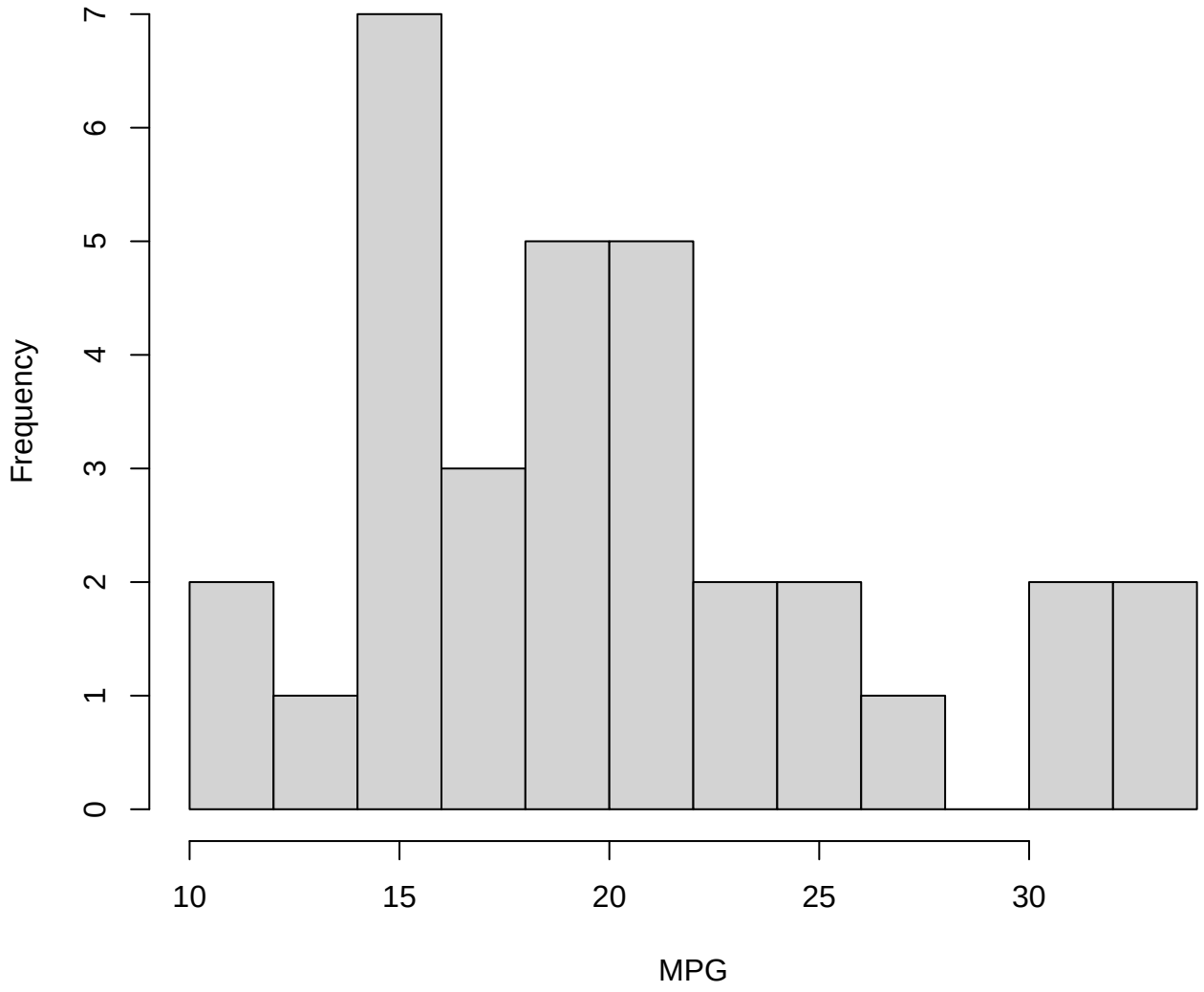
Histogram

```
> hist(mtcars$mpg, xlab="MPG", main="", col="lightgray")
```



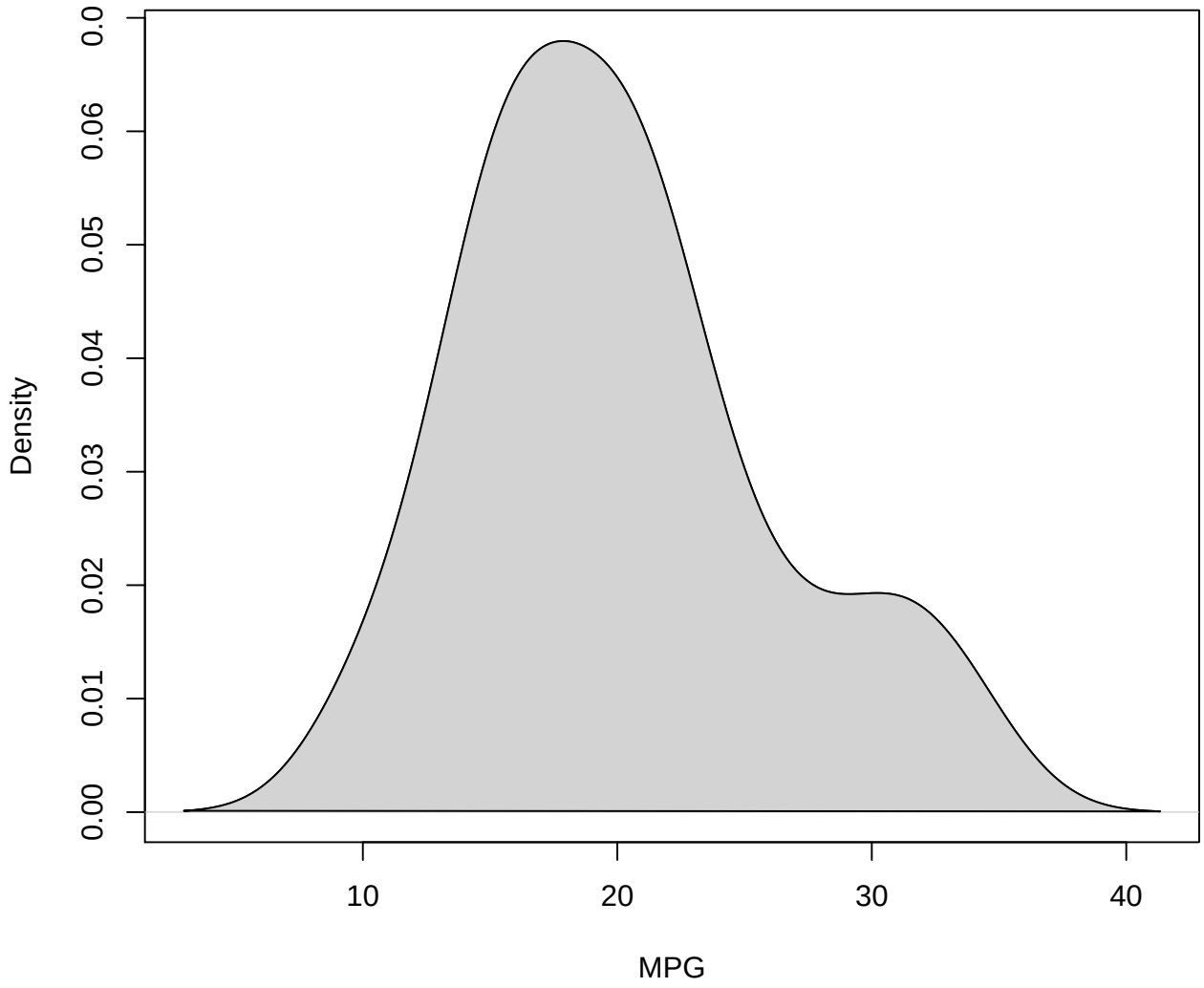
Histogram with More Breaks

```
> hist(mtcars$mpg, breaks=12, xlab="MPG", main="", col="lightgray")
```



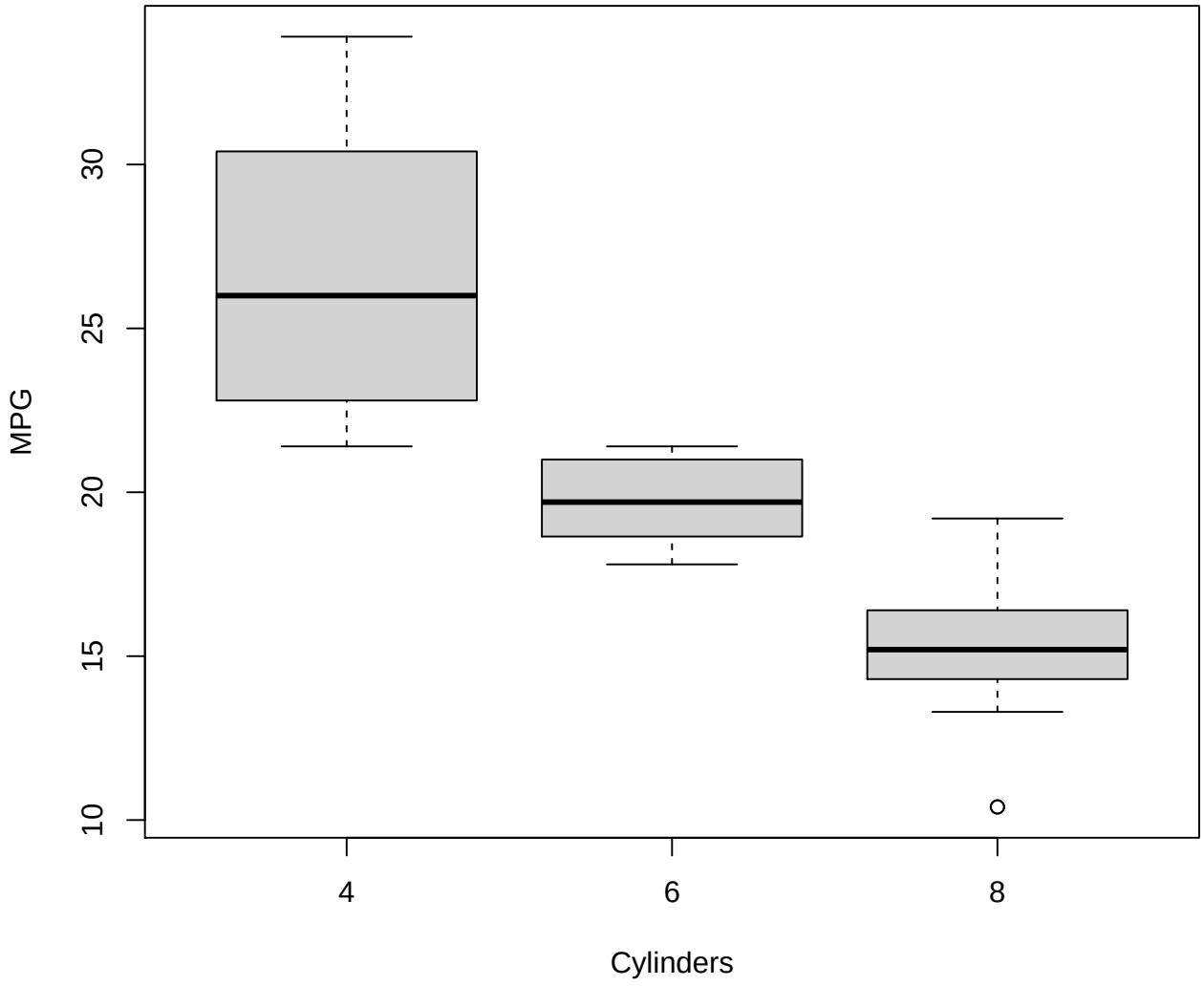
Density Plot

```
> plot(density(mtcars$mpg), xlab="MPG", main="")
> polygon(density(mtcars$mpg), col="lightgray", border="black")
```



Boxplot (Side-By-Side)

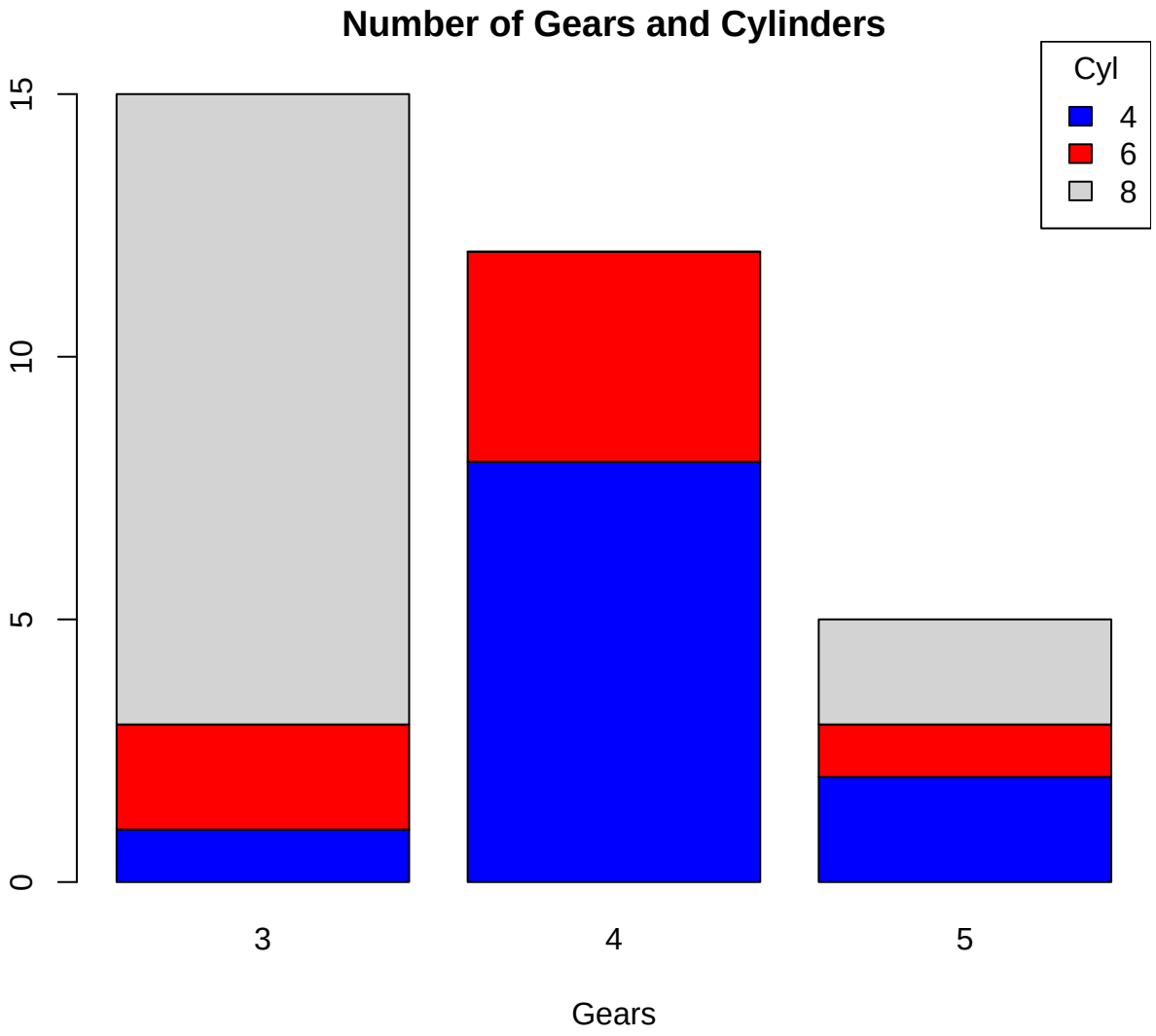
```
> boxplot(mpg ~ cyl, data=mtcars, xlab="Cylinders",
+         ylab="MPG", col="lightgray")
```



Stacked Barplot

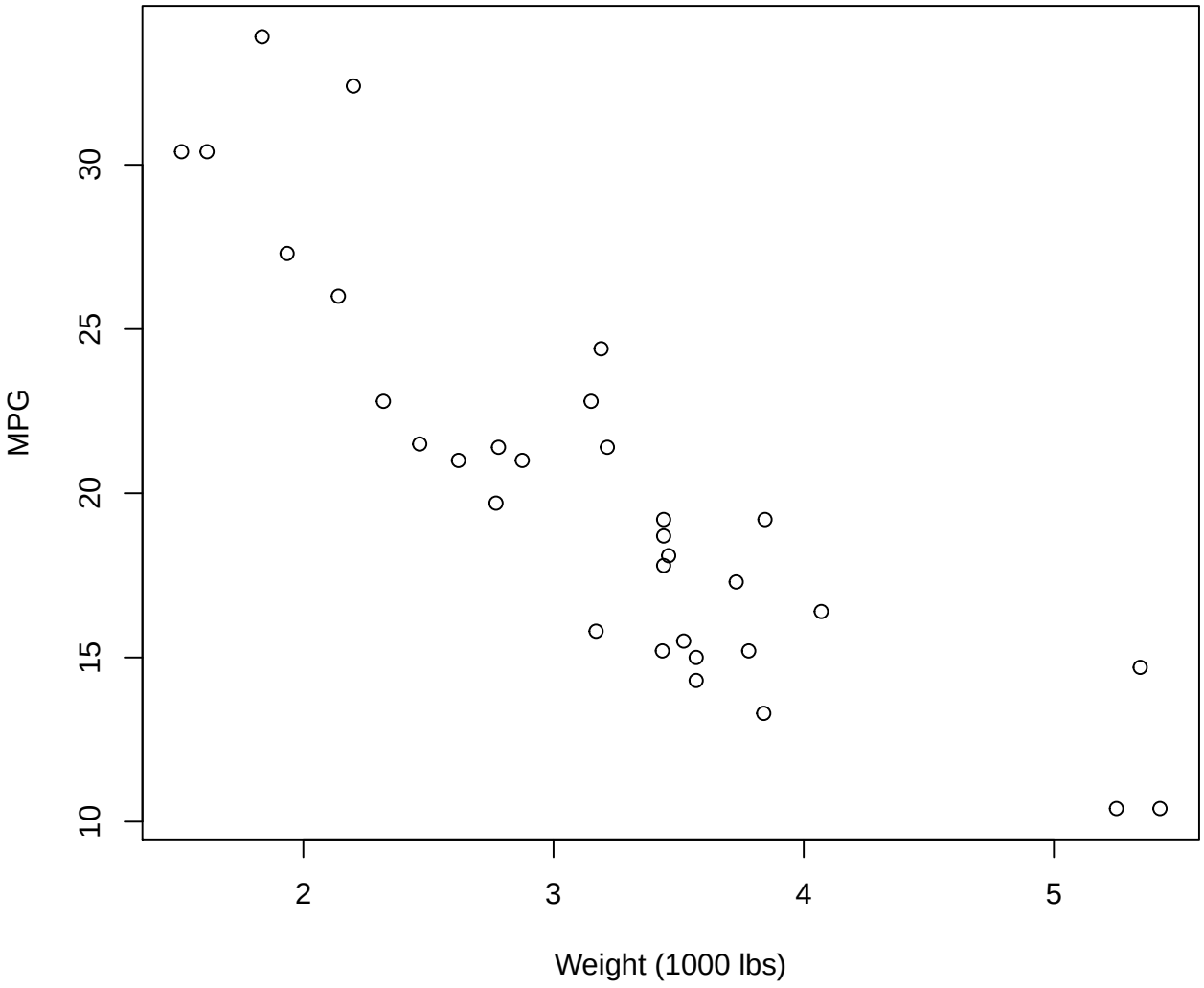
```
> counts <- table(mtcars$cyl, mtcars$gear)
> counts

   3  4  5
4  1  8  2
6  2  4  1
8 12  0  2
```

```
> barplot(counts, main="Number of Gears and Cylinders",
+   xlab="Gears", col=c("blue","red", "lightgray"))
> legend(x="topright", title="Cyl",
+        legend = rownames(counts),
+        fill = c("blue","red", "lightgray"))
```



Scatterplot

```
> plot(mtcars$wt, mtcars$mpg, xlab="Weight (1000 lbs)",
+      ylab="MPG")
```



A Grammar of Graphics

Rationale

A grammar for communicating data visualization:

- *Data*: the data set we are plotting
- *Aesthetics*: the variation or relationships in the data we want to visualize
- *Geometries*: the geometric object by which we render the aesthetics
- *Coordinates*: the coordinate system used (not covered here)
- *Facets*: the layout of plots required to visualize the data
- Other Options: any other customizations we wish to make, such as changing the color scheme or labels

These are strung together like words in a sentence.

Package `ggplot2`

The R package `ggplot2` implements a grammar of graphics along these lines. First, let's load `ggplot2`:

```
> library(ggplot2)
```

Now let's set a theme (more on this later):

```
> theme_set(theme_bw())
```

Pieces of the Grammar

- ggplot()
- aes()
- geom_*()
- facet_*()
- scale_*()
- theme()
- labs()

The * is a placeholder for a variety of terms that we will consider.

Geometries

Perhaps the most important aspect of ggplot2 is to understand the "geoms". We will cover the following:

- geom_bar()
- geom_boxplot()
- geom_violin()
- geom_histogram()
- geom_density()
- geom_line()
- geom_point()
- geom_smooth()
- geom_hex()

Call Format

The most basic ggplot2 plot is made with something like:

```
ggplot(data = <DATA FRAME>) +
 geom_*(mapping = aes(x = <VAR X>, y = <VAR Y>))
```

where <DATA FRAME> is a data frame and <VAR X> and <VAR Y> are variables (i.e., columns) from this data frame. Recall geom_* is a placeholder for a geometry such as geom_boxplot.

Layers

There's a complex "layers" construct occurring in the ggplot2 package. However, for our purposes, it suffices to note that the different parts of the plots are layered together through the + operator:

```
> ggplot(data = mpg) +
+   geom_point(mapping = aes(x = displ, y = hwy, color=drv)) +
+   geom_smooth(mapping = aes(x = displ, y = hwy, color=drv)) +
+   scale_color_brewer(palette = "Set1", name = "Drivetrain") +
+   labs(title = "Highway MPG By Drivetrain and Displacement",
+        x = "Displacement", y = "Highway MPG")
```

Placement of the `aes()` Call

In the previous slide, we saw that the same `aes()` call was made for two `geom`'s. When this is the case, we may more simply call `aes()` from within `ggplot()`:

```
> ggplot(data = mpg, mapping = aes(x = displ, y = hwy, color=drv)) +
+   geom_point() +
+   geom_smooth() +
+   scale_color_brewer(palette = "Set1", name = "Drivetrain") +
+   labs(title = "Highway MPG By Drivetrain and Displacement",
+        x = "Displacement", y = "Highway MPG")
```

There may be cases where different `geom`'s are layered and require different `aes()` calls. This is something to keep in mind as we go through the specifics of the `ggplot2` package.

Original Publications

Wickham, H. (2010) A Layered Grammar of Graphics. *Journal of Computational and Graphical Statistics*, 19 (1): 3–28.

This paper designs an implementation of *The Grammar of Graphics* by Leland Wilkinson (published in 2005).

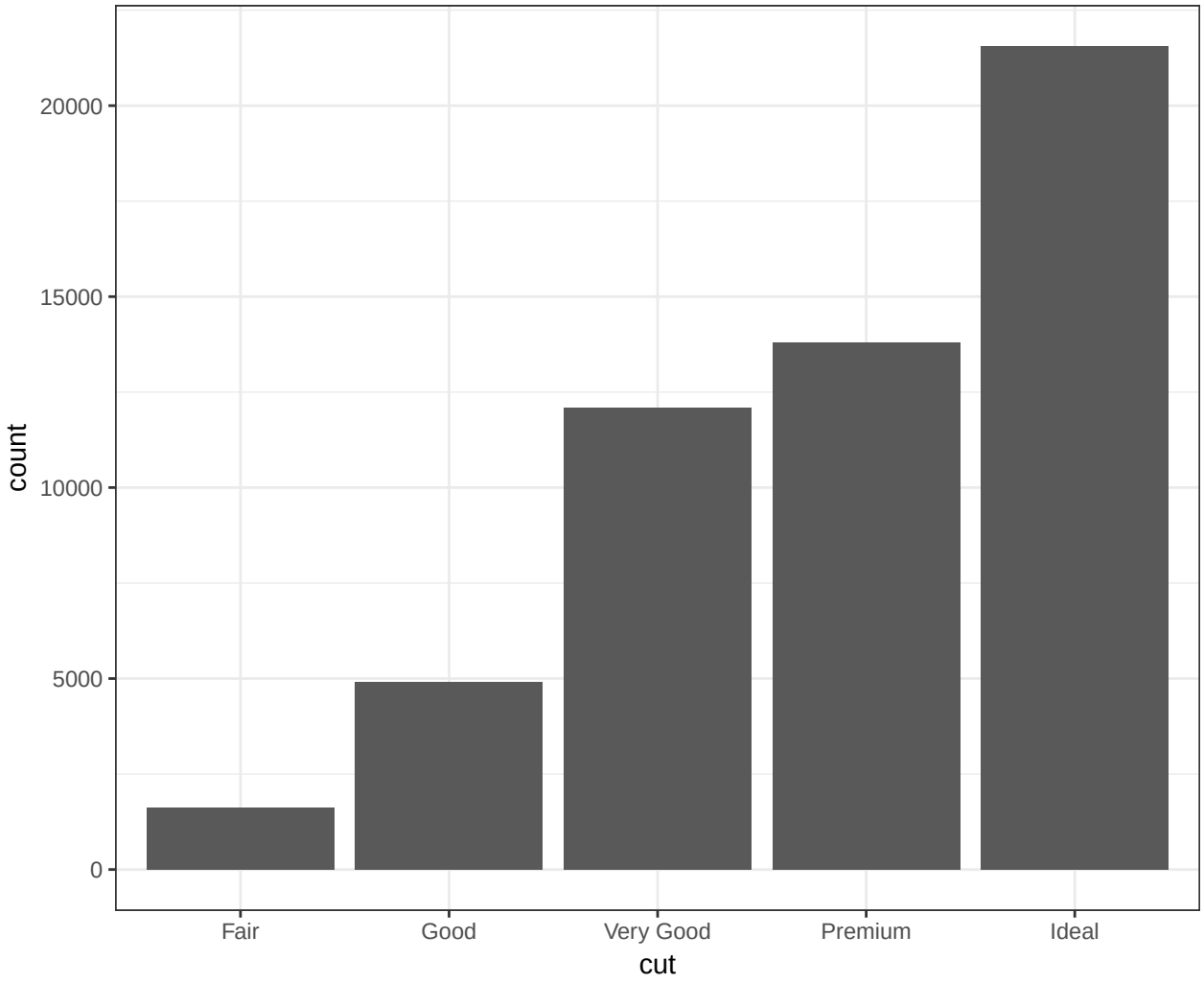
Documentation

- In R: `help(package="ggplot2")`
- http://docs.ggplot2.org/current/
- http://www.cookbook-r.com/Graphs/
- *ggplot2: Elegant Graphics for Data Analysis* (somewhat outdated, but gives clear rationale)

Barplots

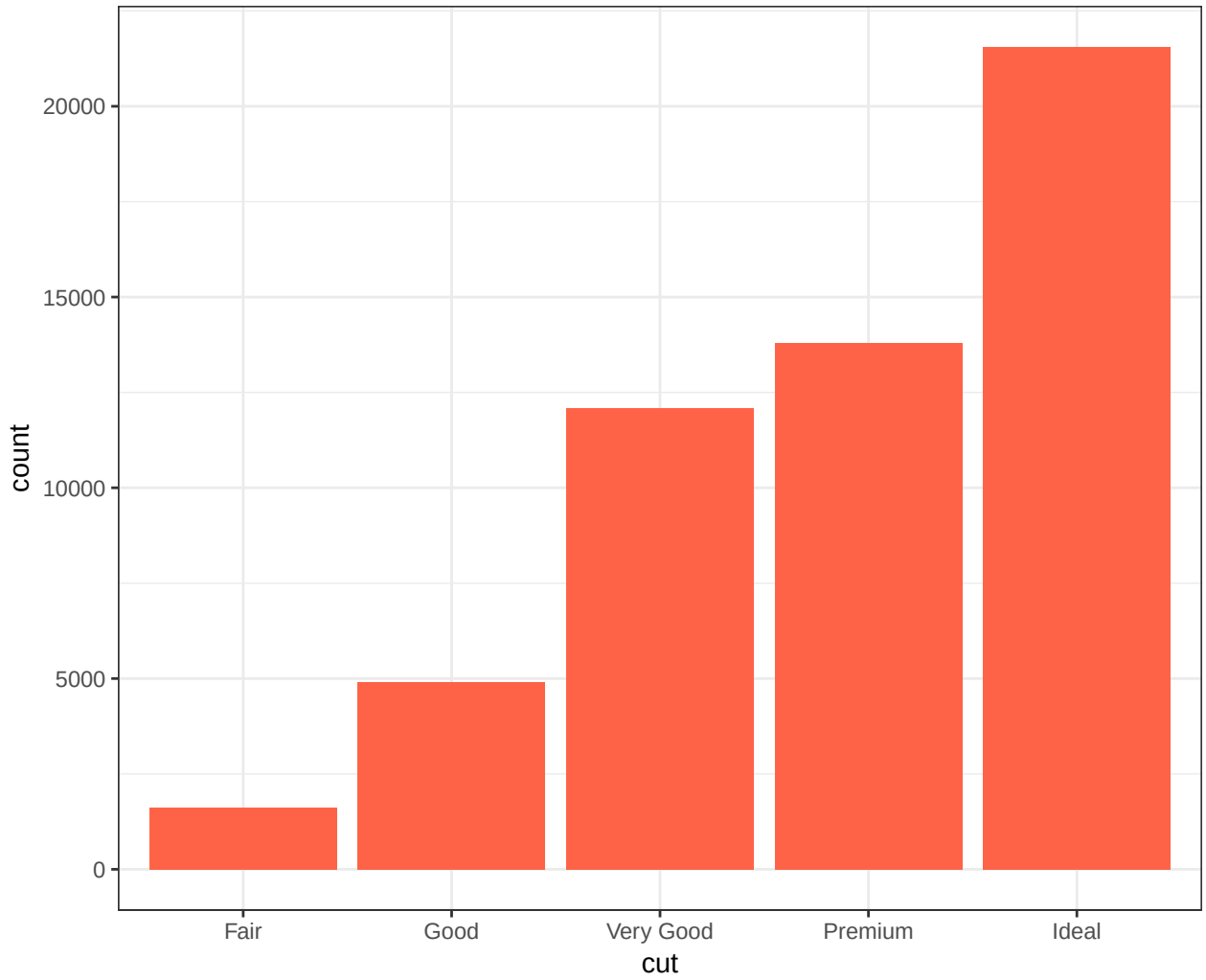
The `geom_bar()` layer forms a barplot and only requires an `x` assignment in the `aes()` call:

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



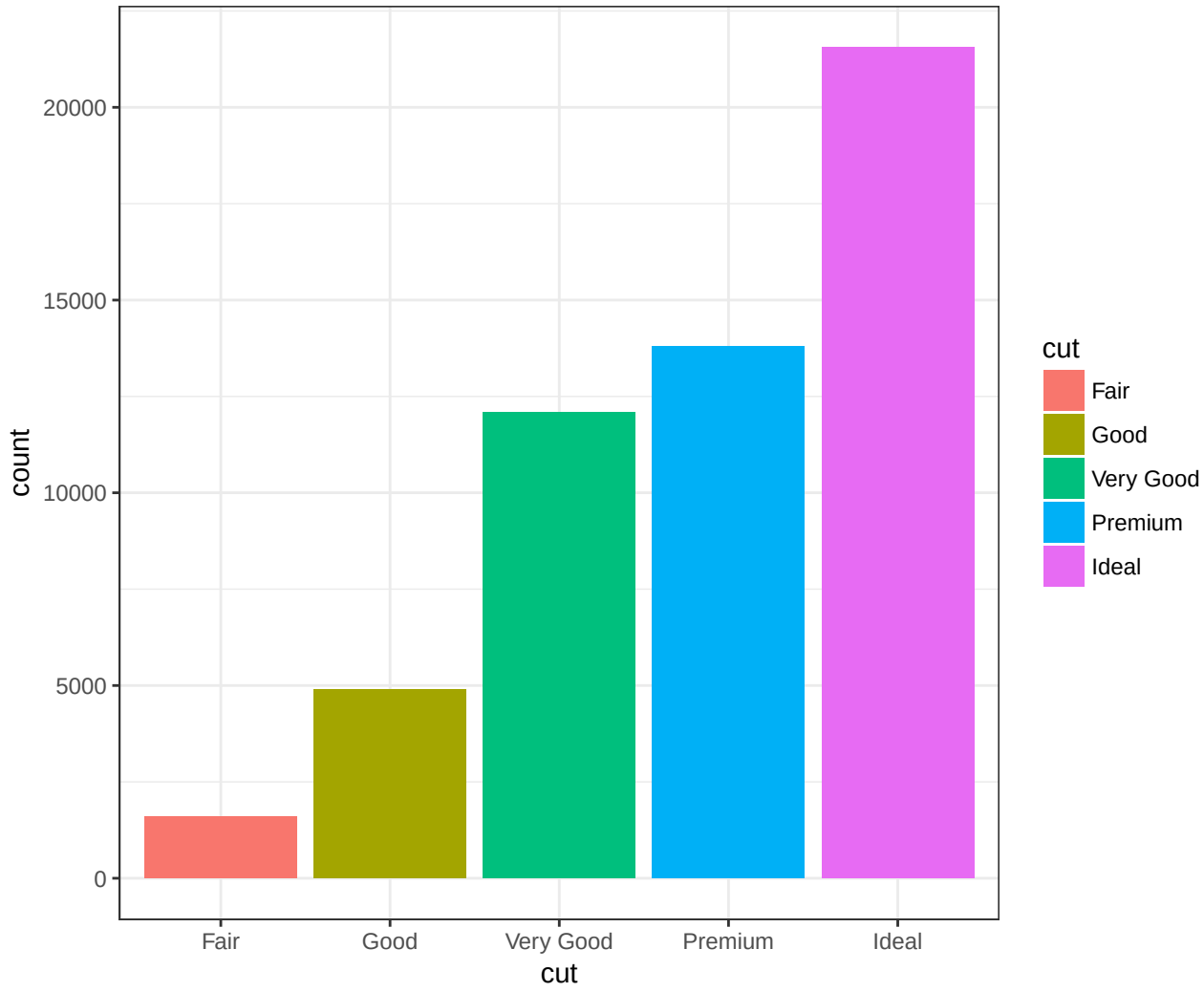
Color in the bars by assigning `fill` in `geom_bar()`, but outside of `aes()`:

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



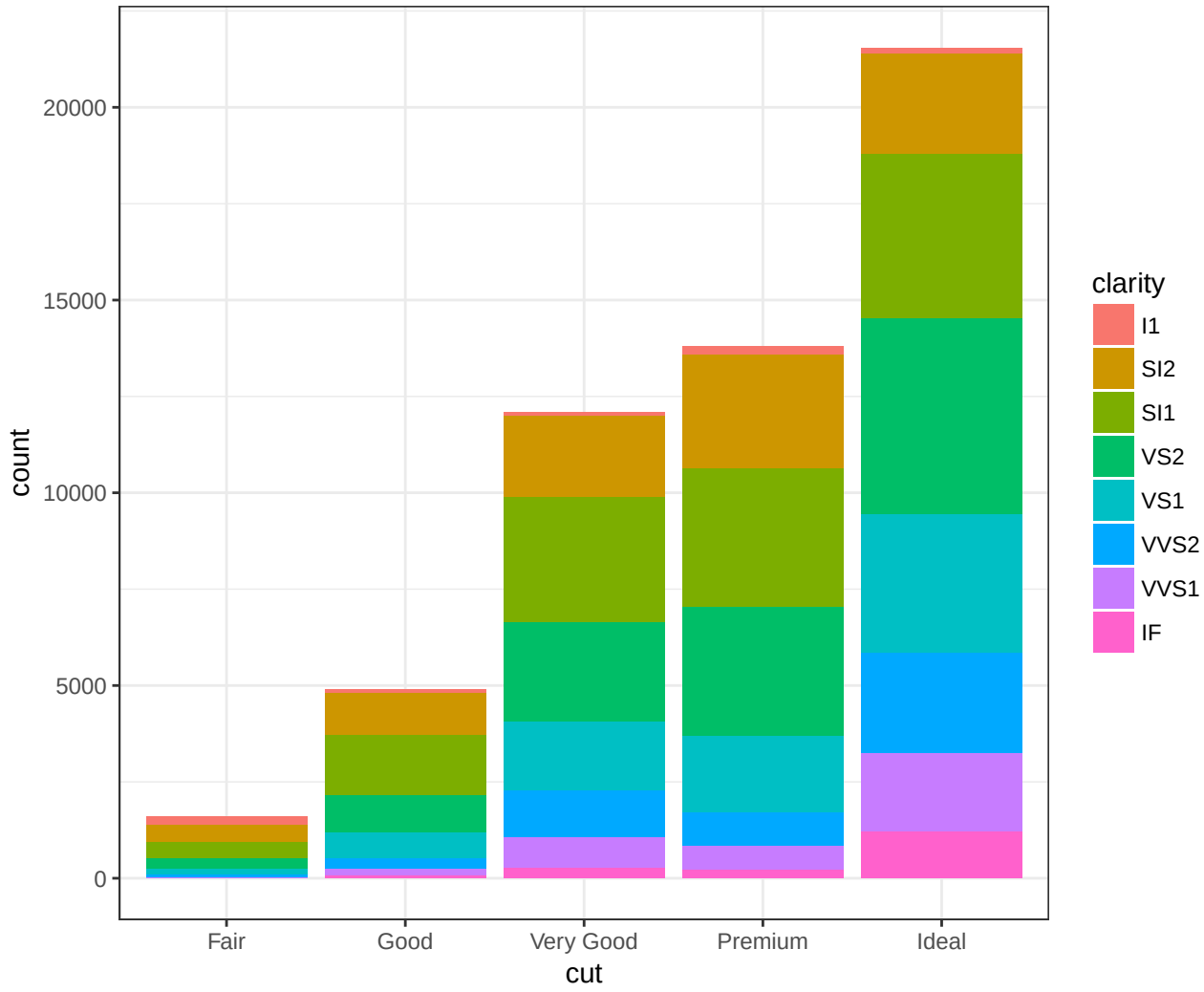
Color *within* the bars according to a variable by assigning `fill` in `geom_bar()` *inside* of `aes()`:

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



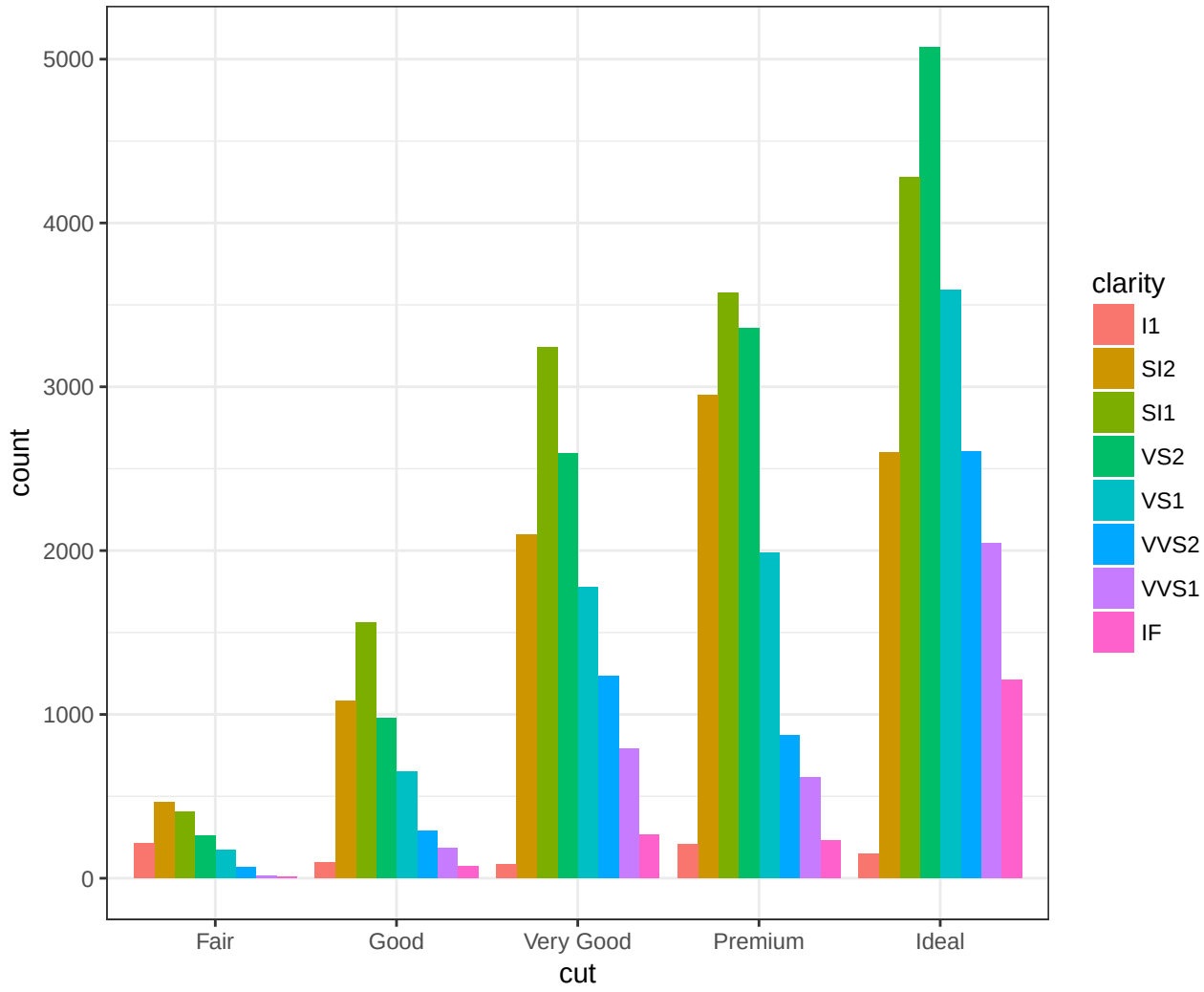
When we use `fill = clarity` within `aes()`, we see that it shows the proportion of each `clarity` value within each `cut` value:

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



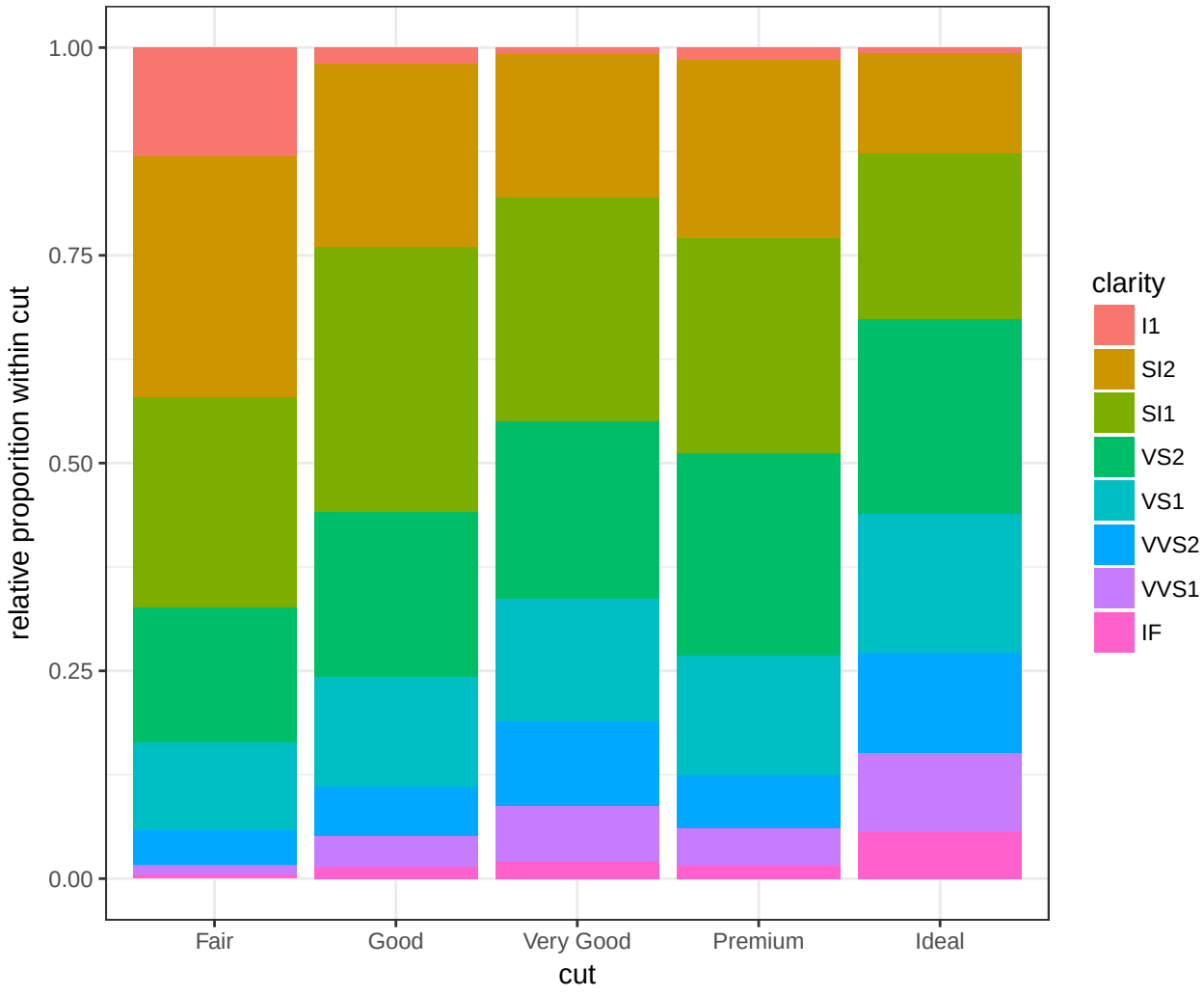
By setting `position = "dodge"` outside of `aes()`, it shows bar charts for the `clarity` values within each `cut` value:

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



By setting `position = "fill"`, it shows the proportion of `clarity` values within each `cut` value and no longer shows the `cut` values:

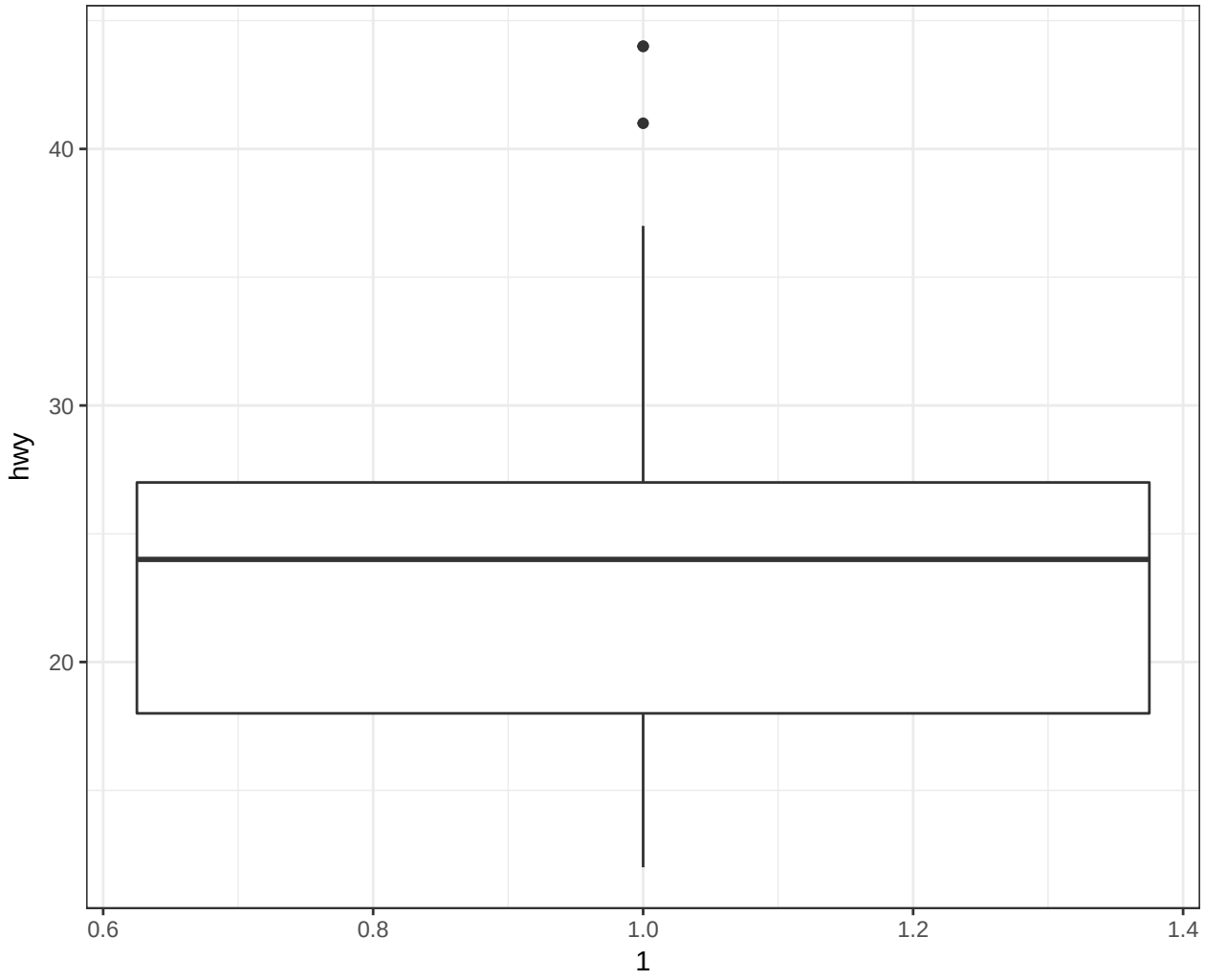
```
> ggplot(data = diamonds) +
+   geom_bar(mapping=aes(x = cut, fill = clarity),
+            position = "fill") +
+   labs(x = "cut", y = "relative proporition within cut")
```



Boxplots and Violin Plots

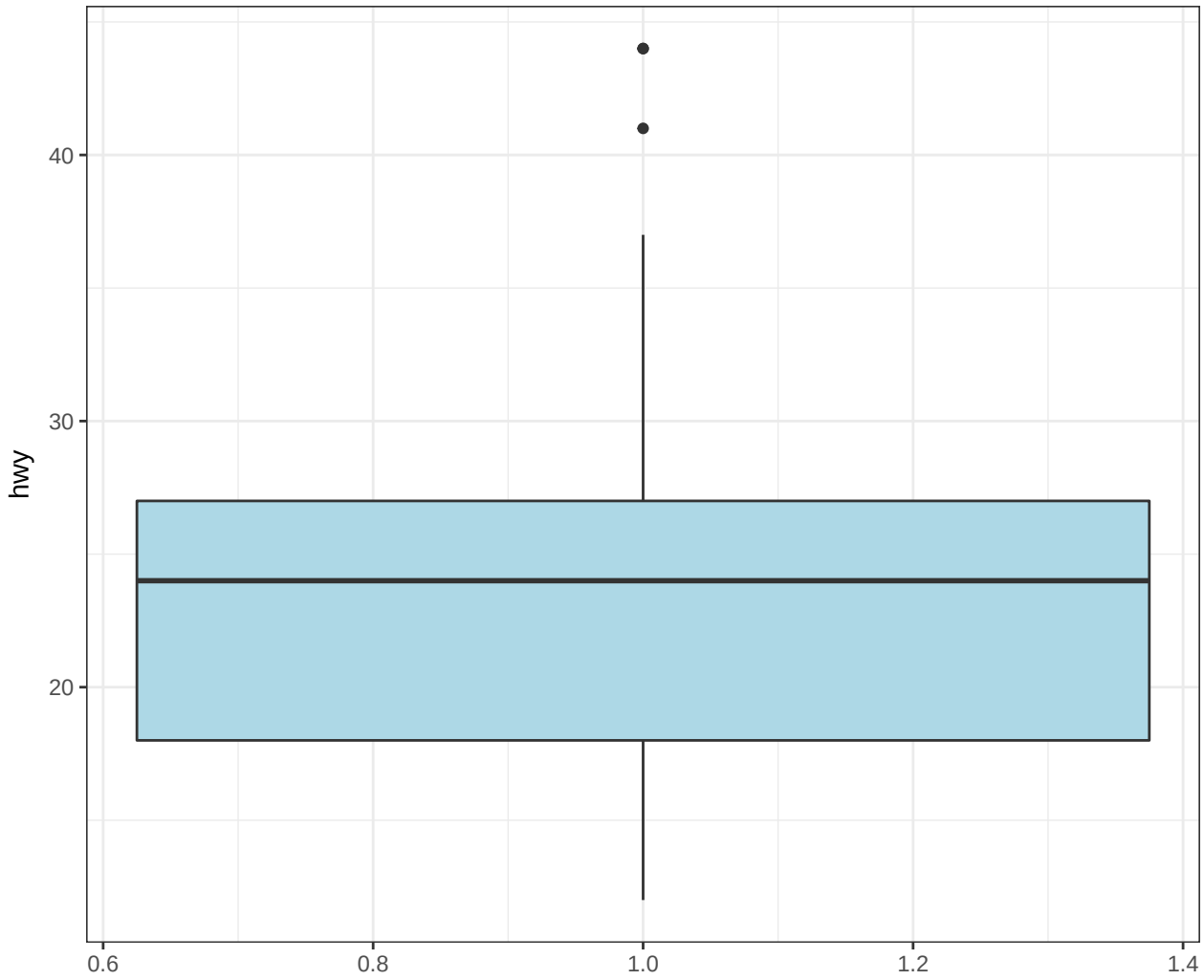
The `geom_boxplot()` layer forms a boxplot and requires both `x` and `y` assignments in the `aes()` call, even when plotting a single boxplot:

```
> ggplot(data = mpg) +
+   geom_boxplot(mapping = aes(x = 1, y = hwy))
```



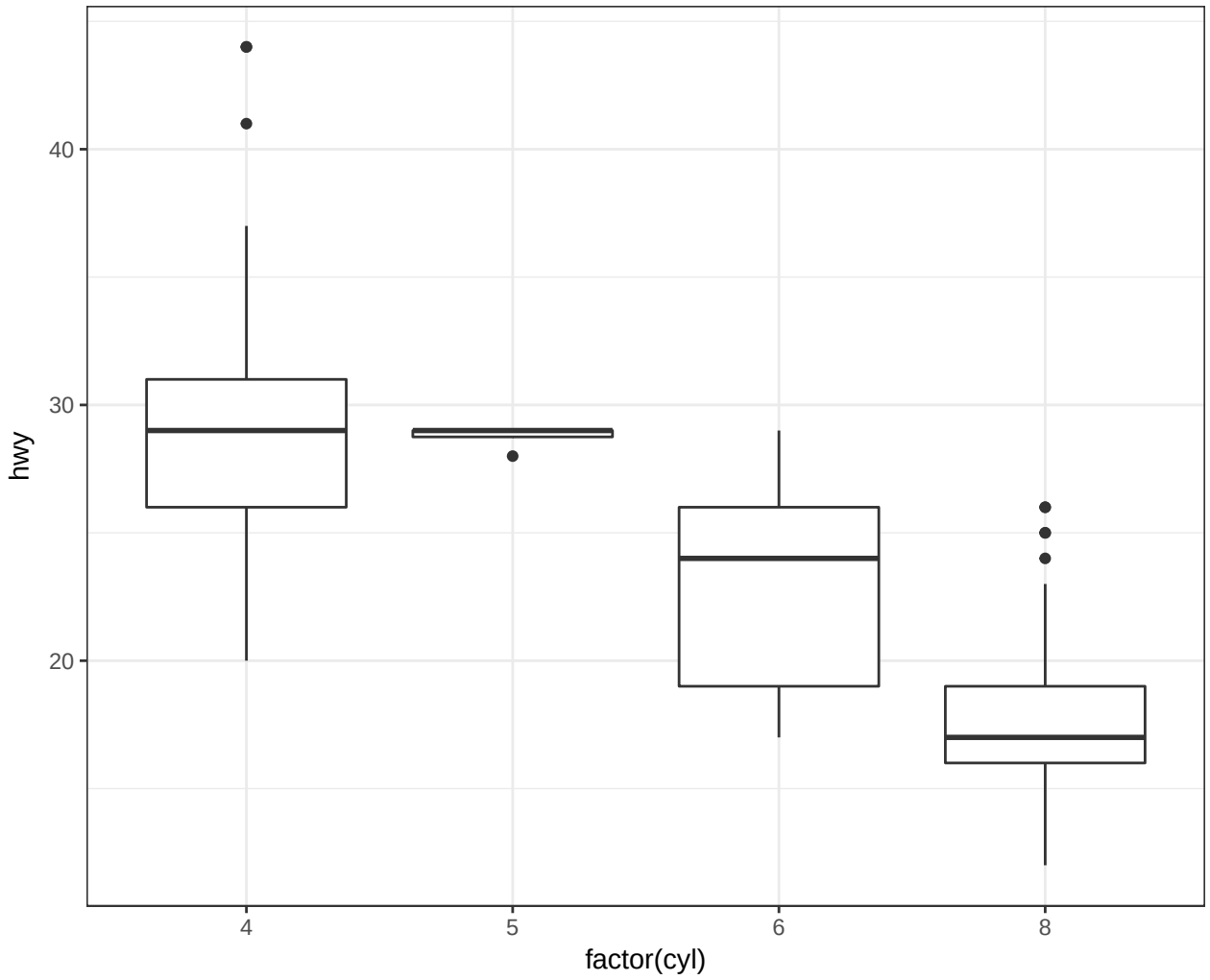
Color in the boxes by assigning `fill` in `geom_boxplot()`, but outside of `aes()`:

```
> ggplot(data = mpg) +
+   geom_boxplot(mapping = aes(x = 1, y = hwy),
+                fill="lightblue") +
+   labs(x=NULL)
```



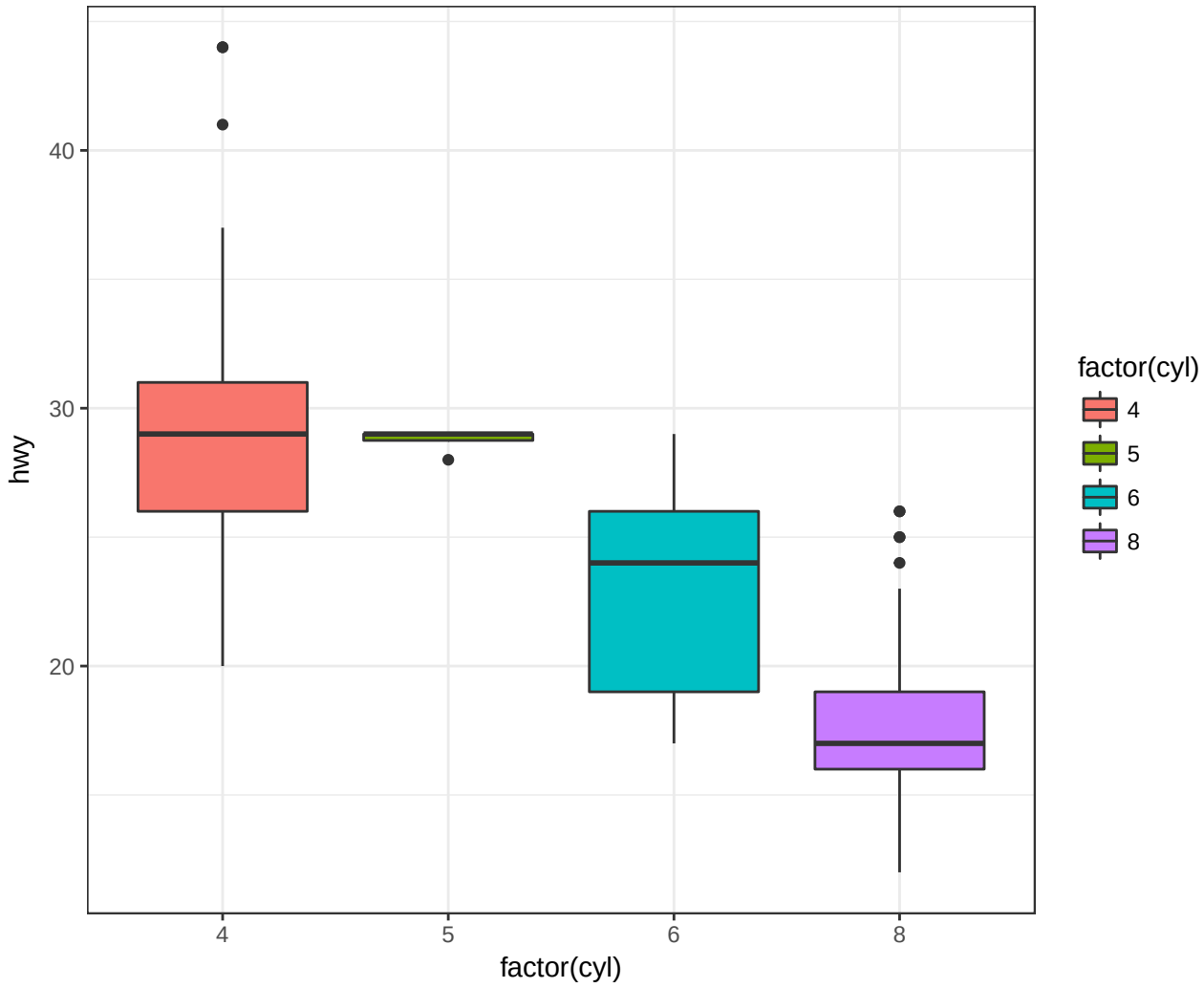
Show a boxplot for the `y` values occurring within each `x` factor level by making these assignments in `aes()`:

```
> ggplot(data = mpg) +
+   geom_boxplot(mapping = aes(x = factor(cyl), y = hwy))
```



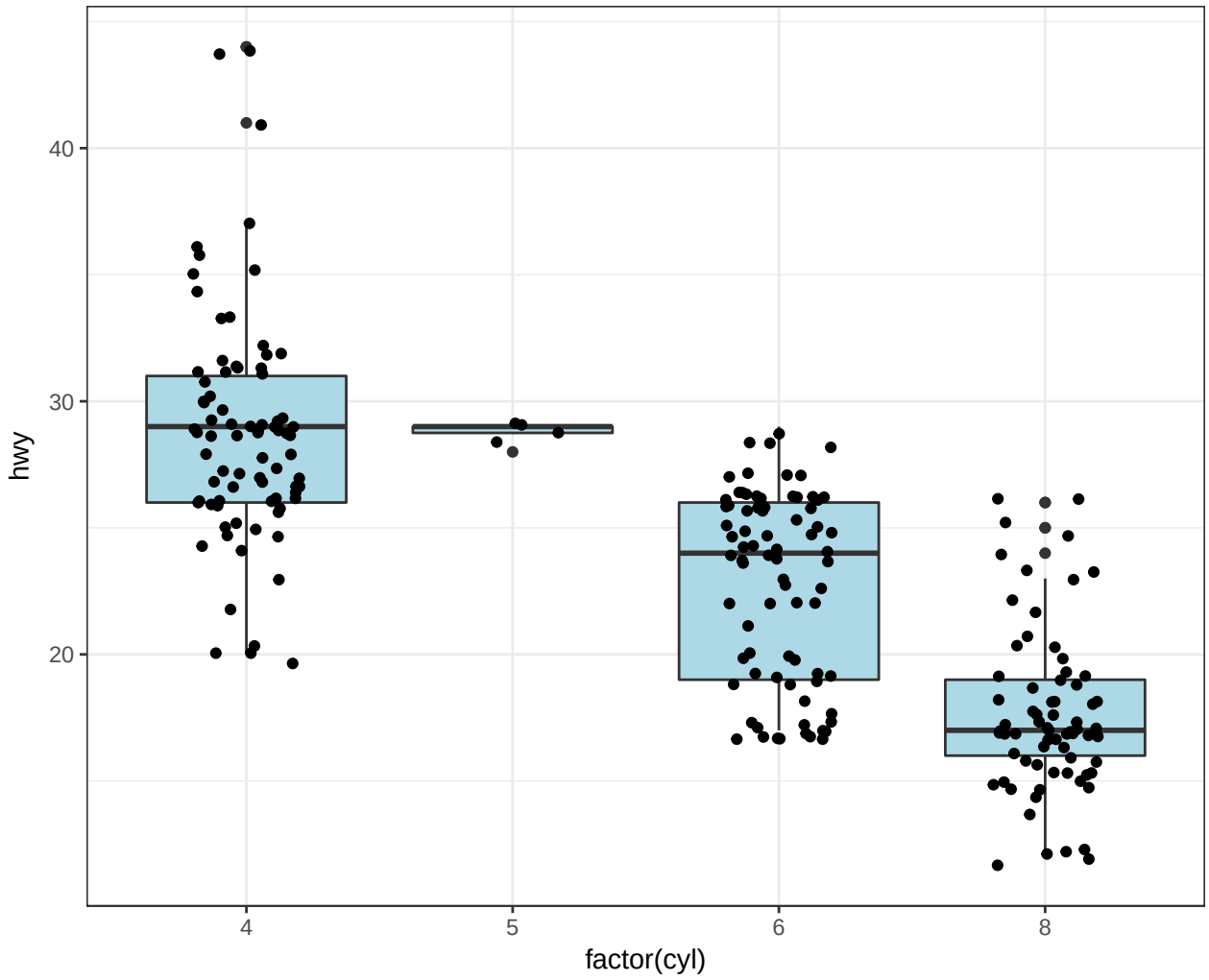
By assigning the `fill` argument *within* `aes()`, we can color each boxplot according to the x-axis factor variable:

```
> ggplot(data = mpg) +
+   geom_boxplot(mapping = aes(x = factor(cyl), y = hwy,
+                              fill = factor(cyl)))
```



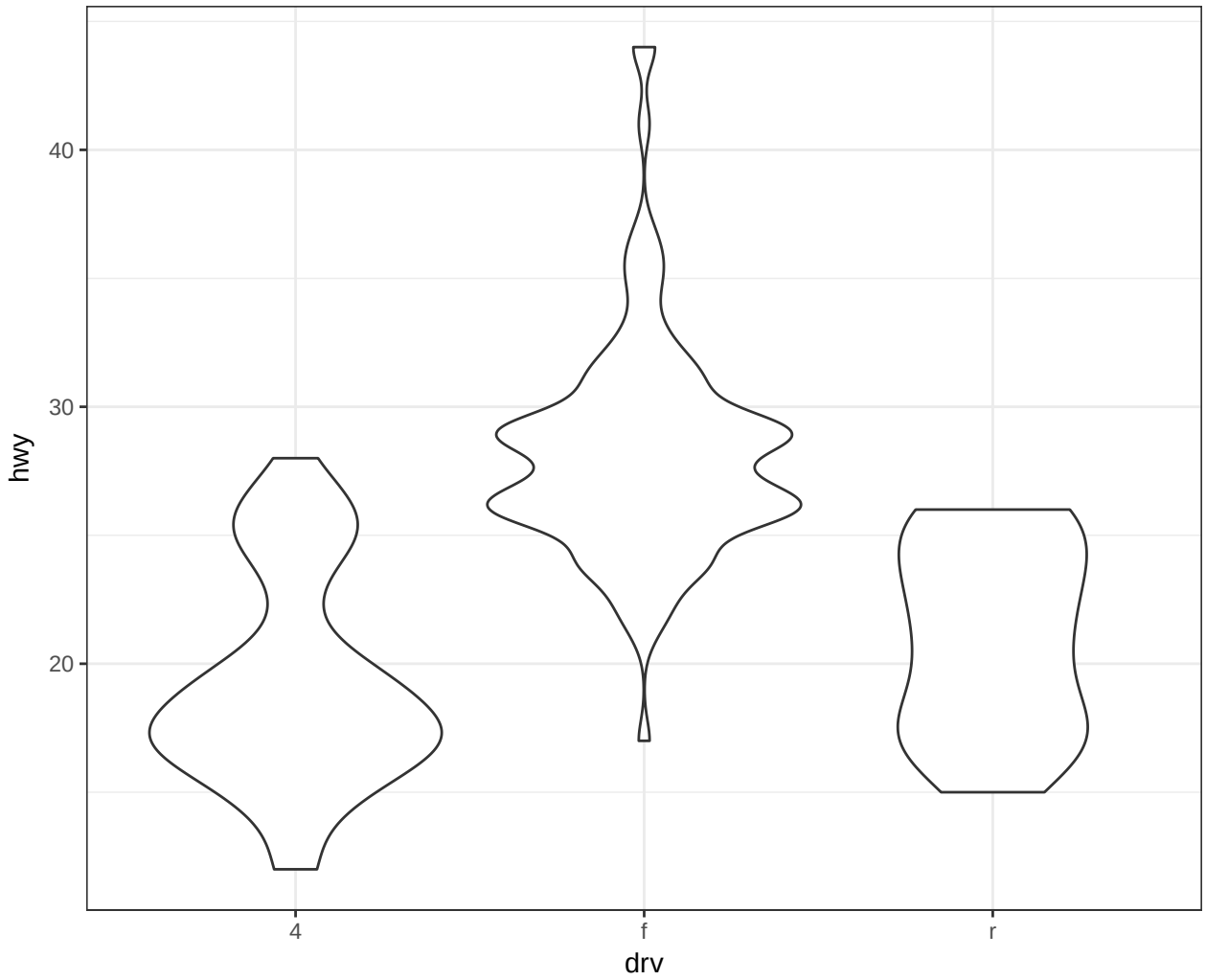
The `geom_jitter()` function plots the data points and randomly jitters them so we can better see all of the points:

```
> ggplot(data = mpg, mapping = aes(x=factor(cyl), y=hwy)) +
+   geom_boxplot(fill = "lightblue") +
+   geom_jitter(width = 0.2)
```



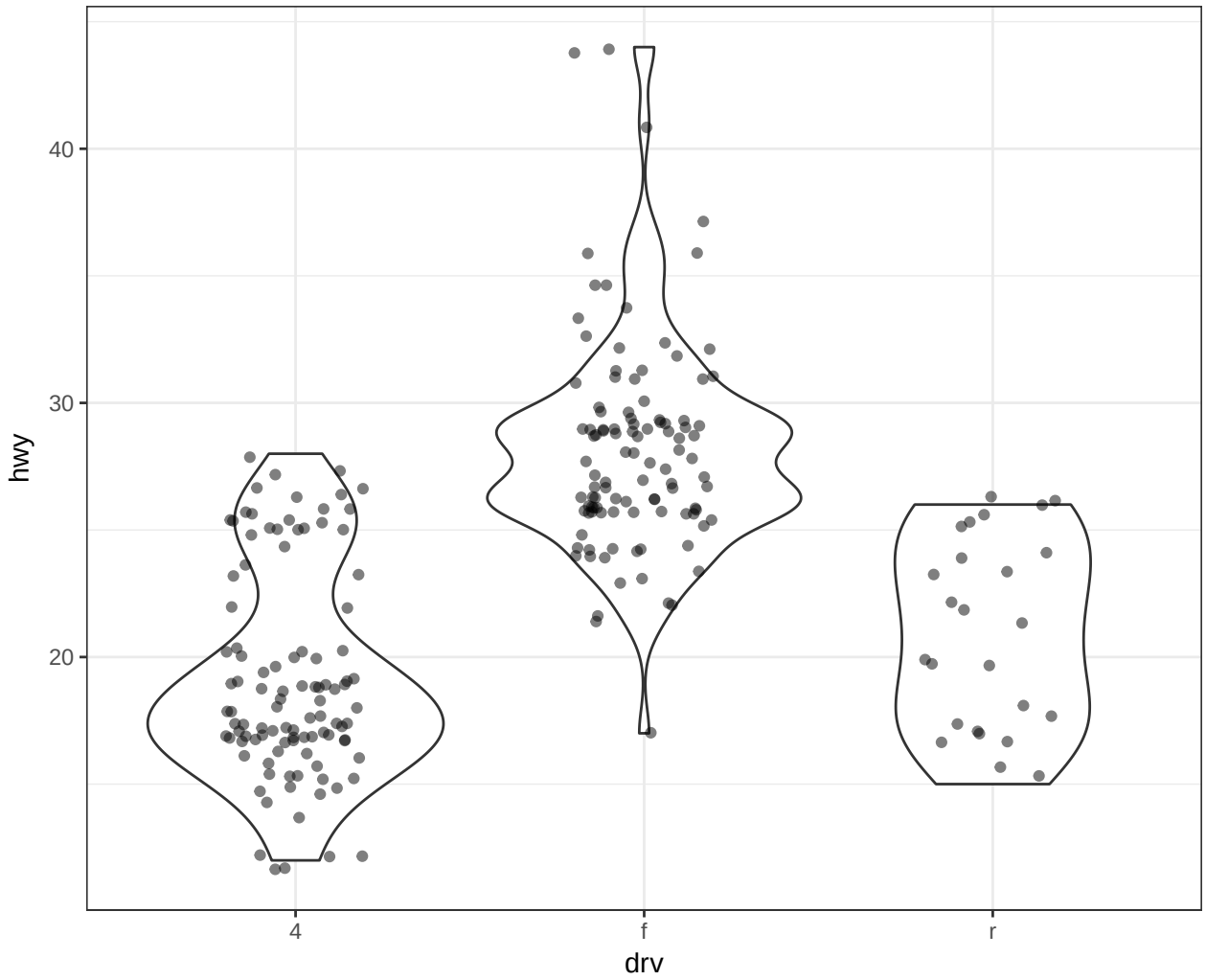
A violin plot, called via `geom_violin()`, is similar to a boxplot, except shows a density plot turned on its side and reflected across its vertical axis:

```
> ggplot(data = mpg) +
+   geom_violin(mapping = aes(x = drv, y = hwy))
```



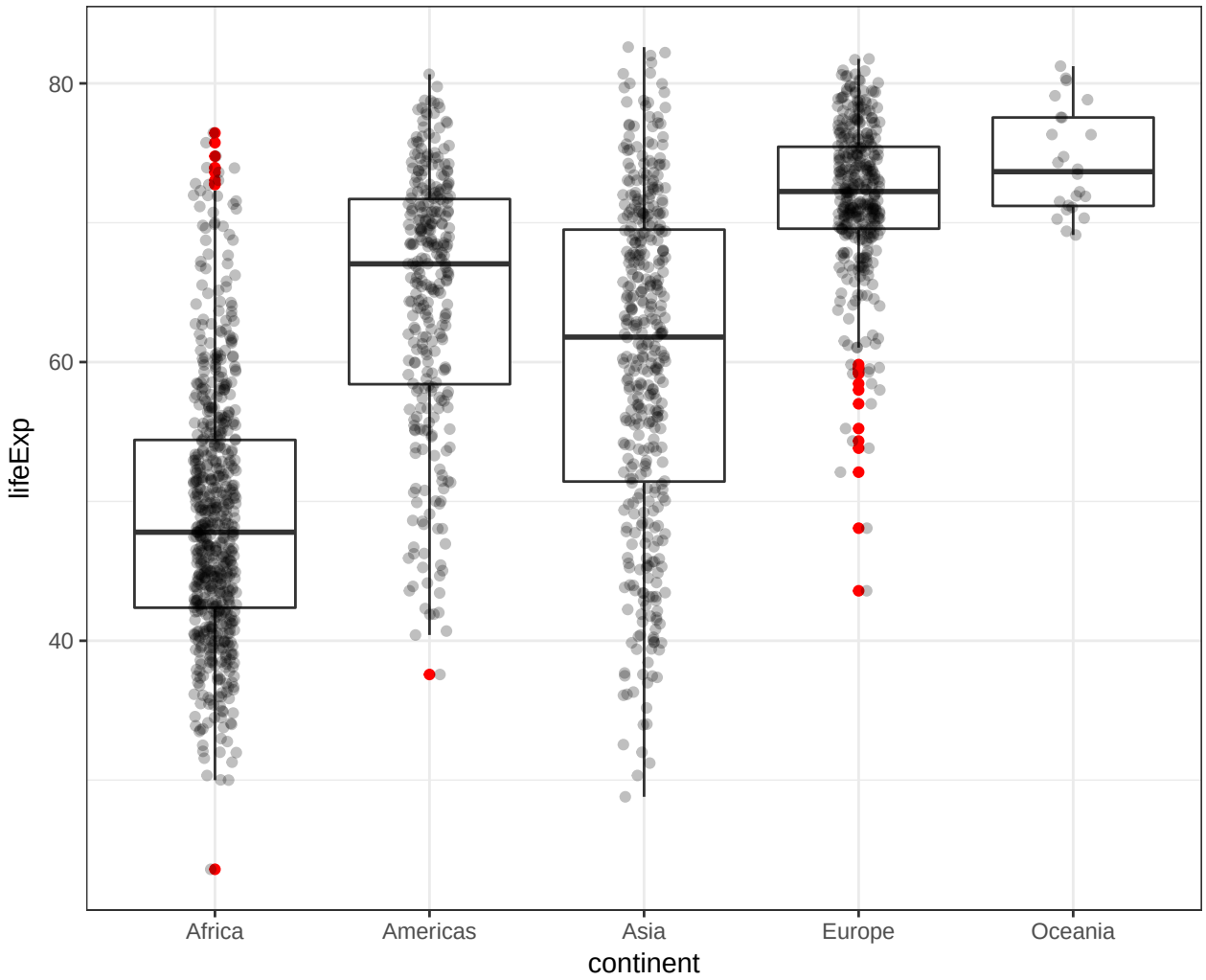
Add a `geom_jitter()` to see how the original data points relate to the violin plots:

```
> ggplot(data = mpg, mapping = aes(x = drv, y = hwy)) +
+   geom_violin(adjust=1.2) +
+   geom_jitter(width=0.2, alpha=0.5)
```



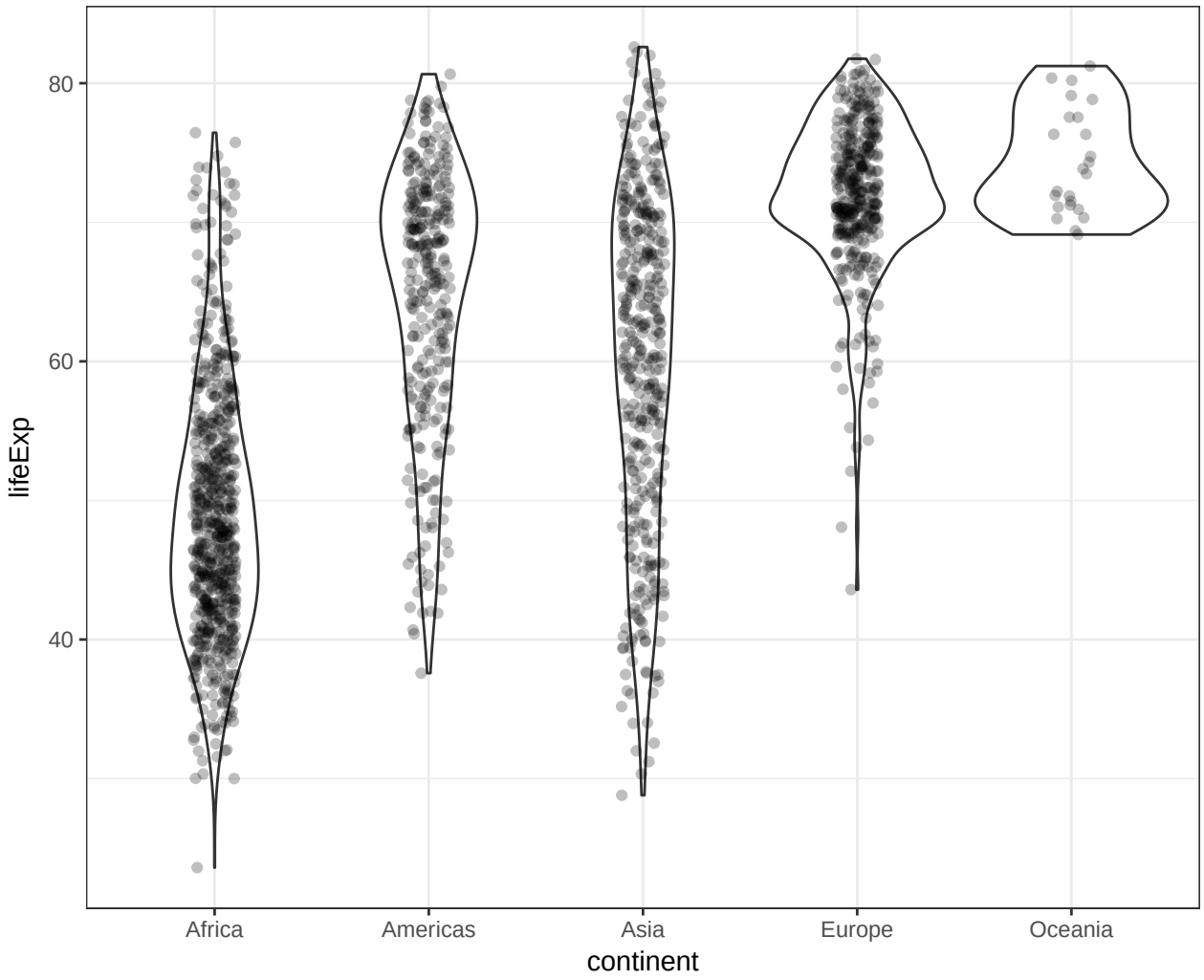
Boxplot example on the `gapminder` data:

```
> ggplot(gapminder, aes(x = continent, y = lifeExp)) +
+   geom_boxplot(outlier.colour = "red") +
+   geom_jitter(width = 0.1, alpha = 0.25)
```



Analogous violin plot example on the `gapminder` data:

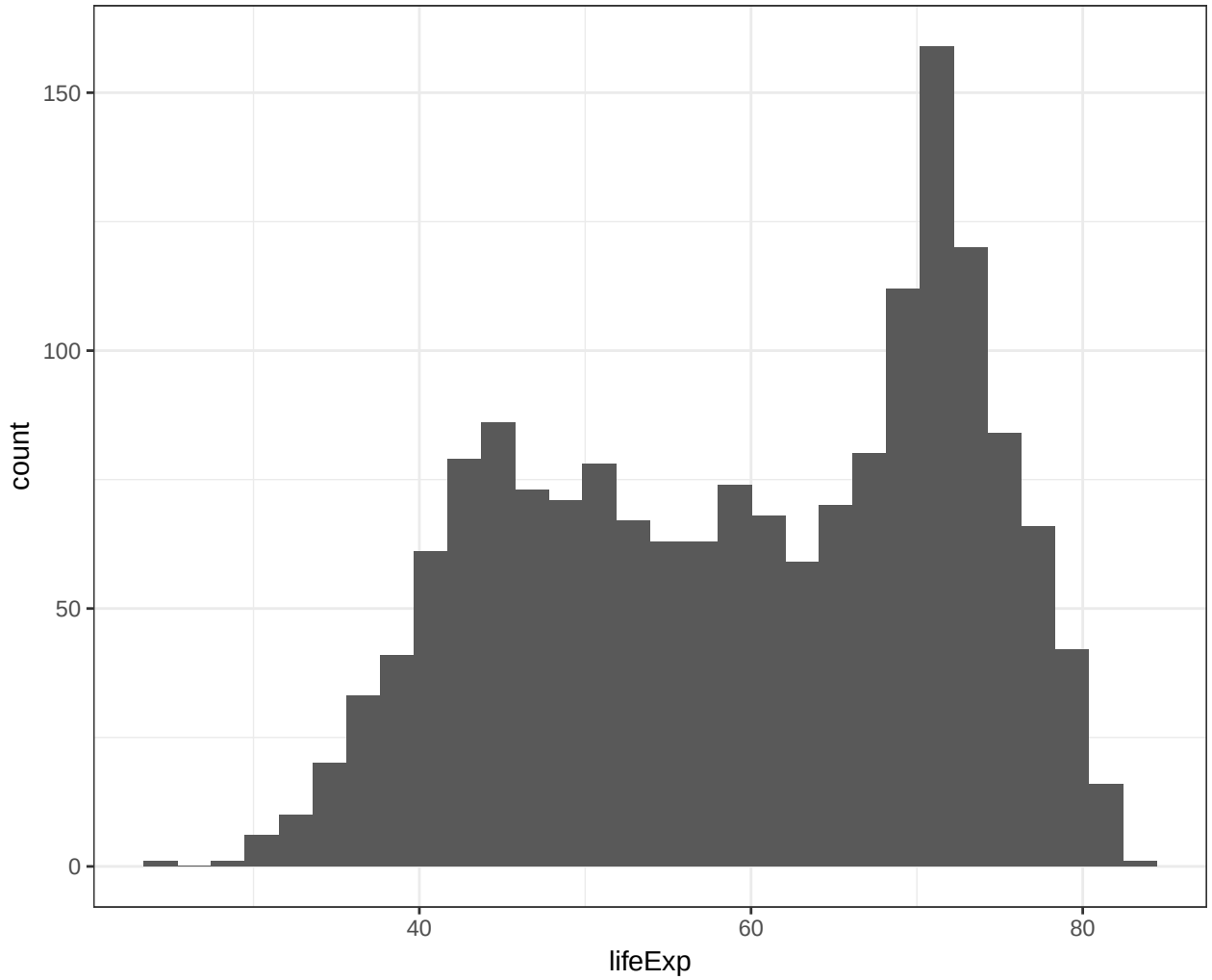
```
> ggplot(gapminder, aes(x = continent, y = lifeExp)) +
+   geom_violin() +
+   geom_jitter(width = 0.1, alpha = 0.25)
```



Histograms and Density Plots

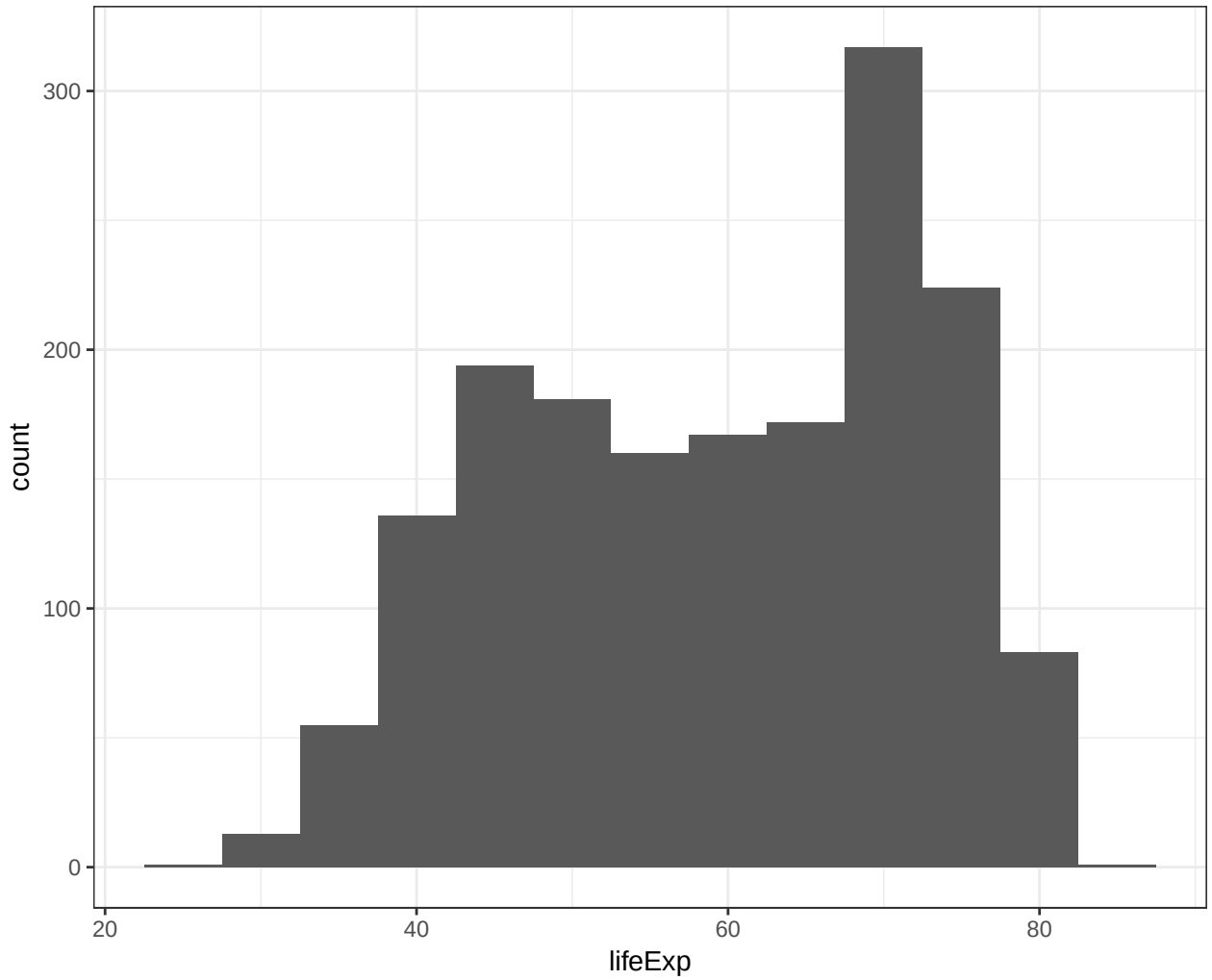
We can create a histogram using the `geom_histogram()` layer, which requires an `x` argument only in the `aes()` call:

```
> ggplot(gapminder) +
+   geom_histogram(mapping = aes(x=lifeExp))
```



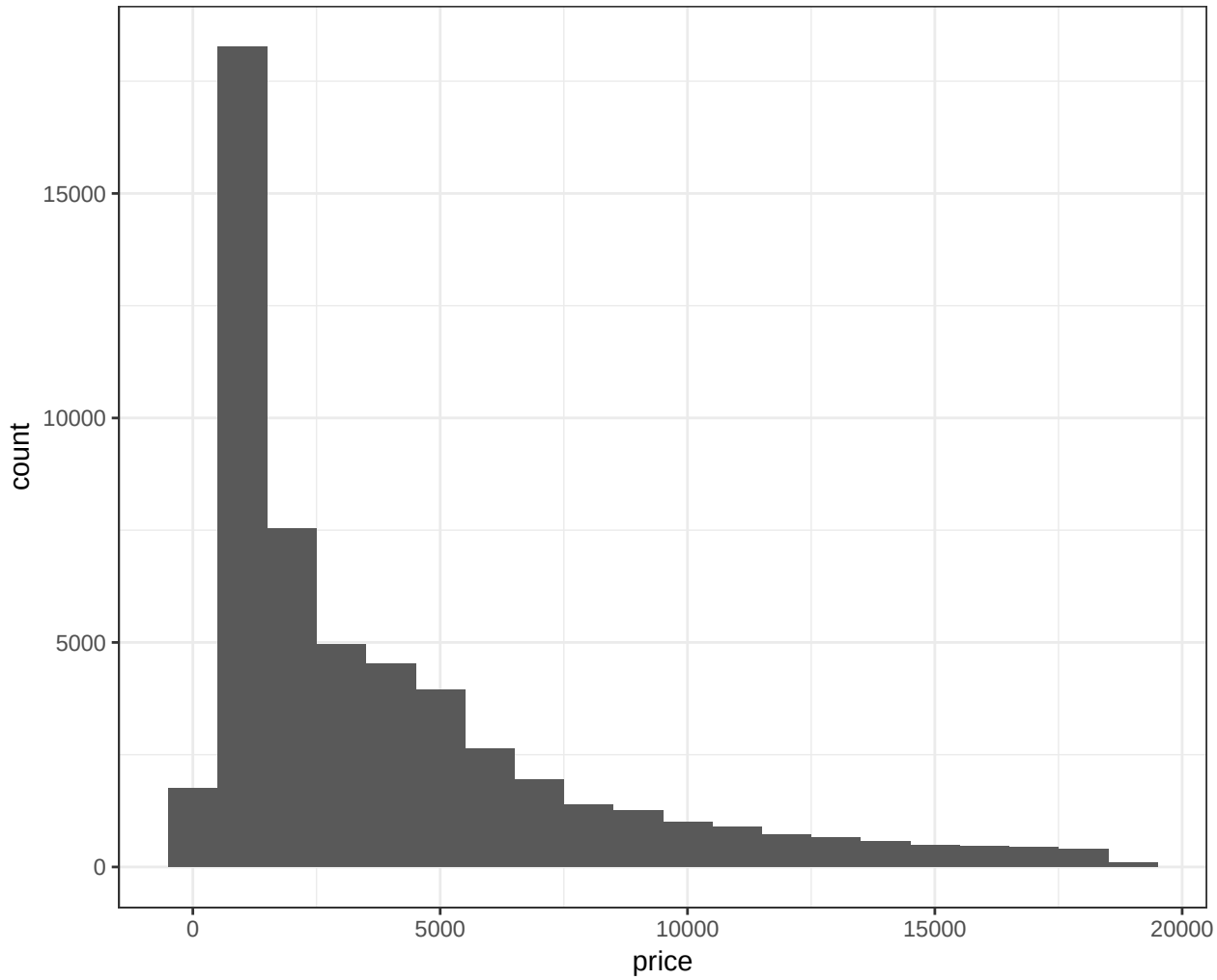
We can change the bin width directly in the histogram, which is an intuitive parameter to change based on visual inspection:

```
> ggplot(gapminder) +
+   geom_histogram(mapping = aes(x=lifeExp), binwidth=5)
```



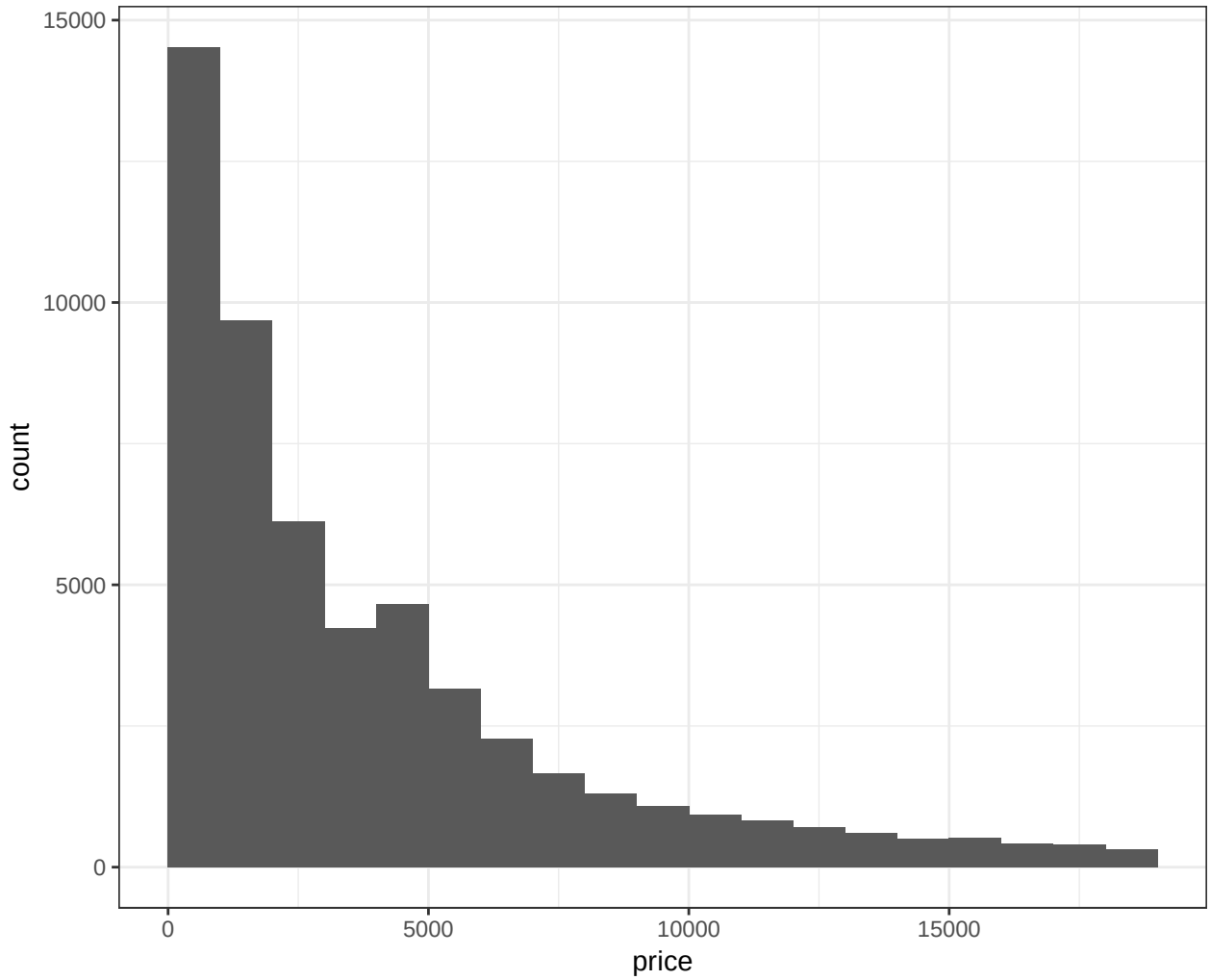
The bins are sometimes centered in an unexpected manner in `ggplot2`:

```
> ggplot(diamonds) +
+   geom_histogram(mapping = aes(x=price), binwidth = 1000)
```



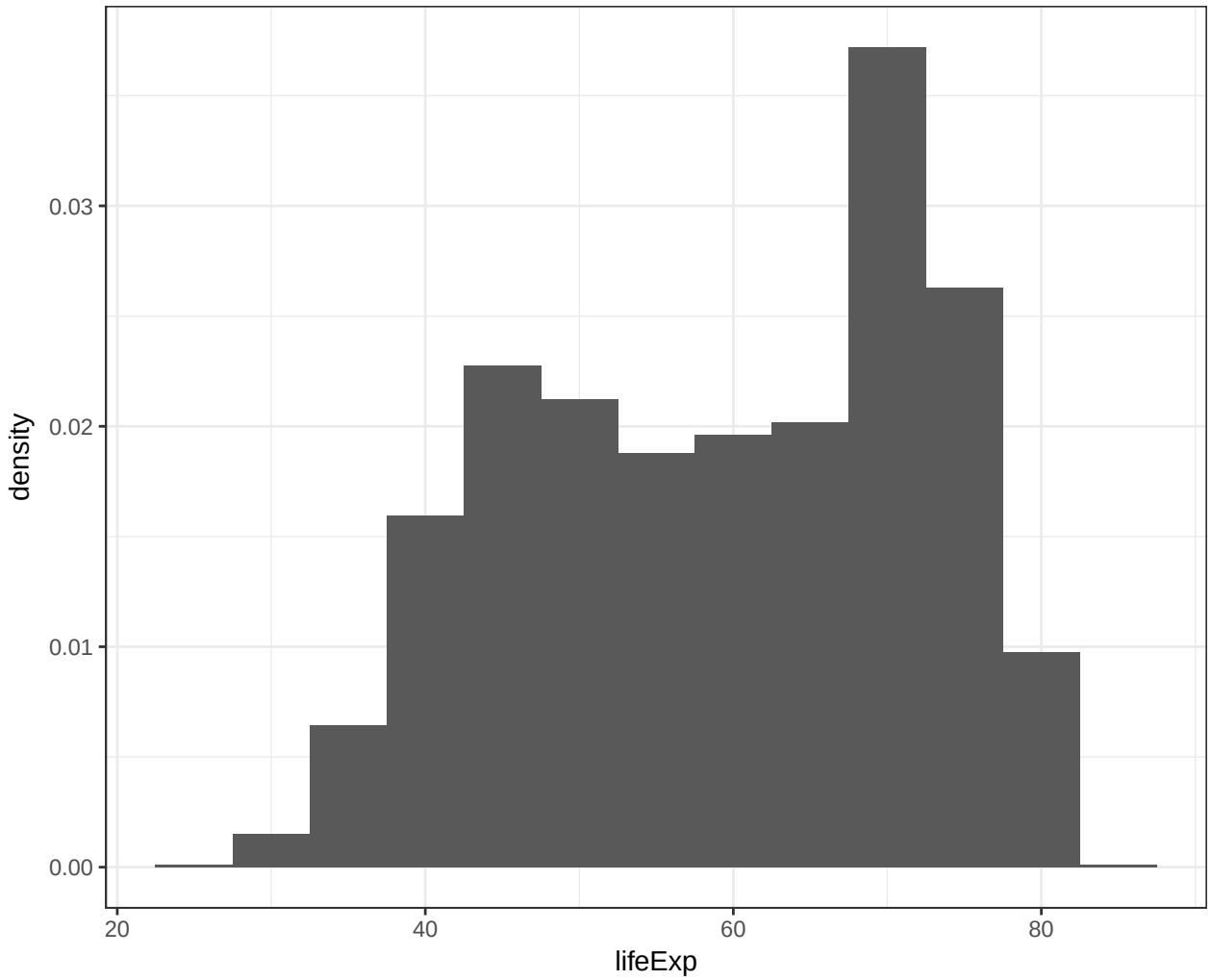
Let's fix how the bins are centered (make `center` half of `binwidth`).

```
> ggplot(diamonds) +
+   geom_histogram(mapping = aes(x=price), binwidth = 1000,
+                  center=500)
```



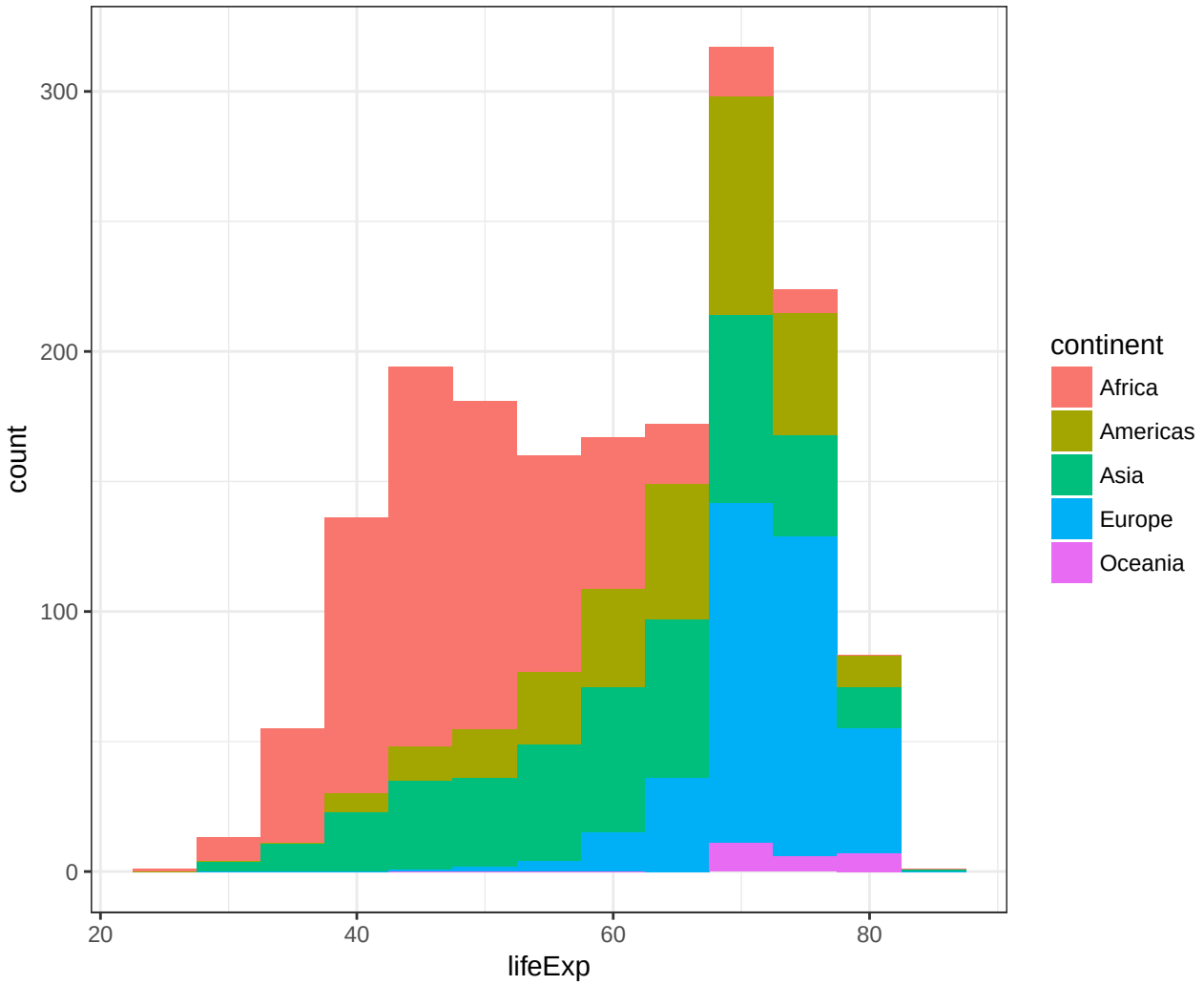
Instead of counts on the y-axis, we may instead want the area of the bars to sum to 1, like a probability density:

```
> ggplot(gapminder) +
+   geom_histogram(mapping = aes(x=lifeExp, y=..density..),
+                  binwidth=5)
```



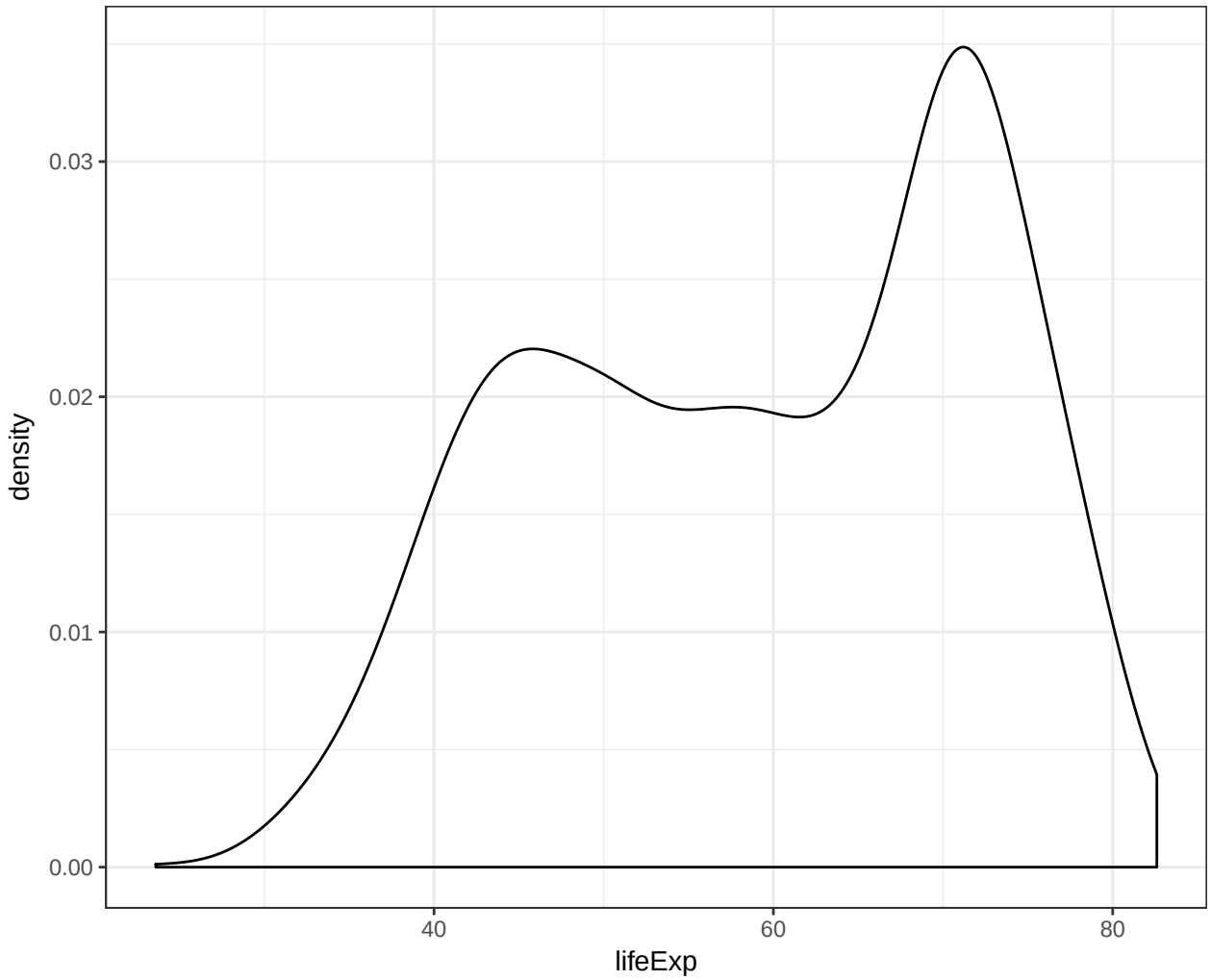
When we use `fill = continent` within `aes()`, we see that it shows the counts of each `continent` value within each `lifeExp` bin:

```
> ggplot(gapminder) +
+   geom_histogram(mapping = aes(x=lifeExp, fill = continent),
+                  binwidth = 5)
```



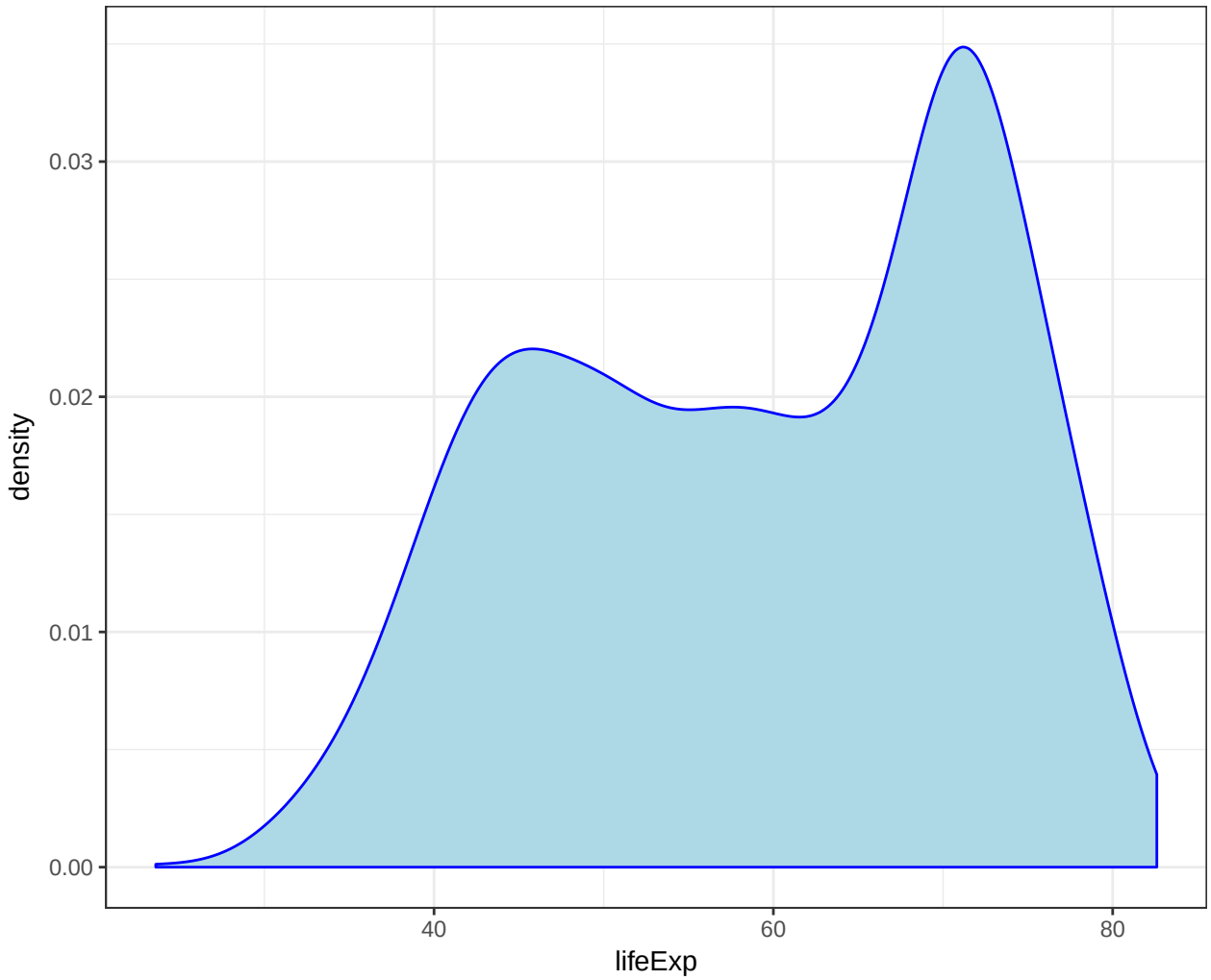
Display a density plot using the `geom_density()` layer:

```
> ggplot(gapminder) +
+   geom_density(mapping = aes(x=lifeExp))
```



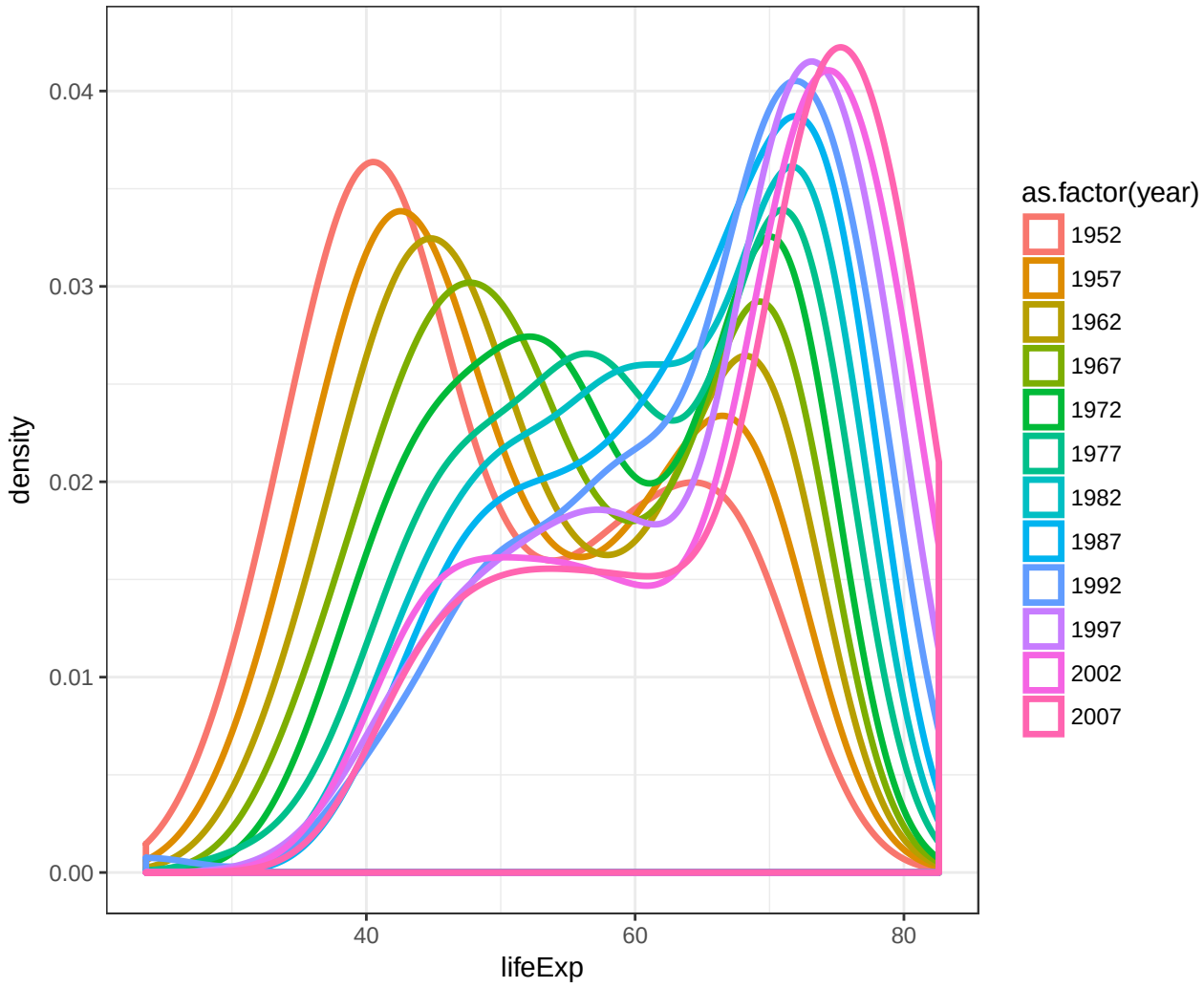
Employ the arguments `color="blue"` and `fill="lightblue"` outside of the `aes()` call to include some colors:

```
> ggplot(gapminder) +
+   geom_density(mapping = aes(x=lifeExp), color="blue",
+                fill="lightblue")
```



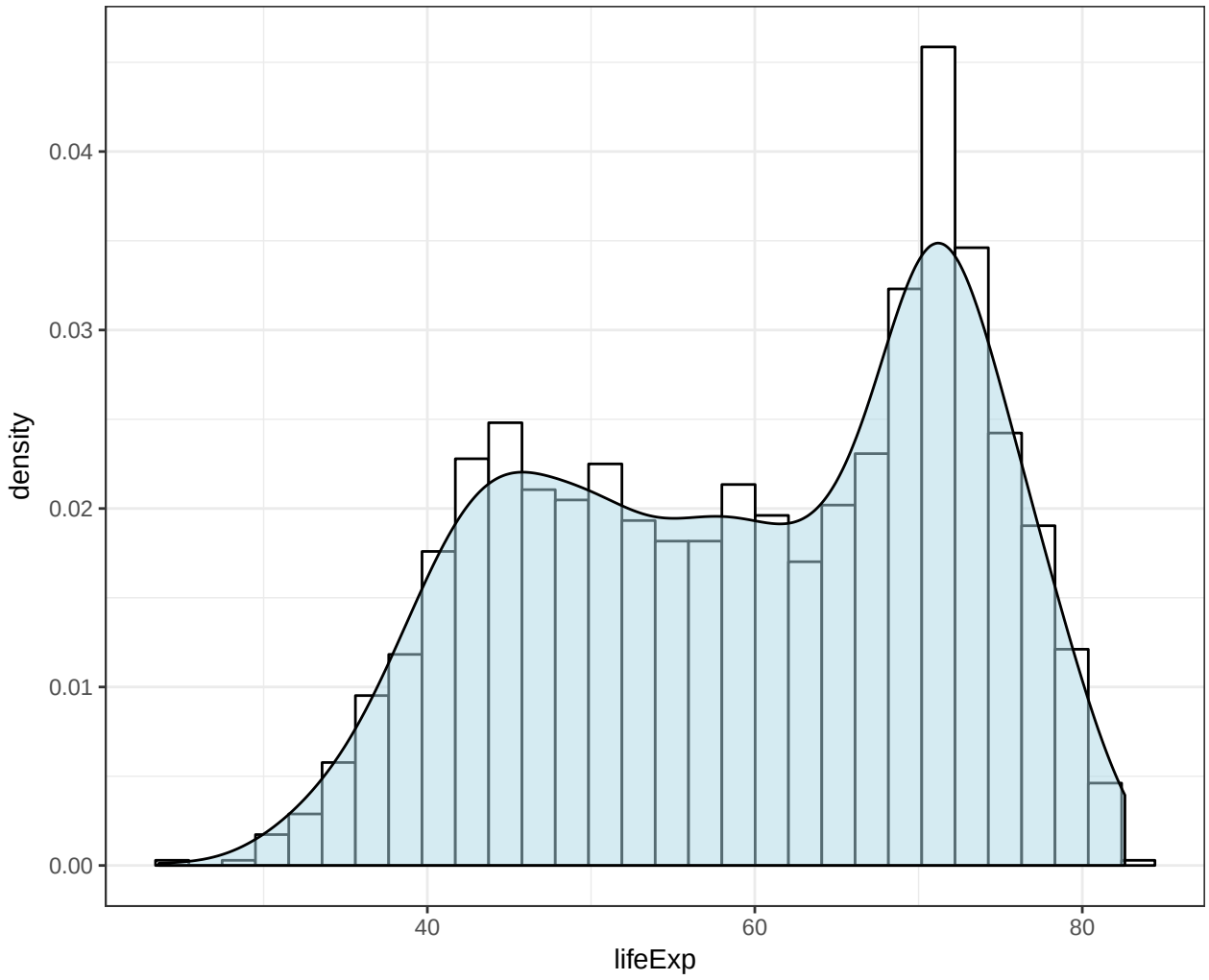
By utilizing `color=as.factor(year)` we plot a density of `lifeExp` stratified by each `year` value:

```
> ggplot(gapminder) +
+   geom_density(aes(x=lifeExp, color=as.factor(year)),
+                size=1.2)
```



Overlay a density plot and a histogram together:

```
> ggplot(gapminder, mapping = aes(x=lifeExp)) +
+   geom_histogram(aes(y=..density..), color="black",
+                  fill="white") +
+   geom_density(fill="lightblue", alpha=.5)
```



Line Plots

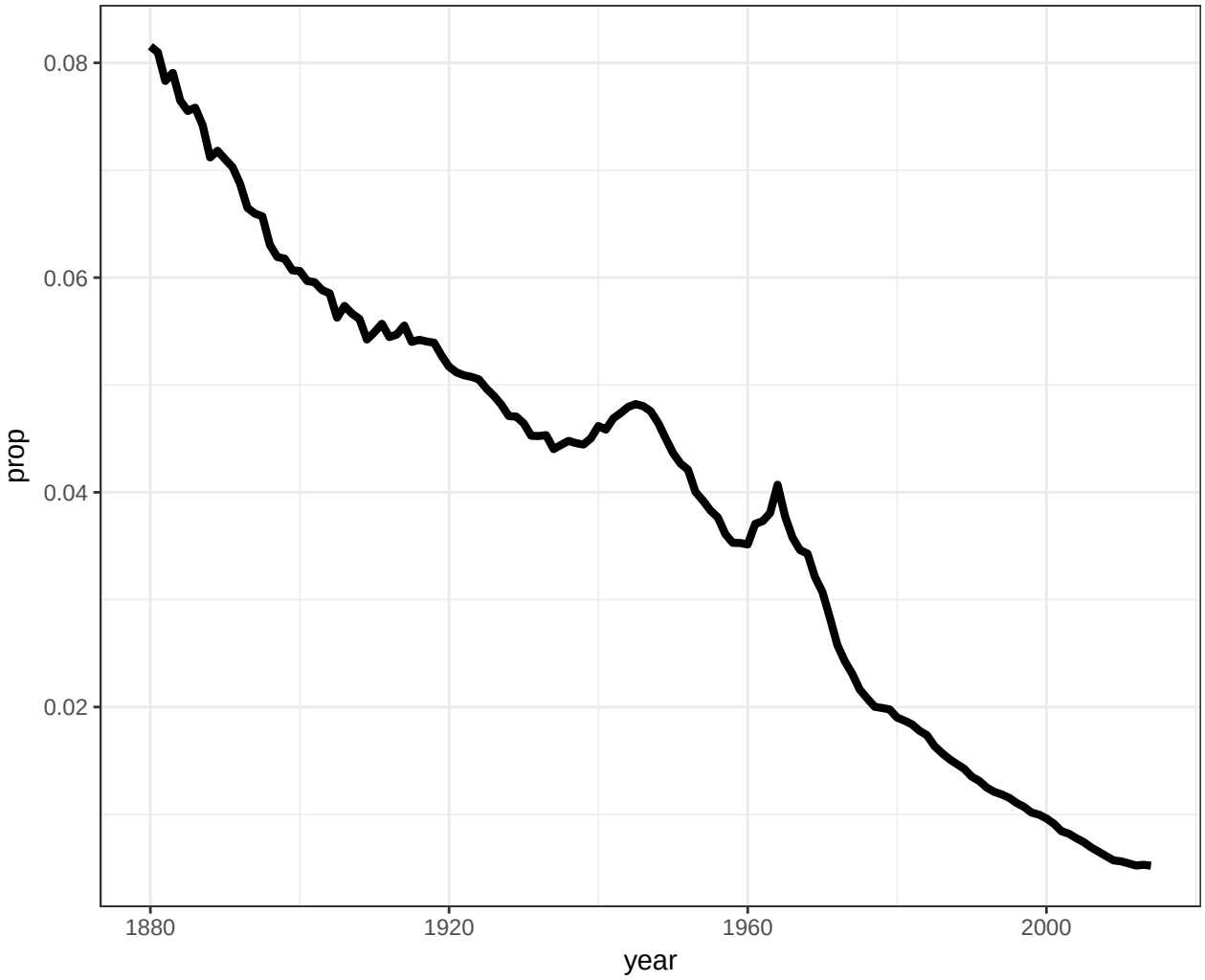
`babynames` Revisited

Let's first create a data frame that captures the number of times "John" is registered in males per year:

```
> library("babynames")
> john <- babynames %>% filter(sex=="M", name=="John")
> head(john)
# A tibble: 6 × 5
   year   sex  name      n       prop
  <dbl> <chr> <chr> <int>      <dbl>
1  1880     M  John   9655 0.08154561
2  1881     M  John   8769 0.08098149
3  1882     M  John   9557 0.07831488
4  1883     M  John   8894 0.07907183
5  1884     M  John   9388 0.07648626
6  1885     M  John   8756 0.07551726
```

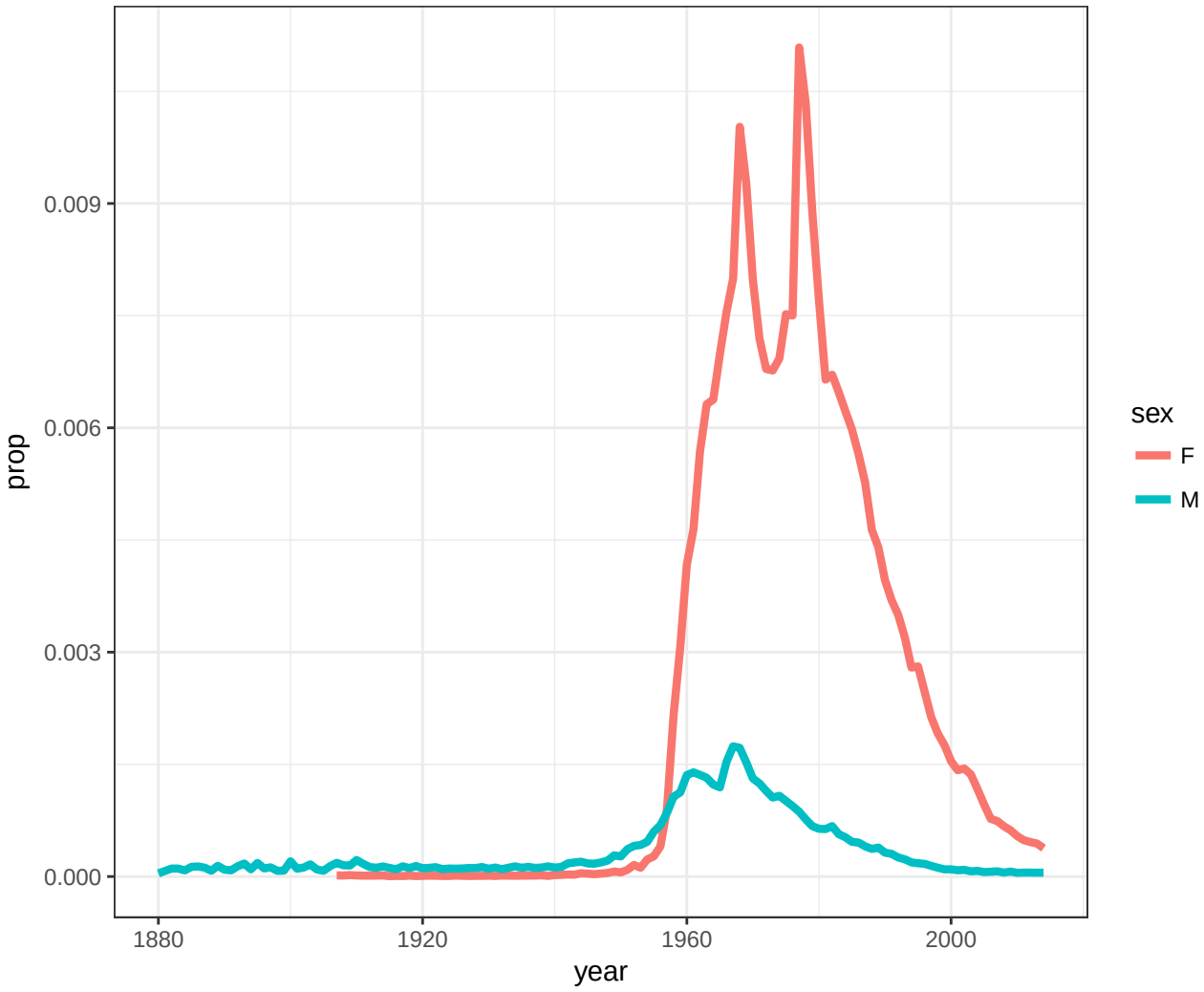
We can `geom_lines()` to plot a line showing the popularity of "John" over time:

```
> ggplot(data = john) +
+   geom_line(mapping = aes(x=year, y=prop), size=1.5)
```



Now let's look at a name that occurs nontrivially in males and females:

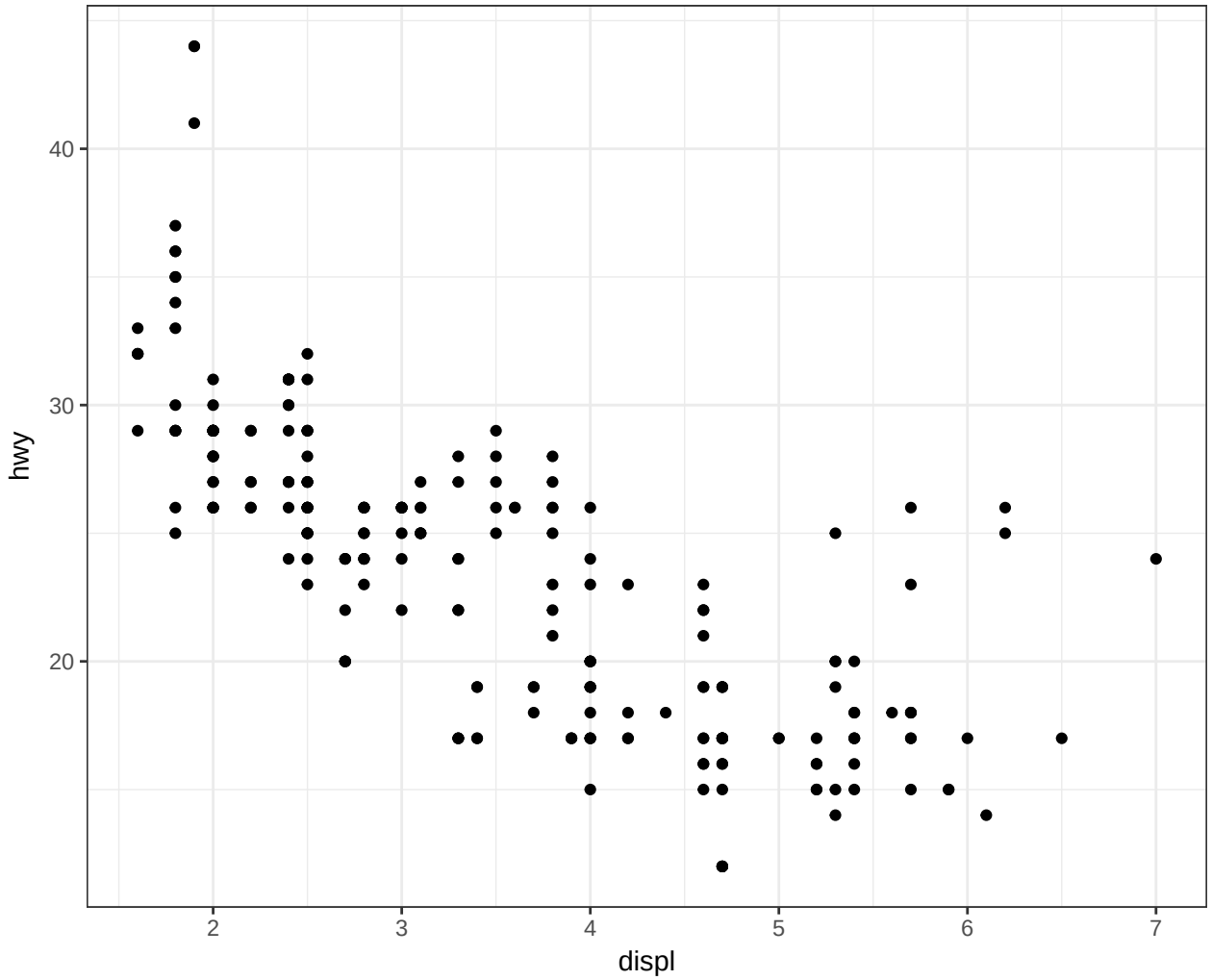
```
> kelly <- babynames %>% filter(name=="Kelly")
> ggplot(data = kelly) +
+   geom_line(mapping = aes(x=year, y=prop, color=sex),
+             size=1.5)
```



Scatterplots

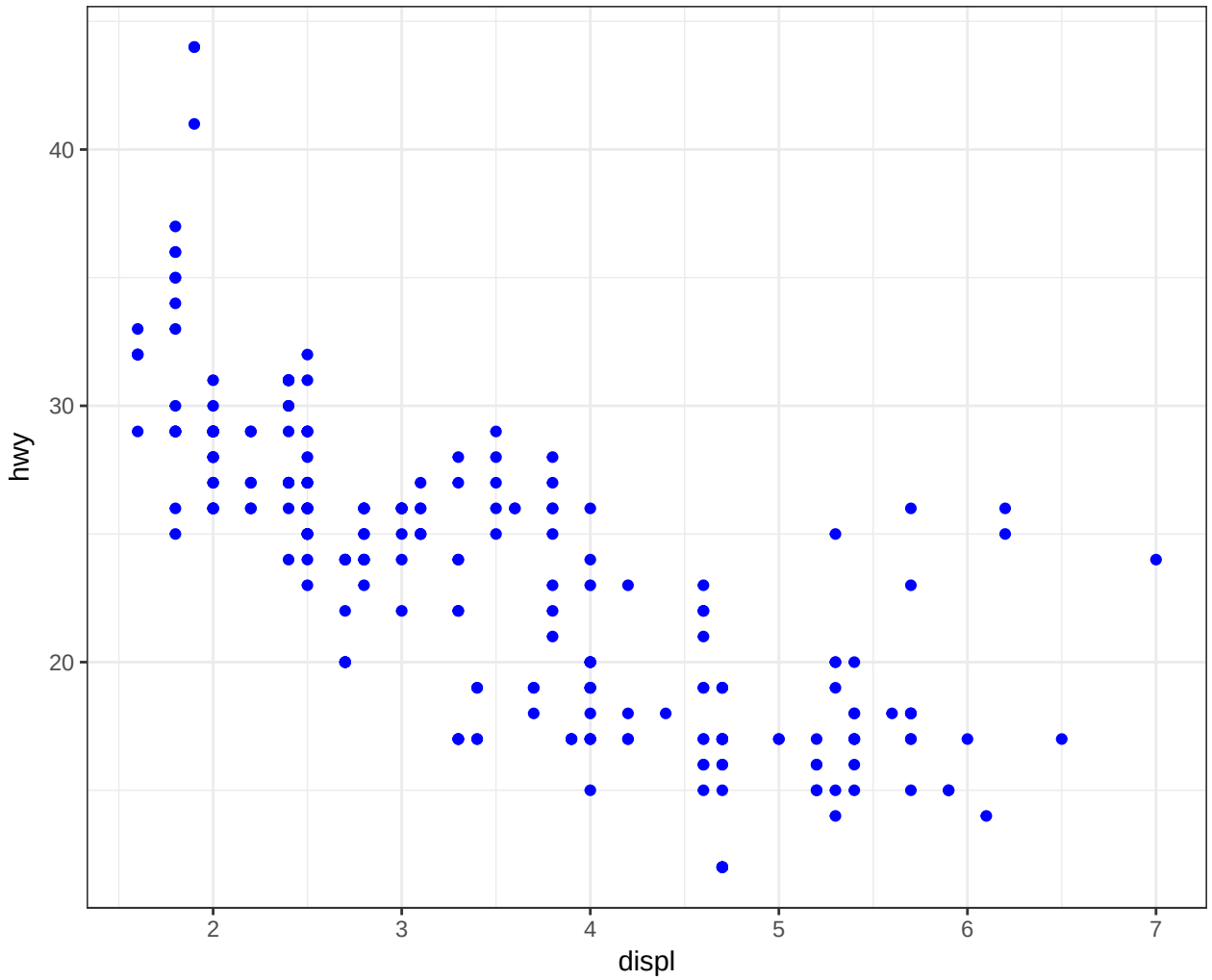
The layer `geom_point()` produces a scatterplot, and the `aes()` call requires `x` and `y` assignment:

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



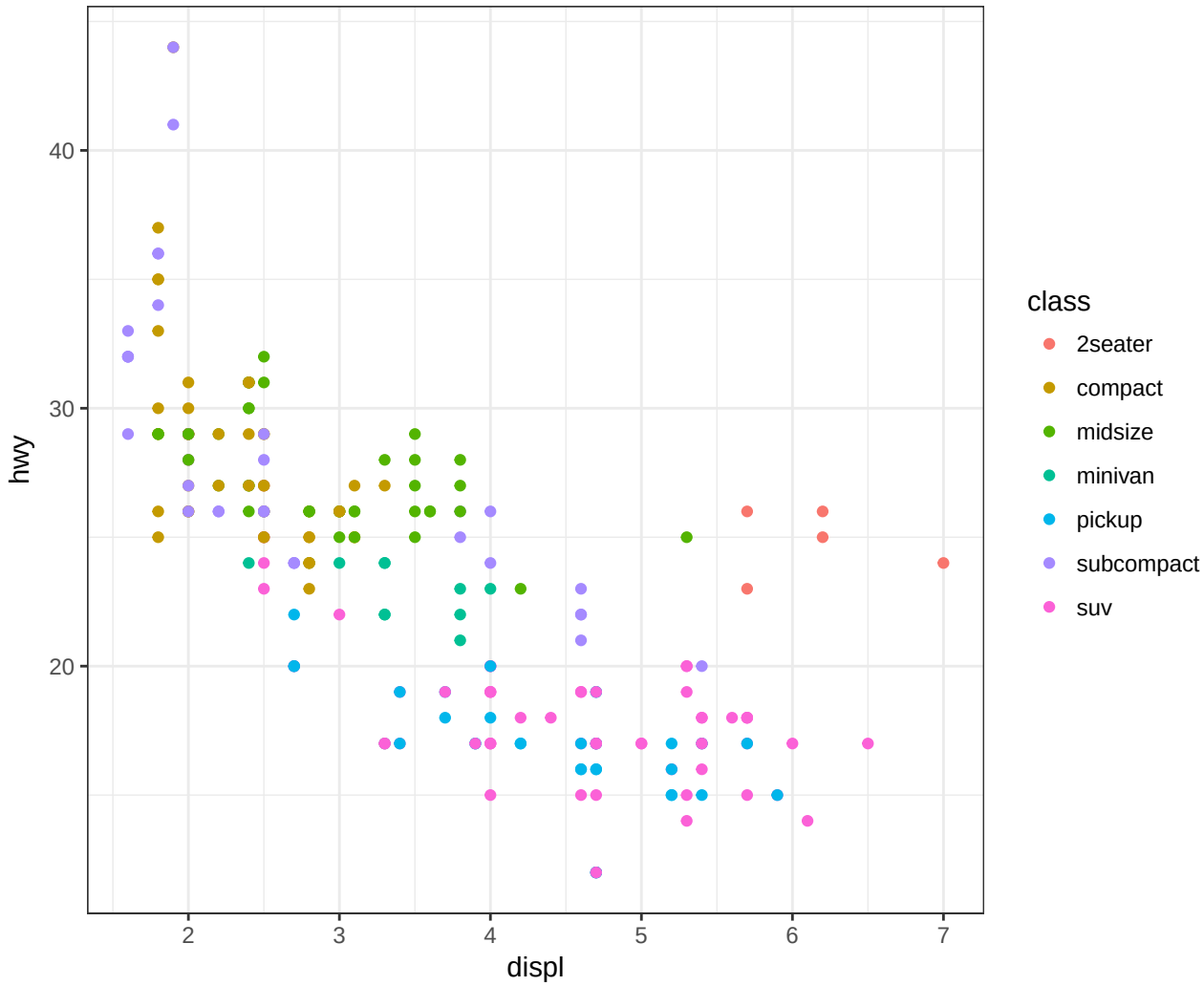
Give the points a color:

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



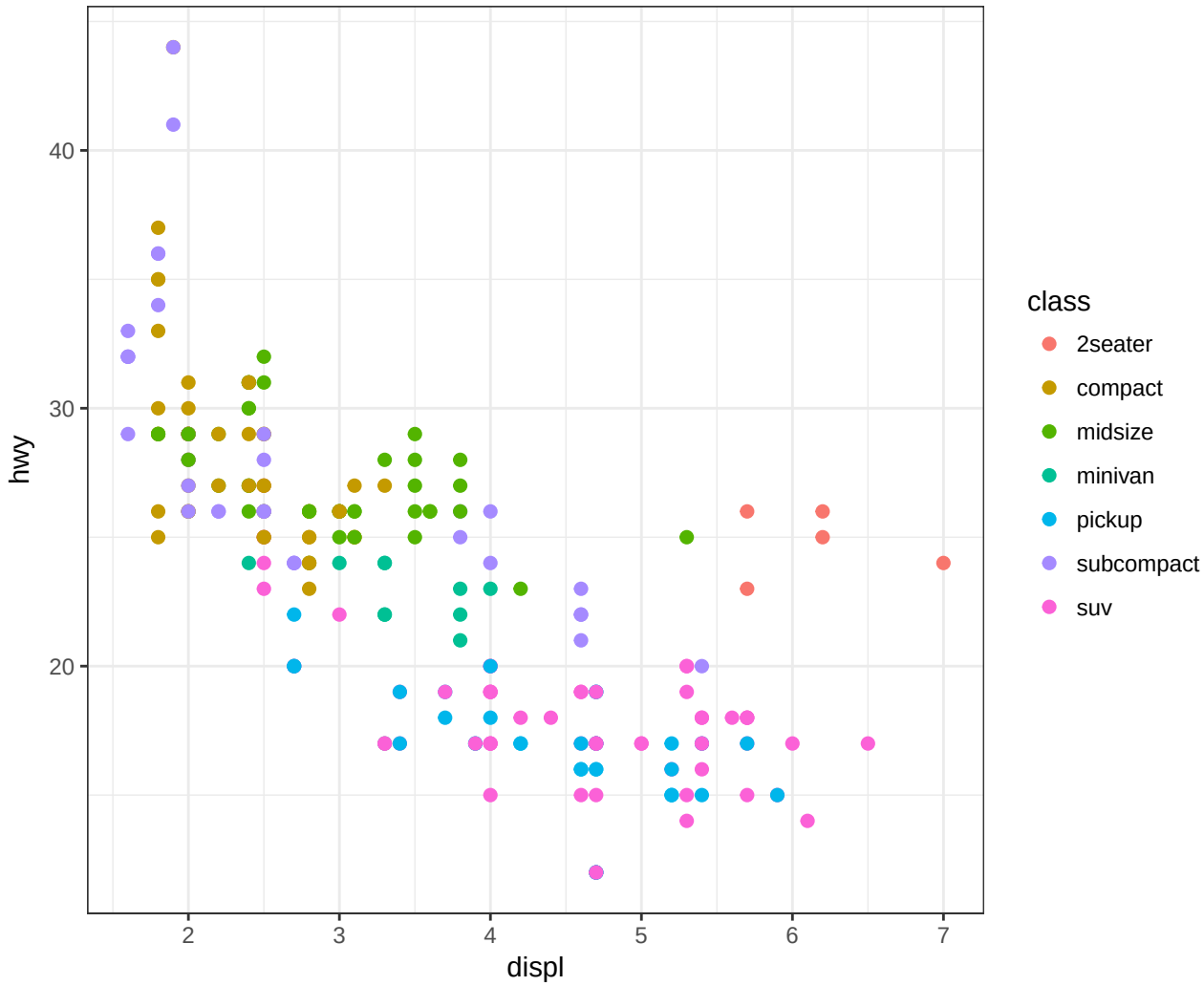
Color the points according to a factor variable by including `color = class` within the `aes()` call:

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



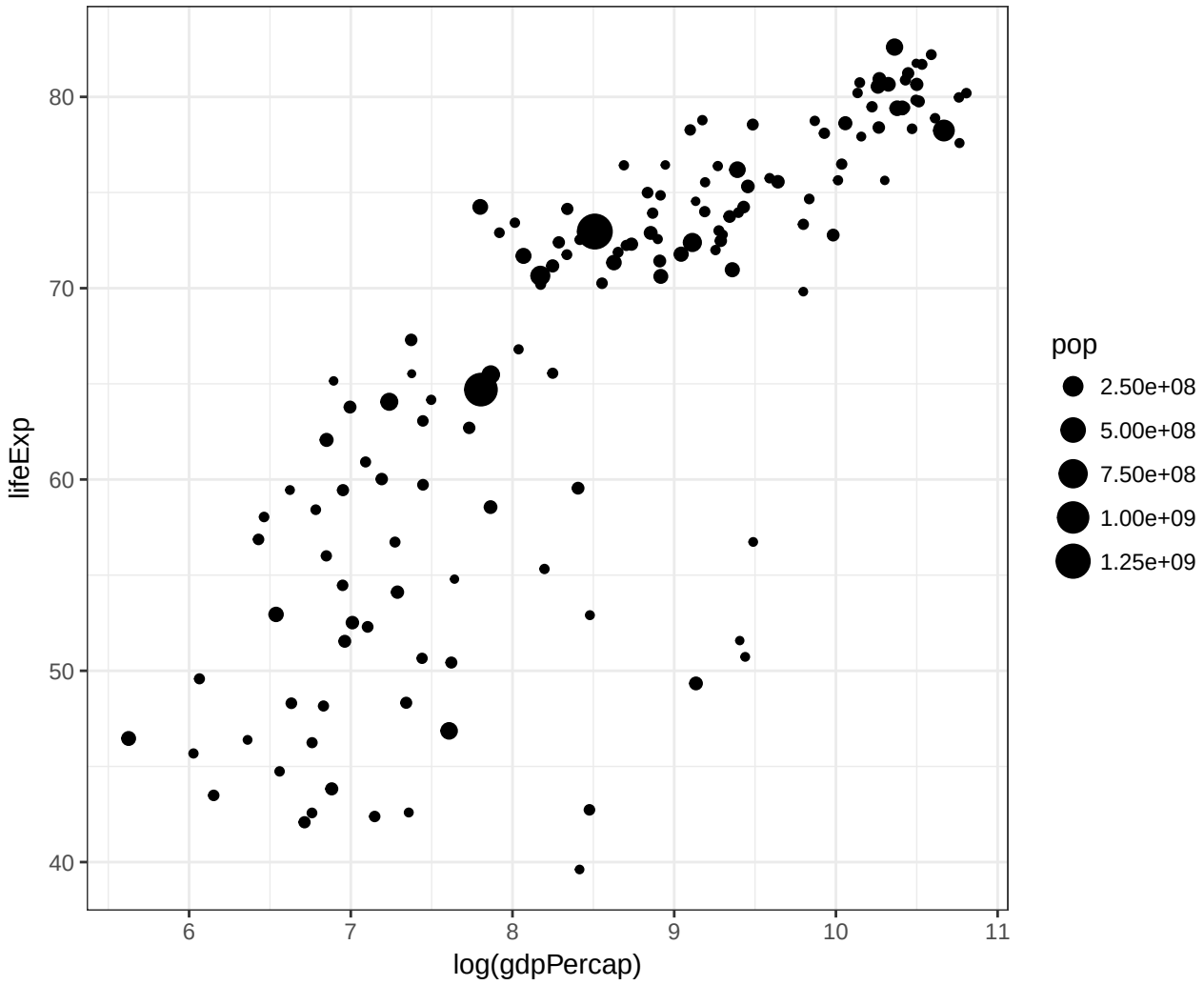
Increase the size of points with `size=2` outside of the `aes()` call:

```
> ggplot(data = mpg) +
+   geom_point(mapping = aes(x = displ, y = hwy,
+                            color = class), size=2)
```



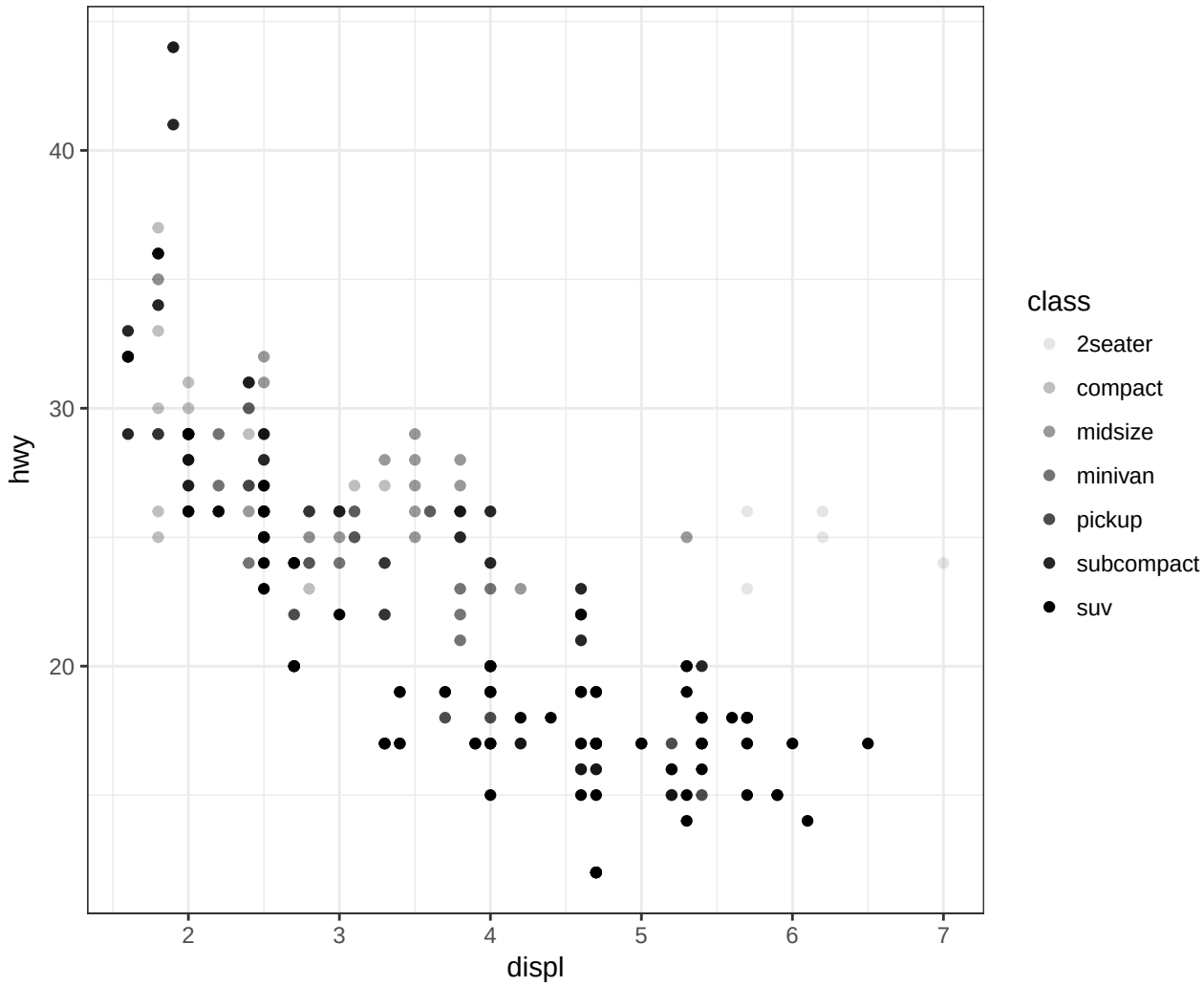
Vary the size of the points according to the pop variable:

```
> gapminder %>% filter(year==2007) %>% ggplot() +
+   geom_point(aes(x = log(gdpPercap), y = lifeExp,
+                  size = pop))
```



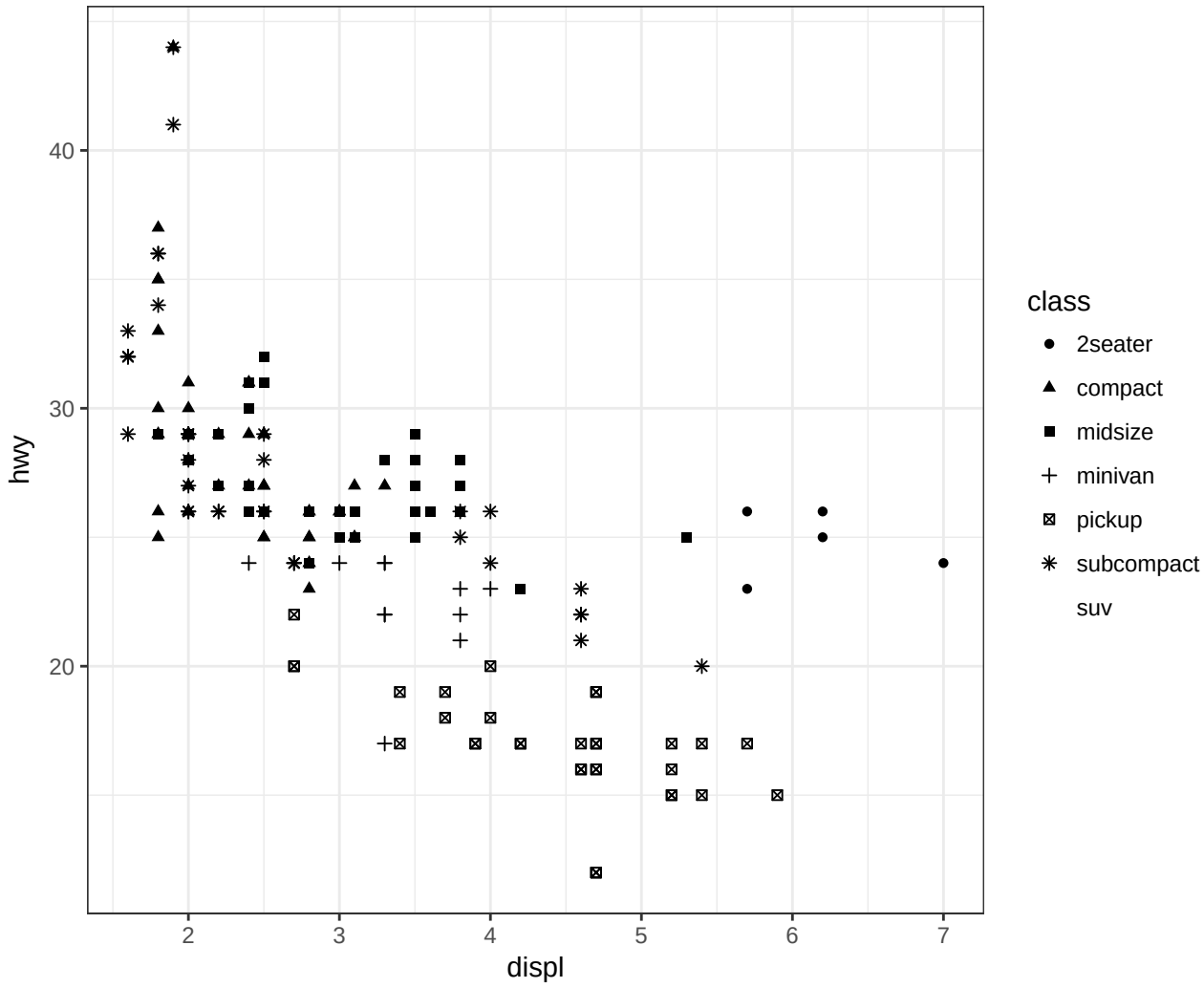
Vary the transparency of the points according to the `class` factor variable by setting `alpha=class` within the `aes()` call:

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



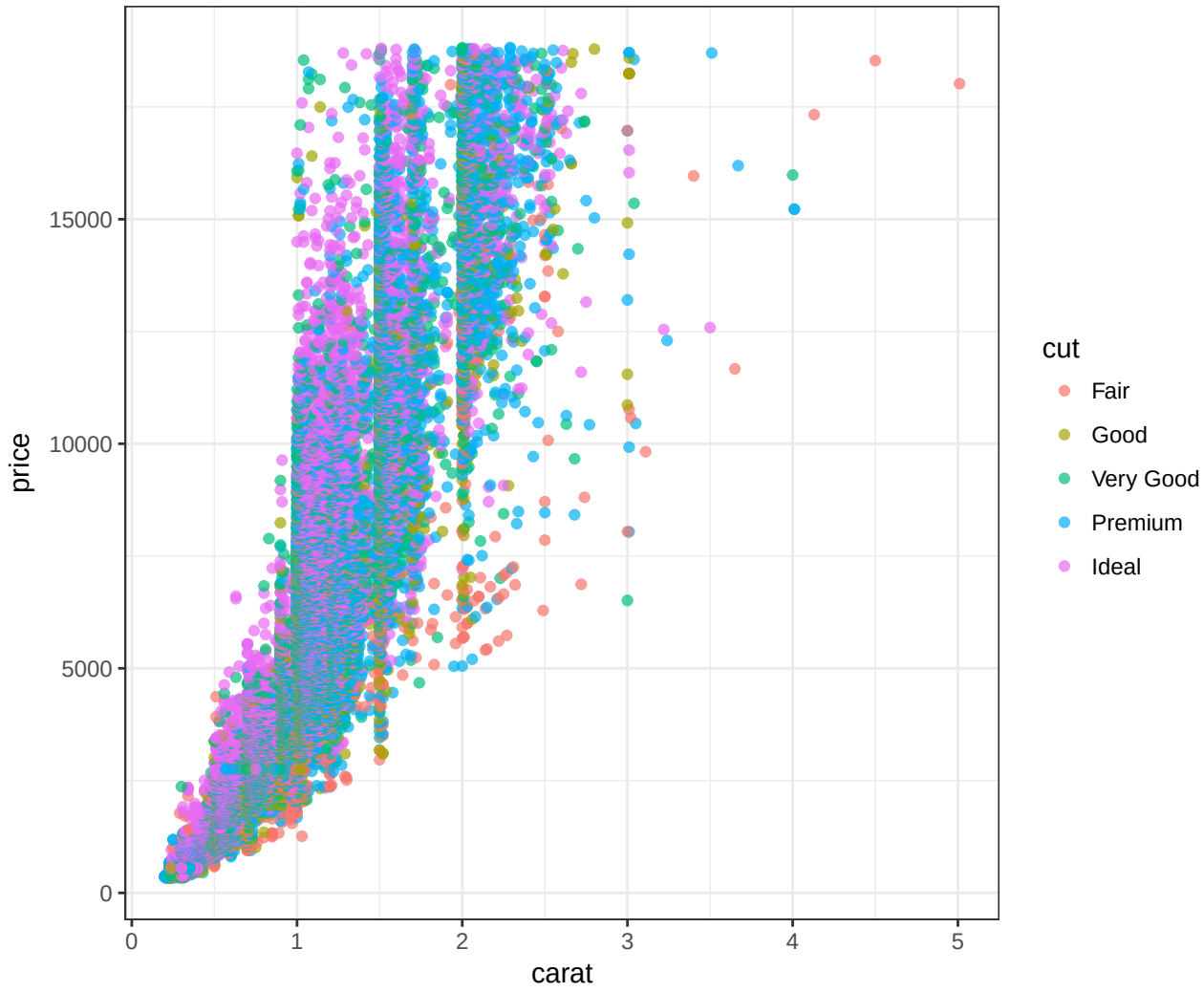
Vary the shape of the points according to the `class` factor variable by setting `alpha=class` within the `aes()` call (maximum 6 possible shapes – oops!):

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



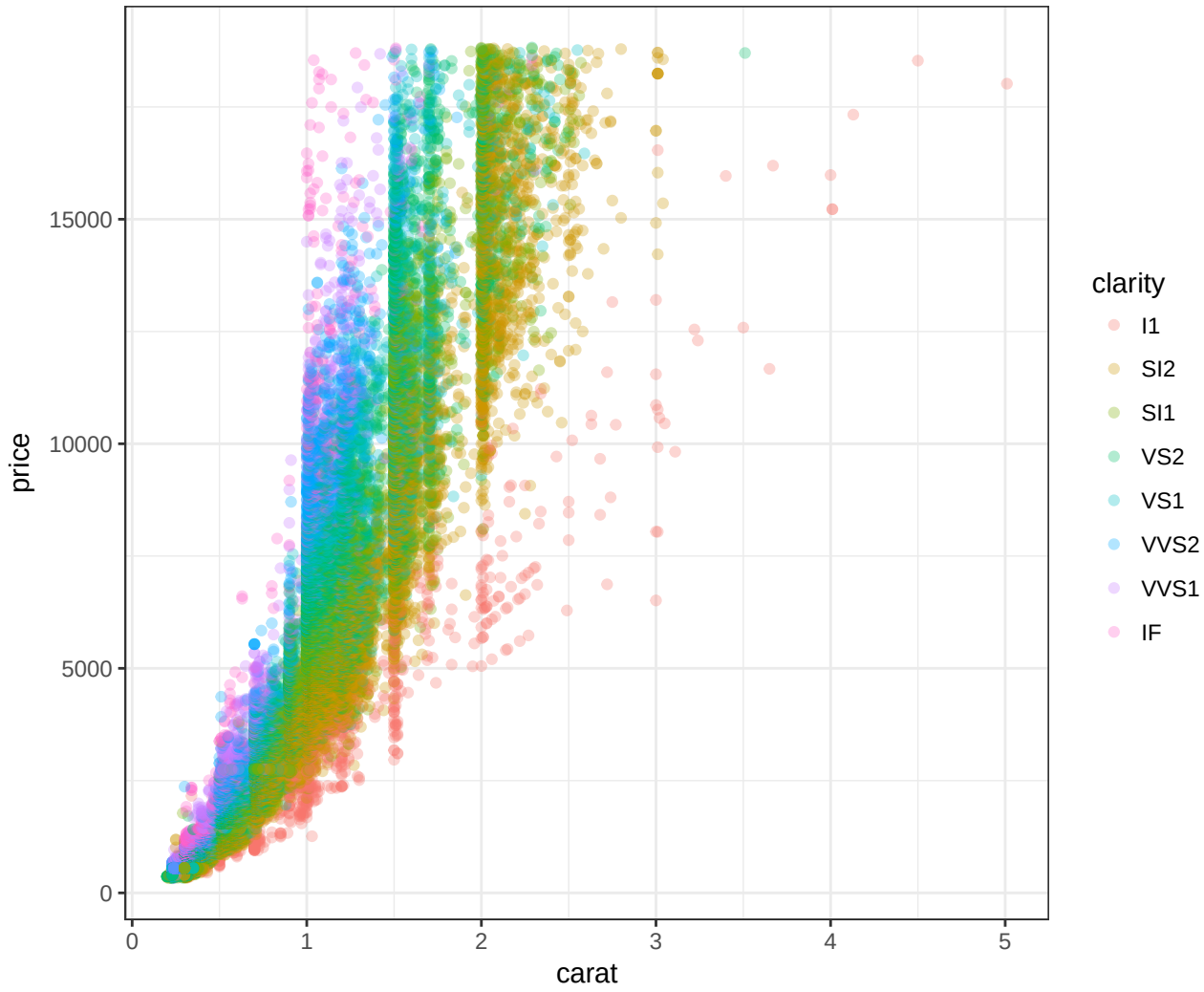
Color the points according to the `cut` variable by setting `color=cut` within the `aes()` call:

```
> ggplot(data = diamonds) +
+   geom_point(mapping = aes(x=carat, y=price, color=cut),
+              alpha=0.7)
```



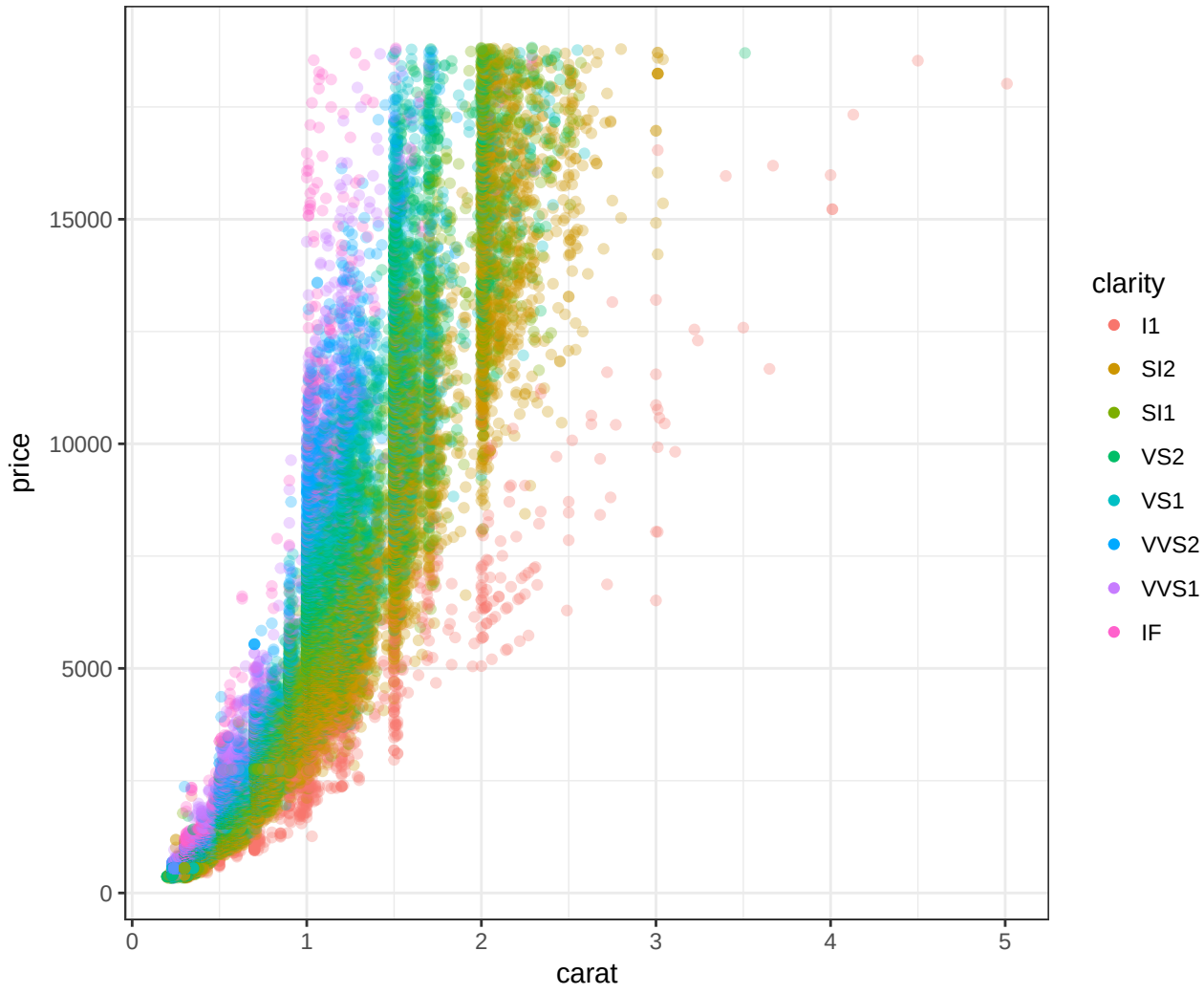
Color the points according to the `clarity` variable by setting `color=clarity` within the `aes()` call:

```
> ggplot(data = diamonds) +
+   geom_point(mapping=aes(x=carat, y=price, color=clarity),
+              alpha=0.3)
```



Override the `alpha=0.3` in the legend:

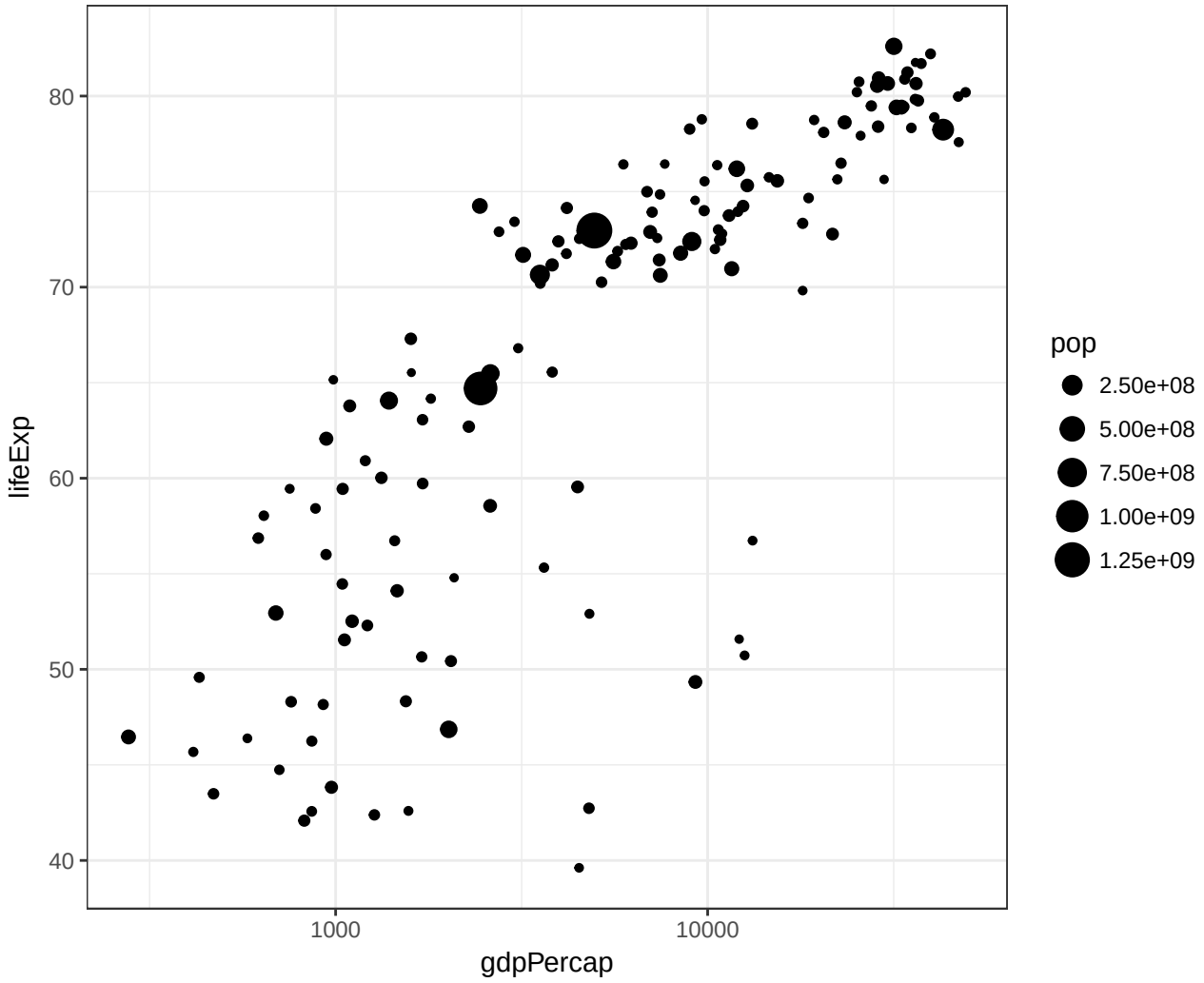
```
> ggplot(data=diamonds) +
+   geom_point(mapping=aes(x=carat, y=price, color=clarity),
+              alpha=0.3) +
+   guides(color=guide_legend(override.aes = list(alpha = 1)))
```



Axis Scales

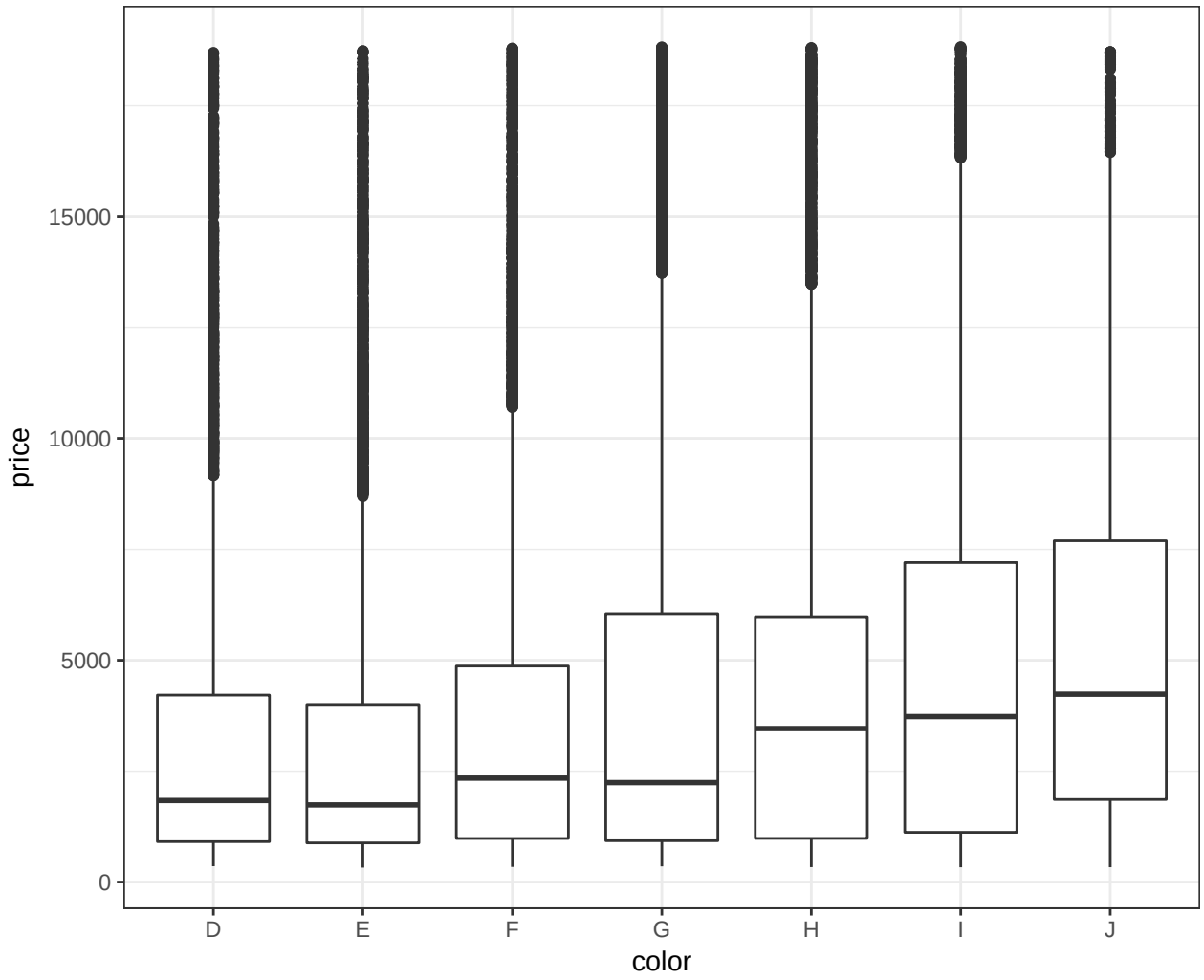
A different way to take the log of `gdpPercap`:

```
> gapminder %>% filter(year==2007) %>% ggplot() +
+   geom_point(aes(x = gdpPercap, y = lifeExp,
+                  size = pop)) +
+   scale_x_log10()
```



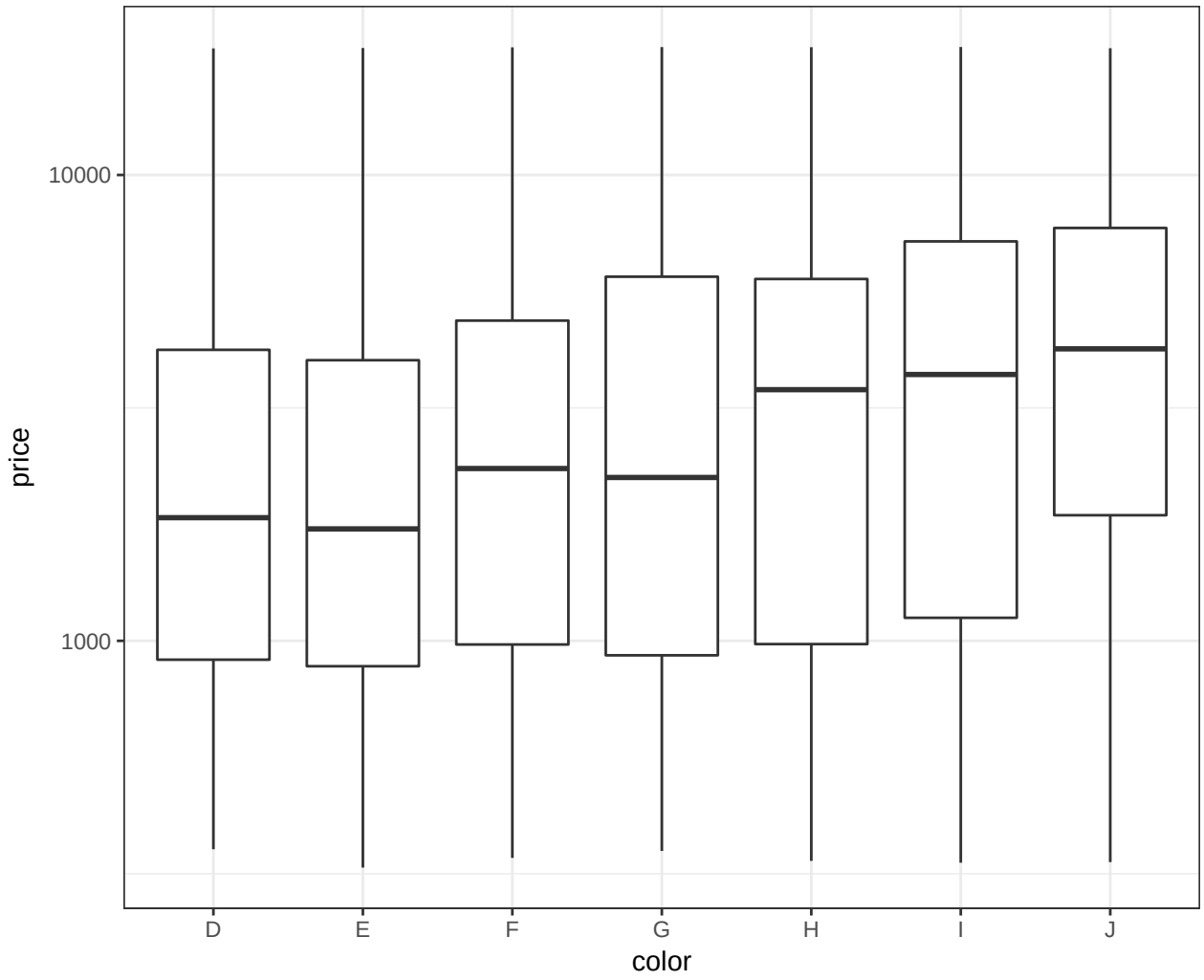
The `price` variable seems to be significantly right-skewed:

```
> ggplot(diamonds) +
+   geom_boxplot(aes(x=color, y=price))
```



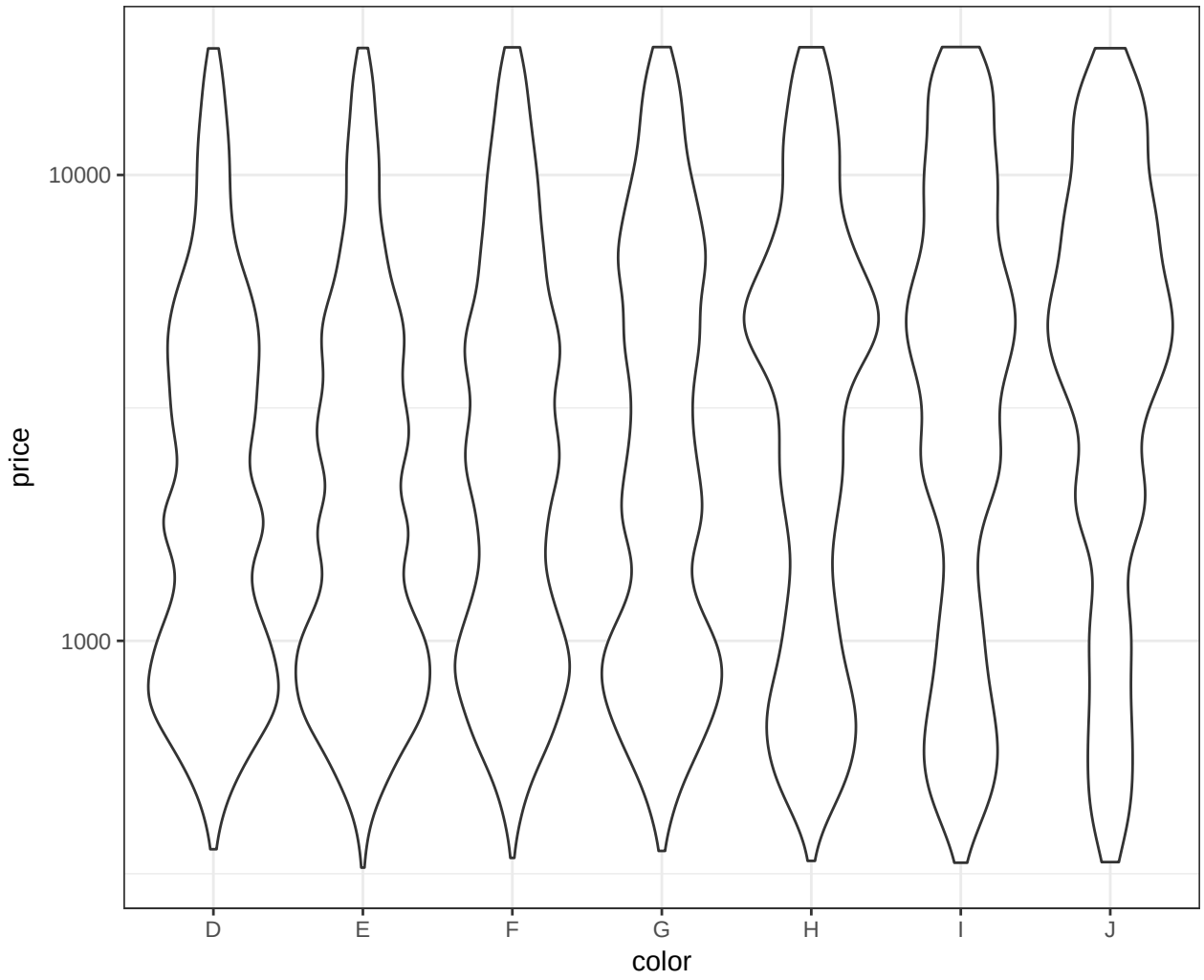
We can try to reduce this skewness by rescaling the variables. We first try to take the `log(base=10)` of the `price` variable via `scale_y_log10()`:

```
> ggplot(diamonds) +
+   geom_boxplot(aes(x=color, y=price)) +
+   scale_y_log10()
```



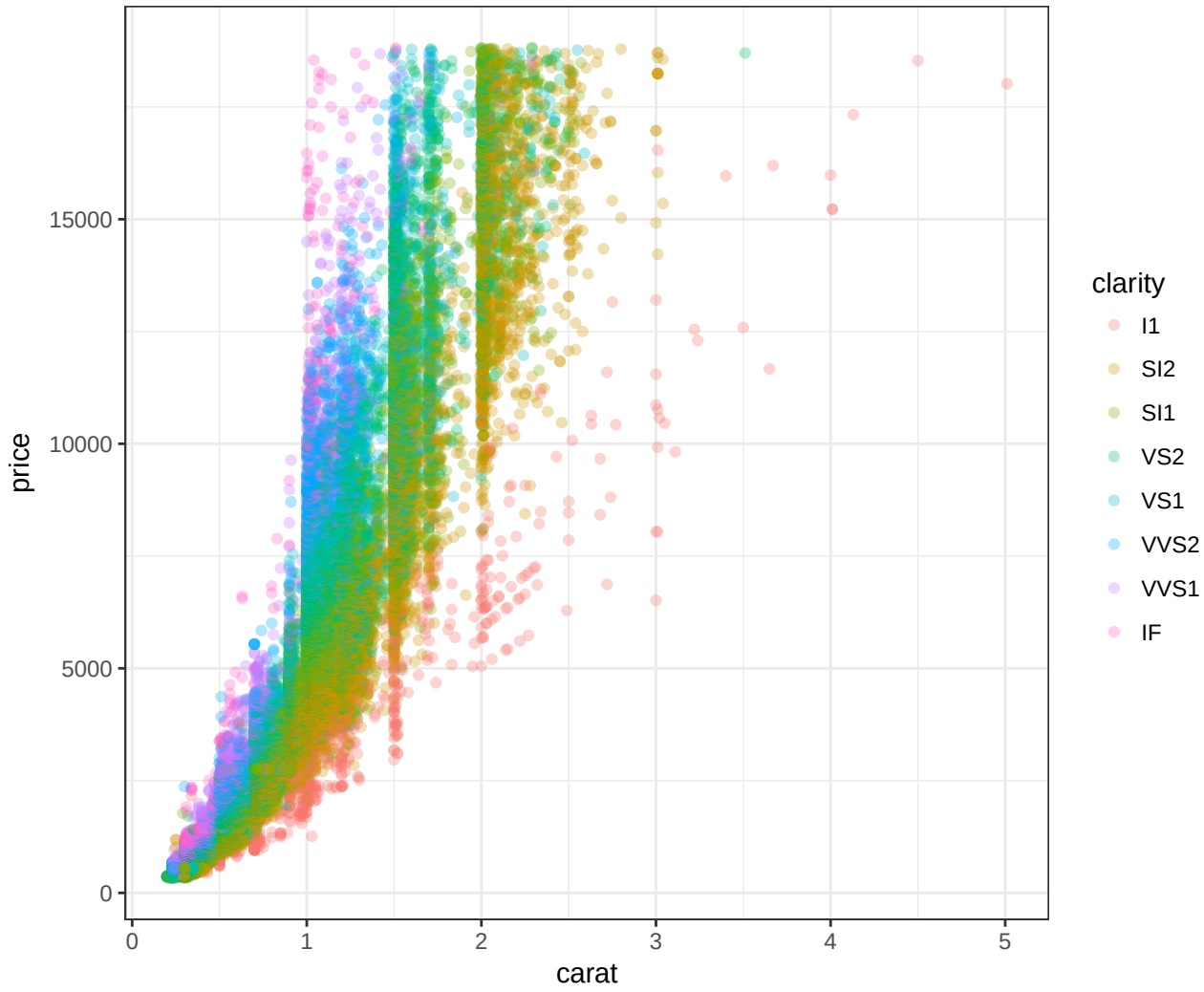
Let's repeat this on the analogous violing plots:

```
> ggplot(diamonds) +
+   geom_violin(aes(x=color, y=price)) +
+   scale_y_log10()
```



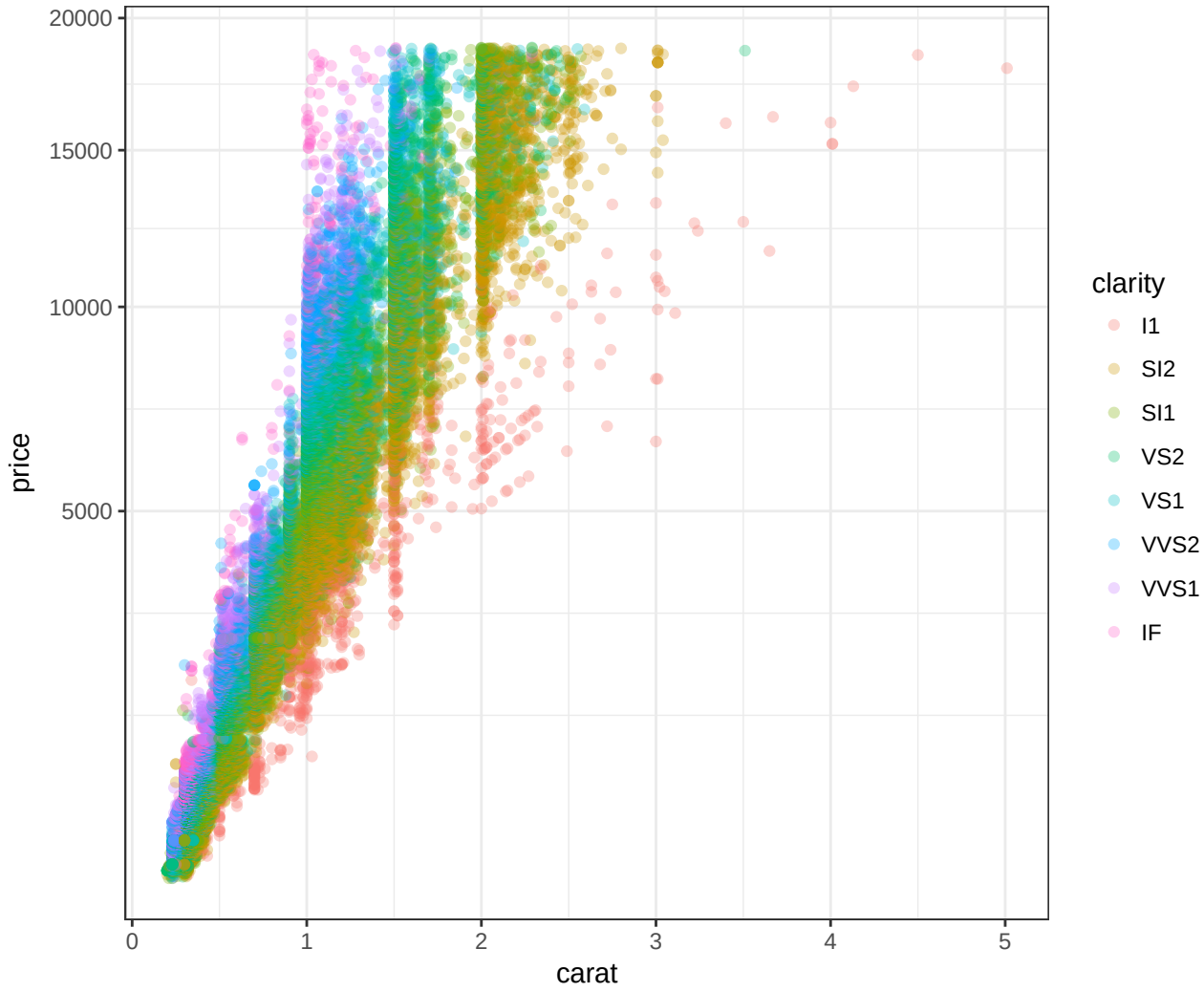
The relationship between `carat` and `price` is nonlinear. Let's explore different transformations to find an approximately linear relationship.

```
> ggplot(data = diamonds) +
+   geom_point(mapping=aes(x=carat, y=price, color=clarity),
+              alpha=0.3)
```



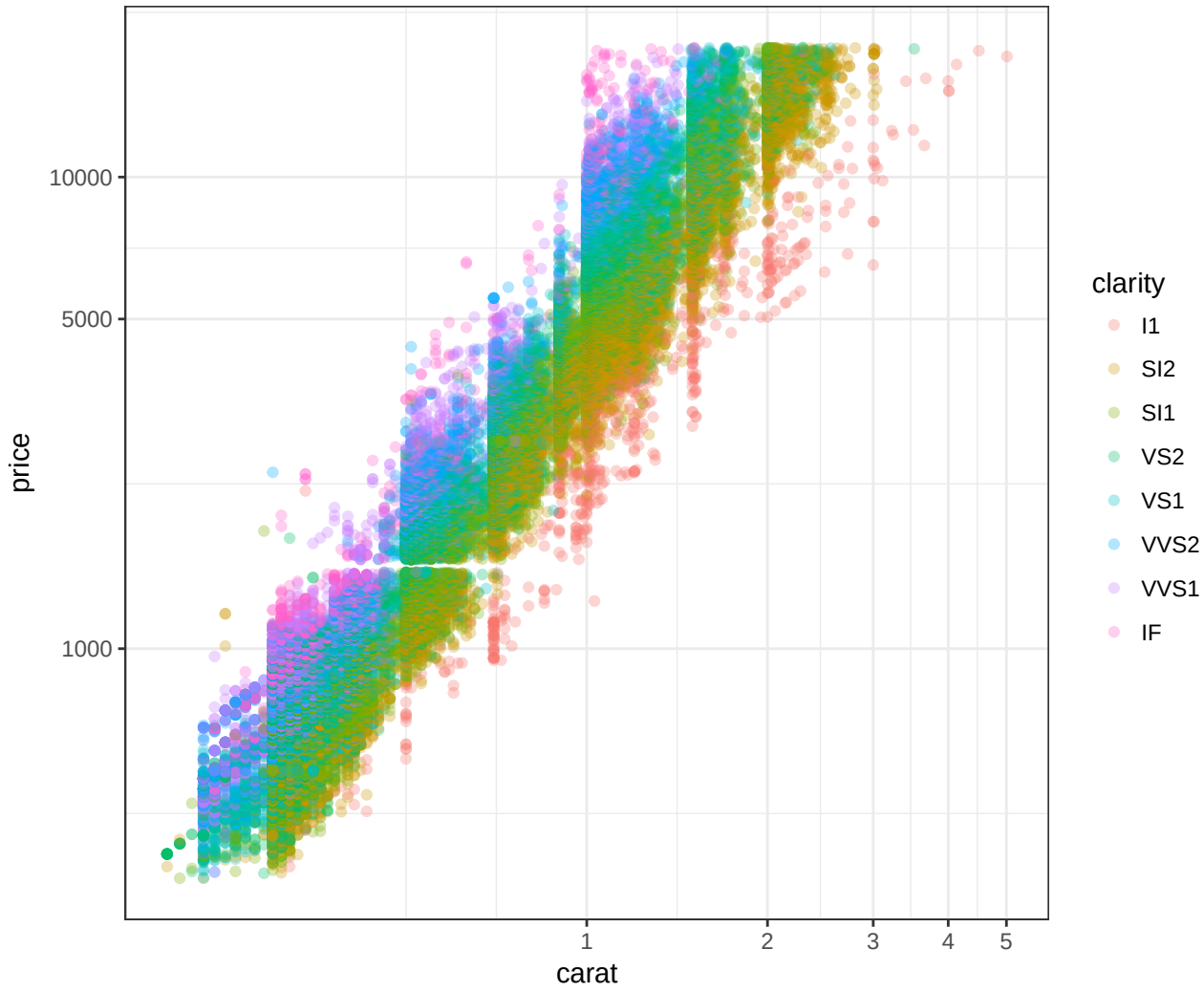
First try to take the squareroot of the the `price` variable:

```
> ggplot(data = diamonds) +
+   geom_point(aes(x=carat, y=price, color=clarity),
+              alpha=0.3) +
+   scale_y_sqrt()
```



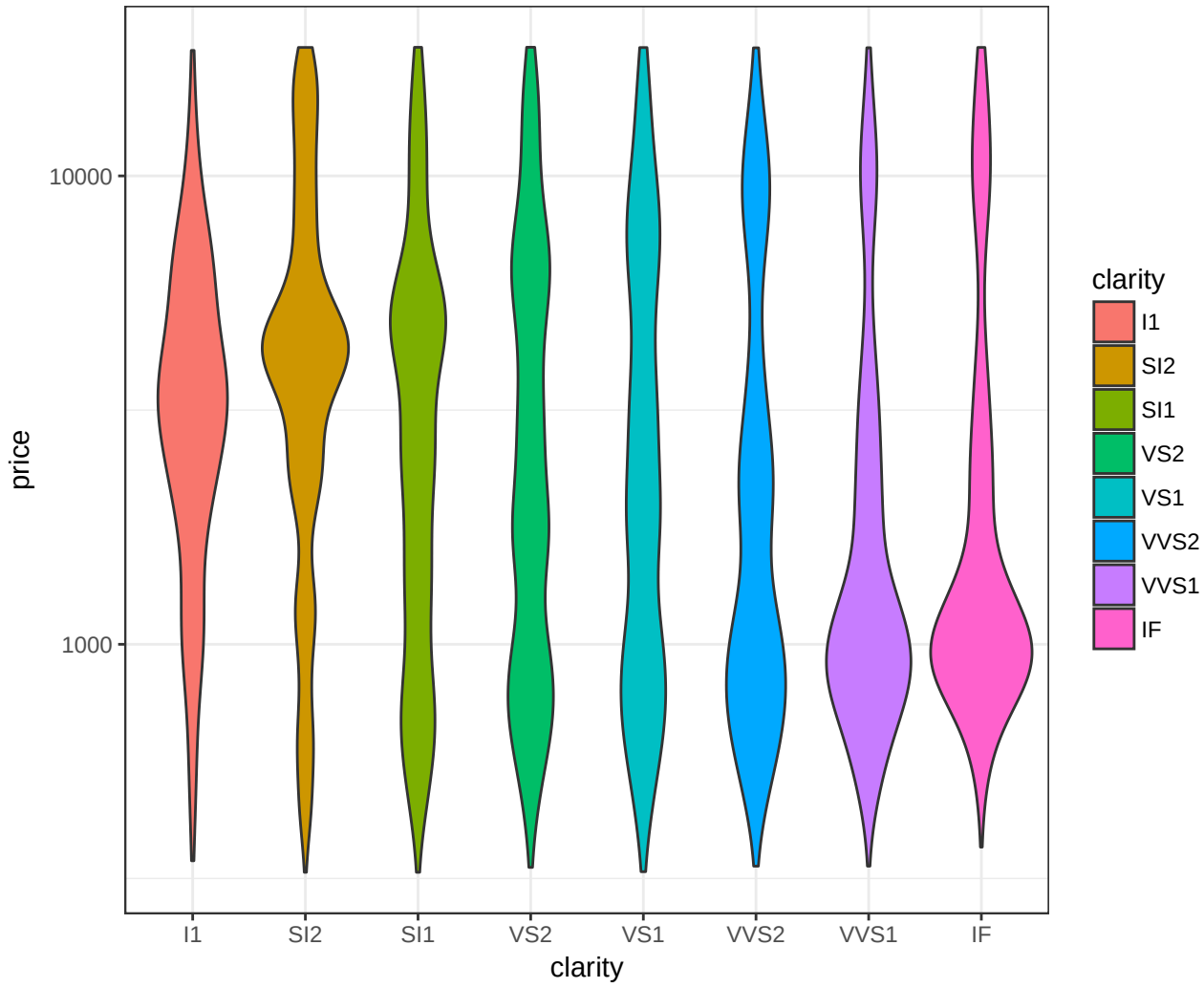
Now let's try to take `log(base=10)` on both the `carat` and `price` variables:

```
> ggplot(data = diamonds) +
+   geom_point(aes(x=carat, y=price, color=clarity), alpha=0.3) +
+   scale_y_log10(breaks=c(1000,5000,10000)) +
+   scale_x_log10(breaks=1:5)
```



Forming a violin plot of `price` stratified by `clarity` and transforming the `price` variable yields an interesting relationship in this data set:

```
> ggplot(diamonds) +
+   geom_violin(aes(x=clarity, y=price, fill=clarity),
+               adjust=1.5) +
+   scale_y_log10()
```



Scatterplot Smoothers

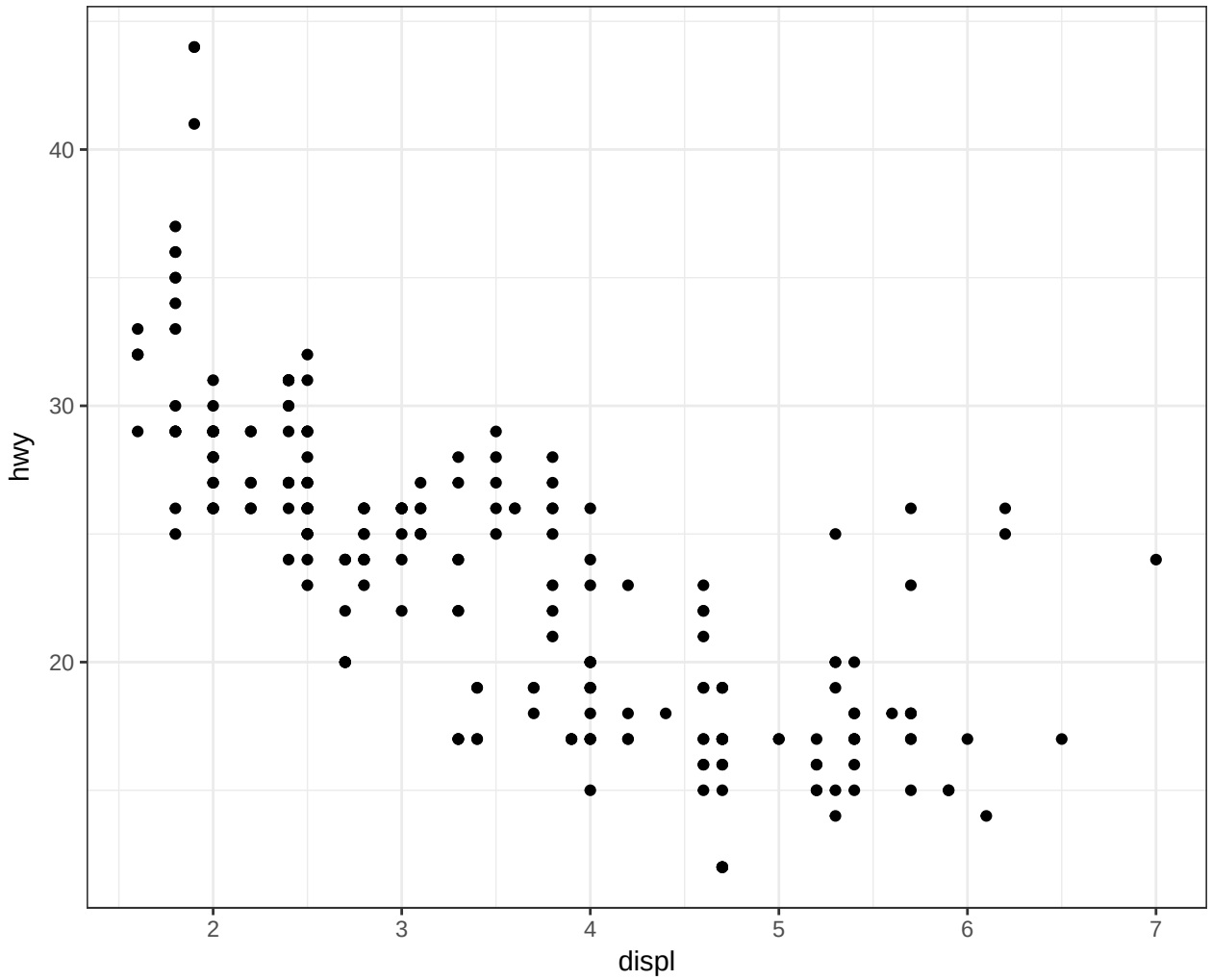
Fitting "Smoothers" and Other Models to Scatterplots

- Later this semester, we will spend several weeks learning how to explain or predict an outcome variable in terms of predictor variables

- We will briefly show here how to plot some simple model fits to scatterplots
- You may want to return to these slides later in the semester once we cover modeling in more detail

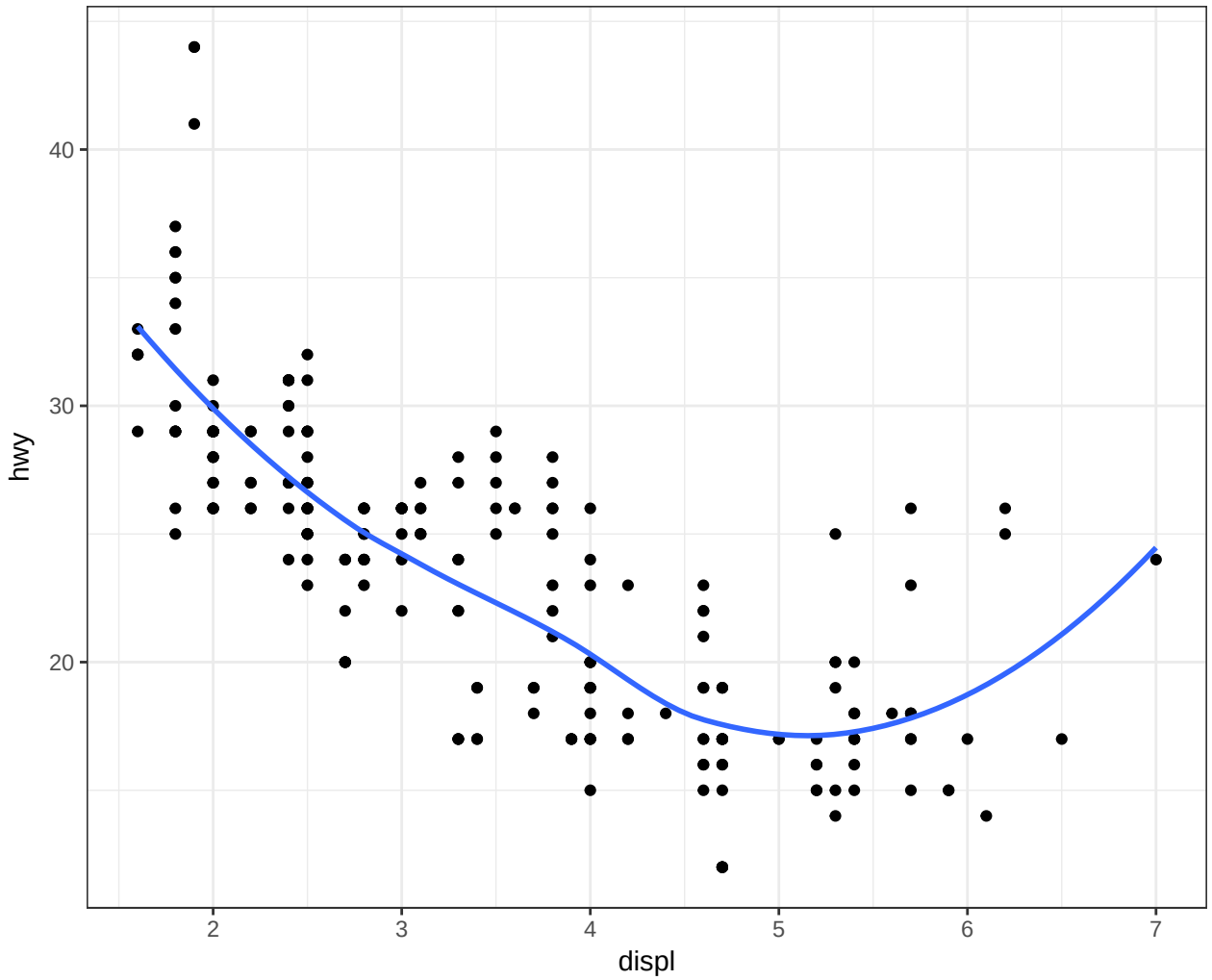
Recall the scatterplot showing the relationship between highway mpg and displacement. How can we plot a smoothed relationship between these two variables?

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



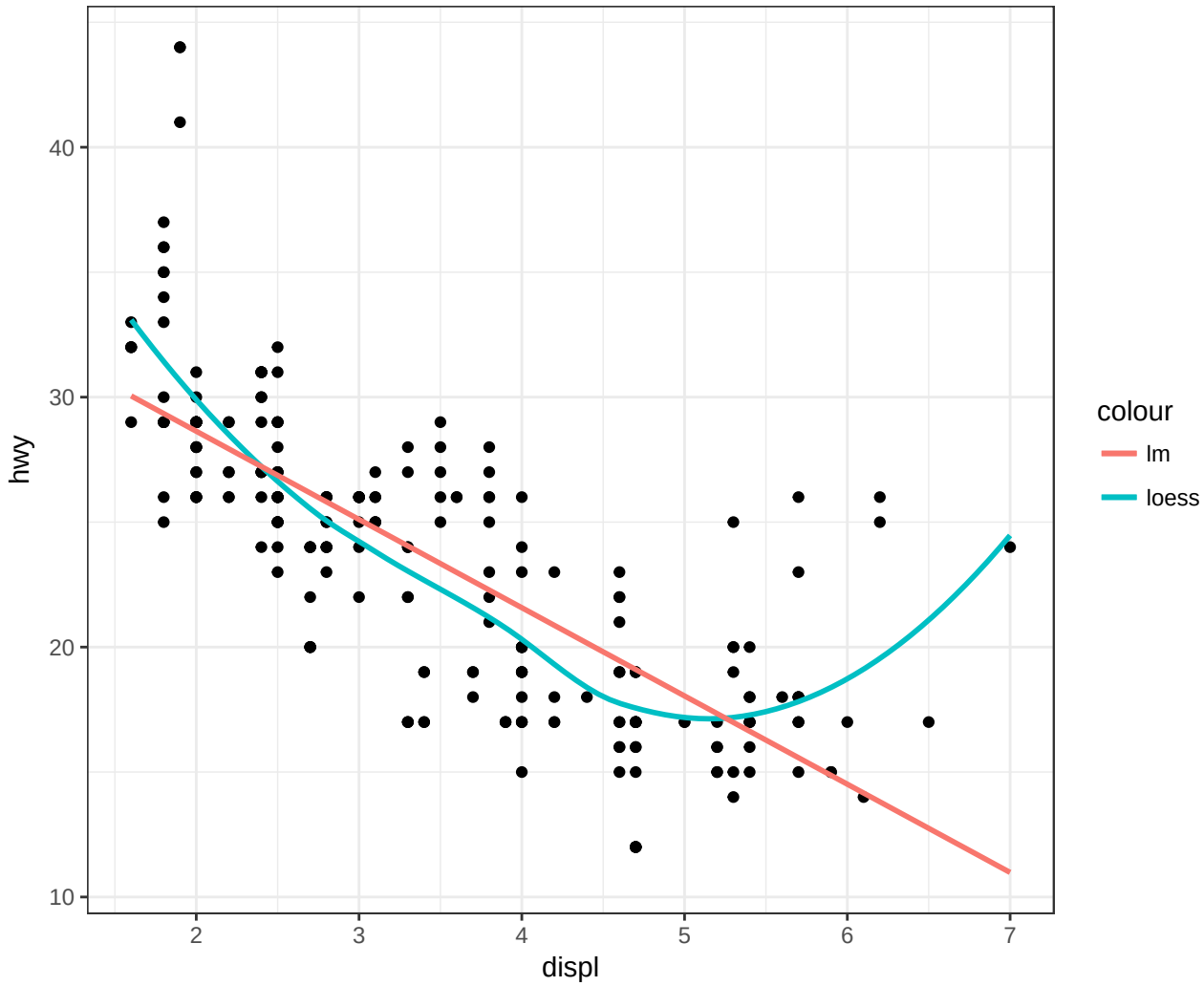
Plot a smoother with `geom_smooth()` using the default settings (other than removing the error bands):

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



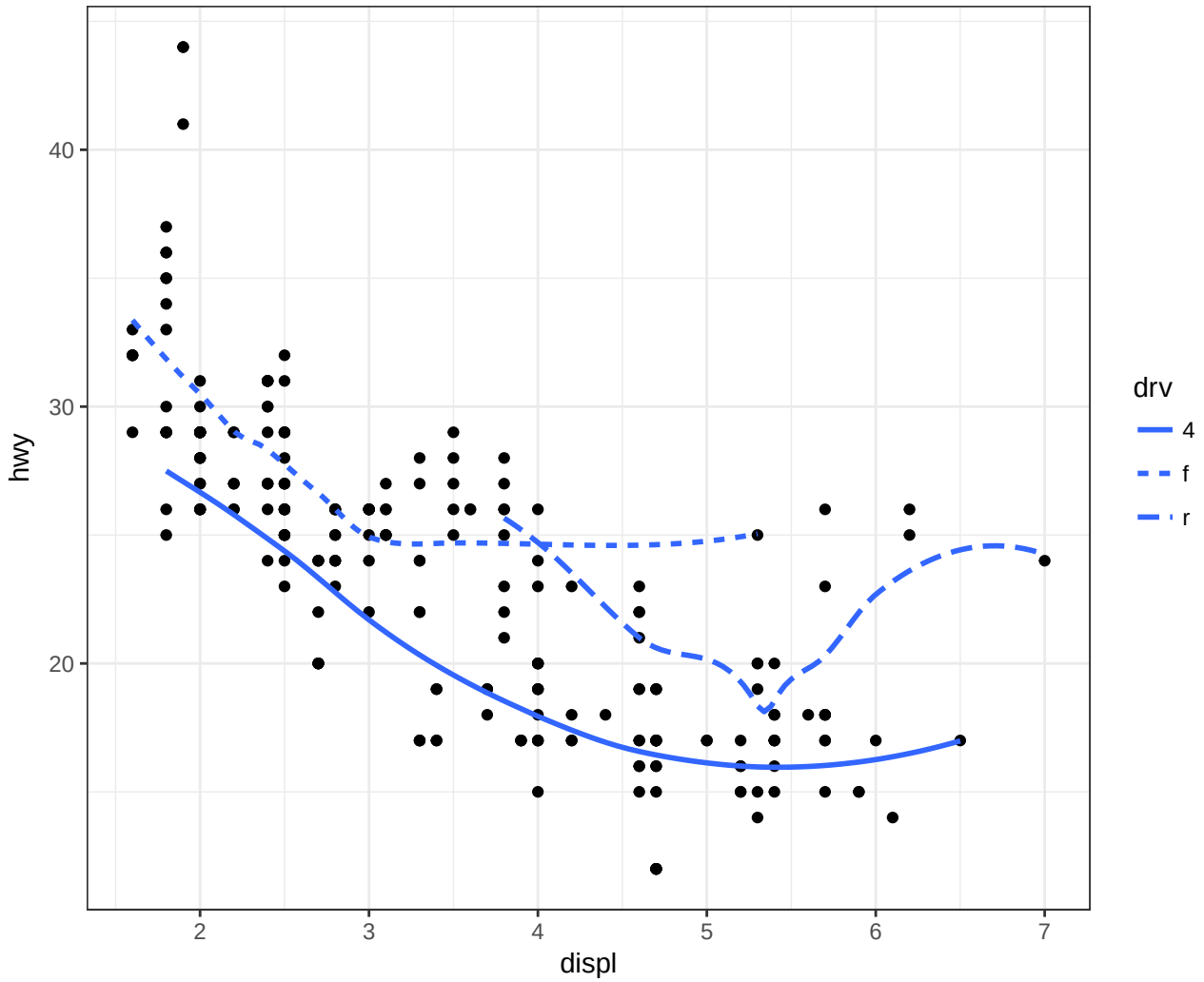
The default smoother here is a "loess" smoother. Let's compare that to the least squares regresson line:

```
> ggplot(data = mpg, mapping = aes(x = displ, y = hwy)) +
+   geom_point() +
+   geom_smooth(aes(colour = "loess"), method = "loess", se = FALSE) +
+   geom_smooth(aes(colour = "lm"), method = "lm", se = FALSE)
```



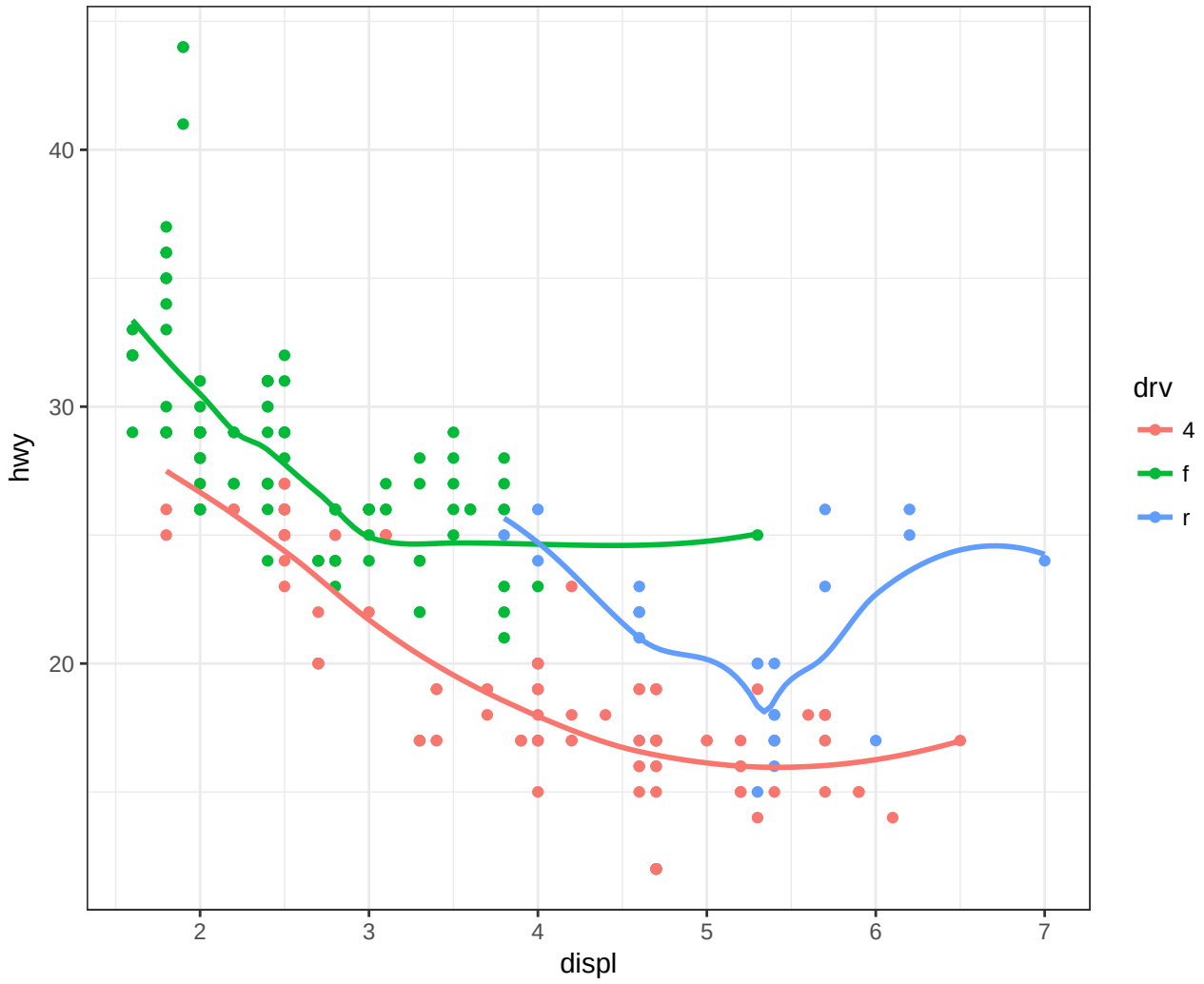
Now let's plot a smoother to the points stratified by the `drv` variable:

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



Instead of different line types, let's instead differentiate them by line color:

```
> ggplot(data = mpg, mapping = aes(x = displ, y = hwy,
+                                  color=drv)) +
+   geom_point() +
+   geom_smooth(se=FALSE)
```



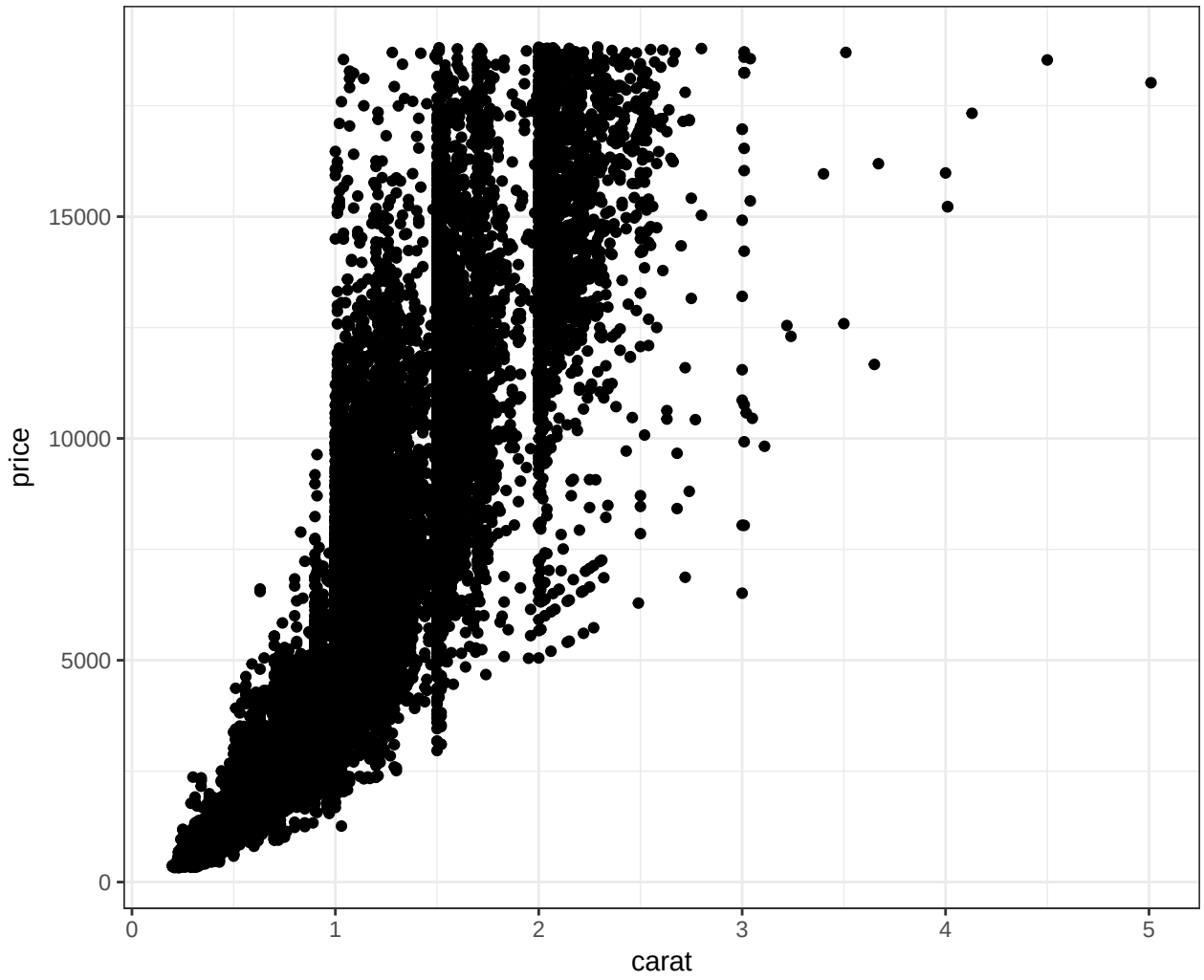
Overplotting

Definition

- Overplotting occurs when there are many observations, resulting in many objects being plotted on top of each other
- For example, the `diamonds` data set has 53940 observations per variable
- Let's explore some ways to deal with overplotting

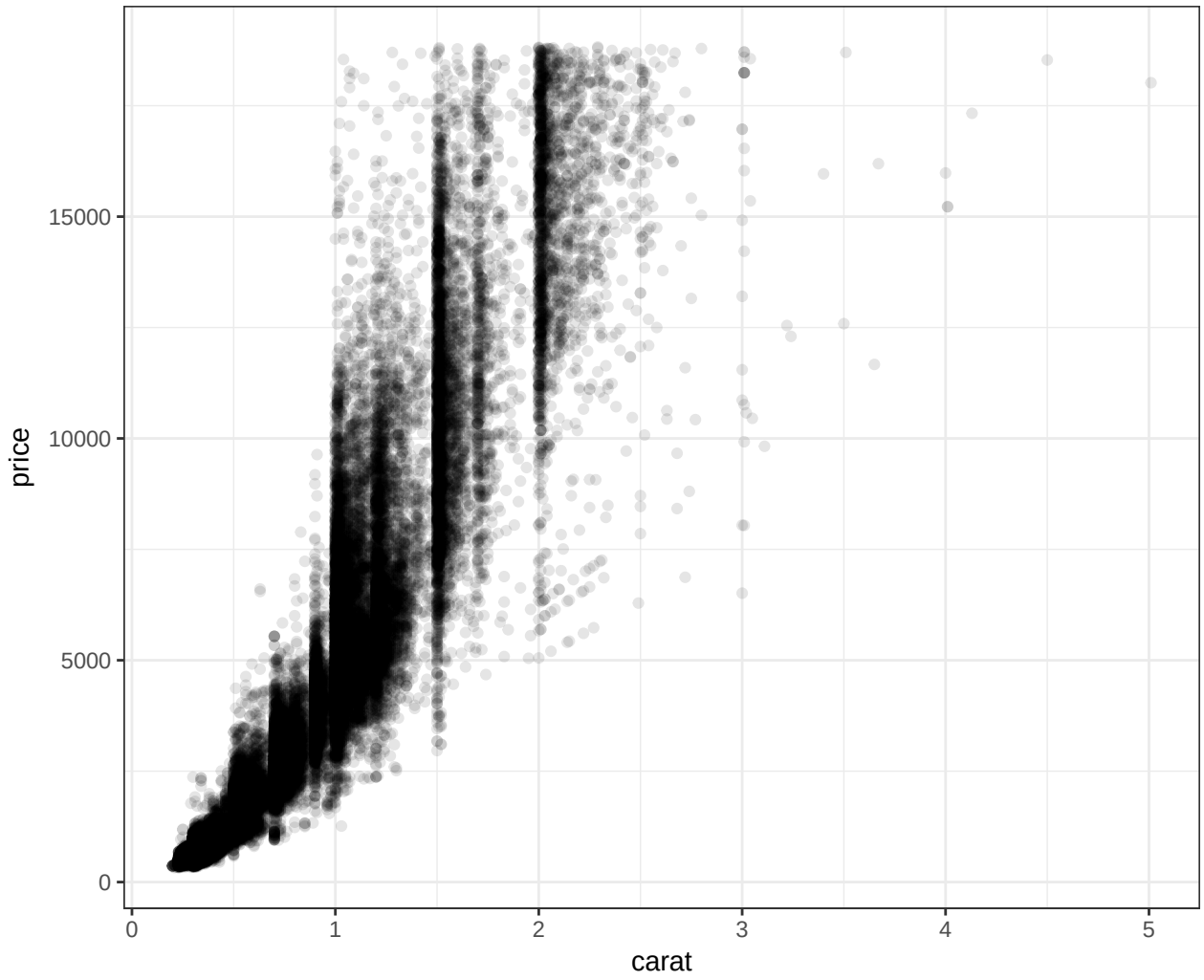
Here is an example of an overplotted scatterplot:

```
> ggplot(data = diamonds, mapping = aes(x=carat, y=price)) +
+   geom_point()
```



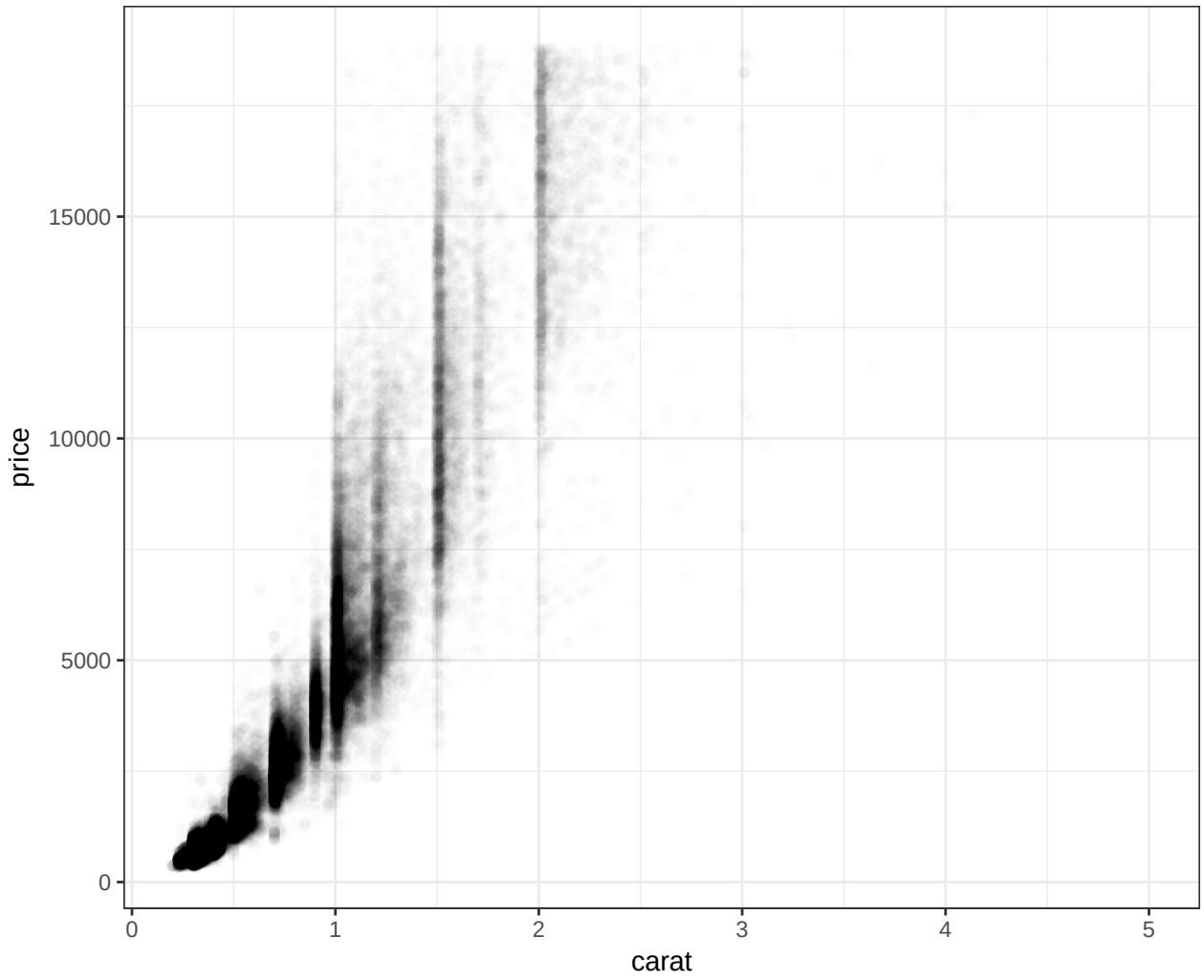
Let's reduce the `alpha` of the points:

```
> ggplot(data = diamonds, mapping = aes(x=carat, y=price)) +
+   geom_point(alpha=0.1)
```



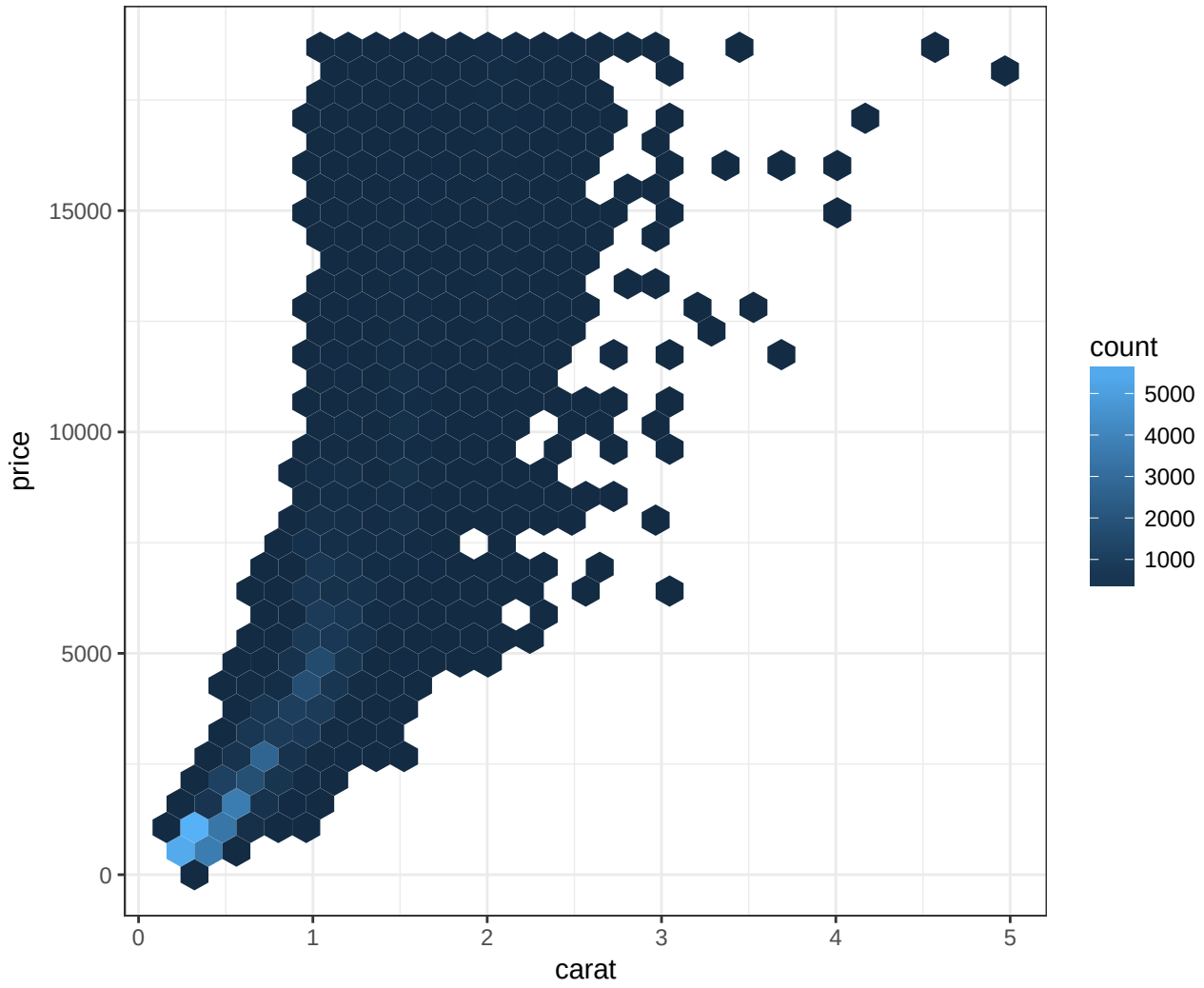
Let's further reduce the `alpha`:

```
> ggplot(data = diamonds, mapping = aes(x=carat, y=price)) +
+   geom_point(alpha=0.01)
```



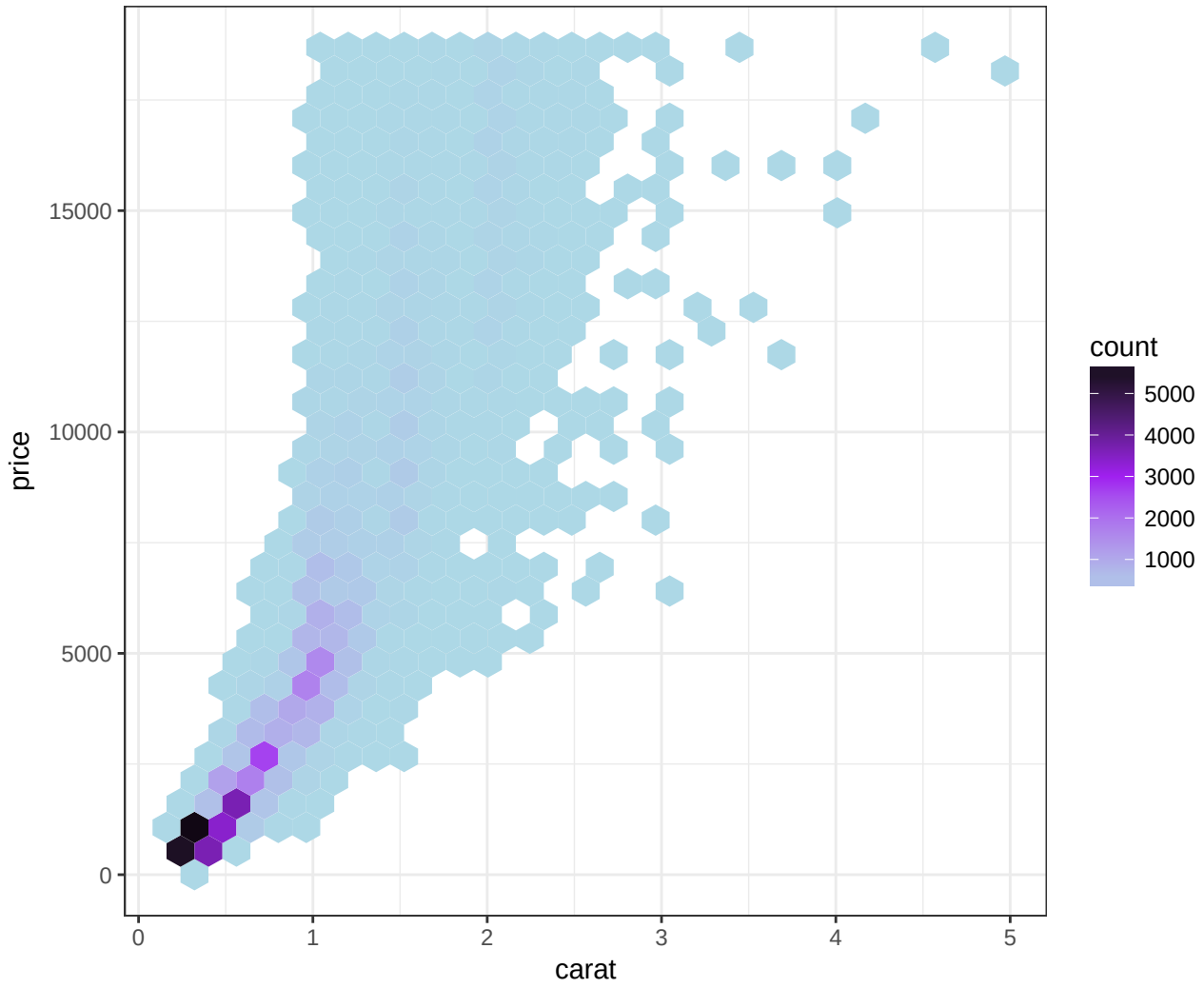
We can bin the points into hexagons, and report how many points fall within each bin. We use the `geom_hex()` layer to do this:

```
> ggplot(data = diamonds, mapping = aes(x=carat, y=price)) +
+   geom_hex()
```



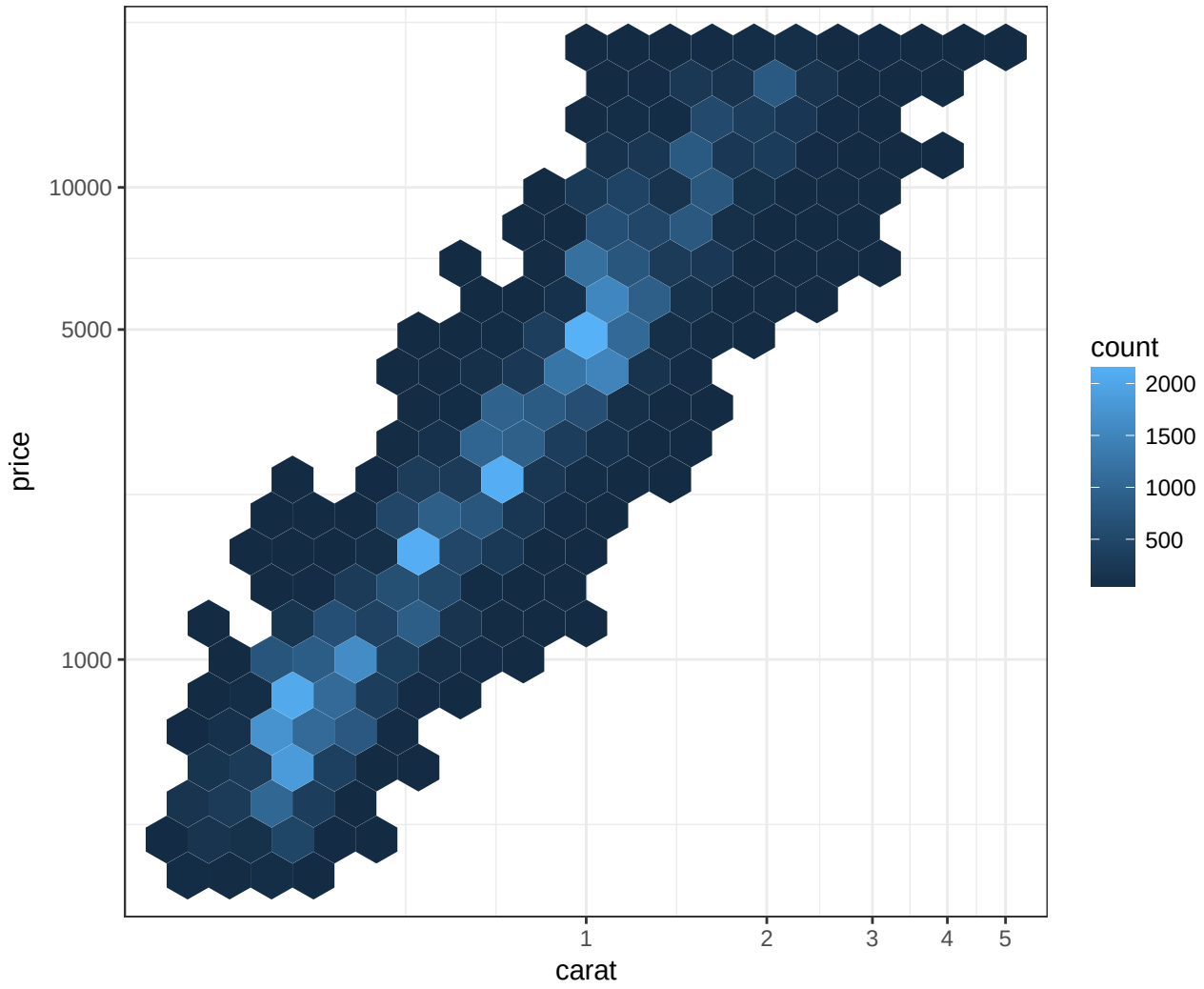
Let's try to improve the color scheme:

```
> ggplot(data = diamonds, mapping = aes(x=carat, y=price)) +
+   geom_hex() +
+   scale_fill_gradient2(low="lightblue", mid="purple", high="black",
+                        midpoint=3000)
```



We can combine the scale transformation used earlier with the "hexbin" plotting method:

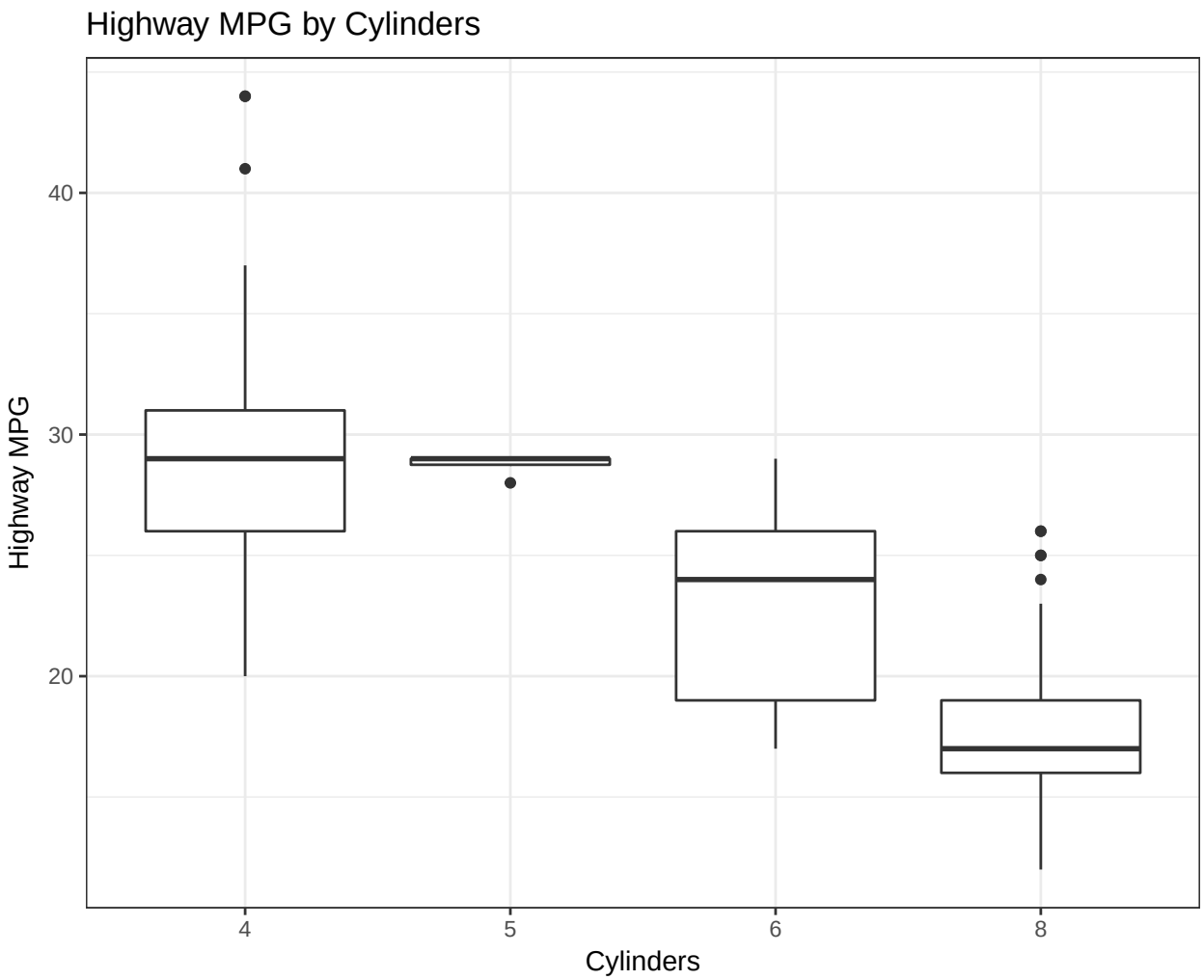
```
> ggplot(data = diamonds, mapping = aes(x=carat, y=price)) +
+   geom_hex(bins=20) +
+   scale_x_log10(breaks=1:5) + scale_y_log10(breaks=c(1000,5000,10000))
```



Labels and Legends

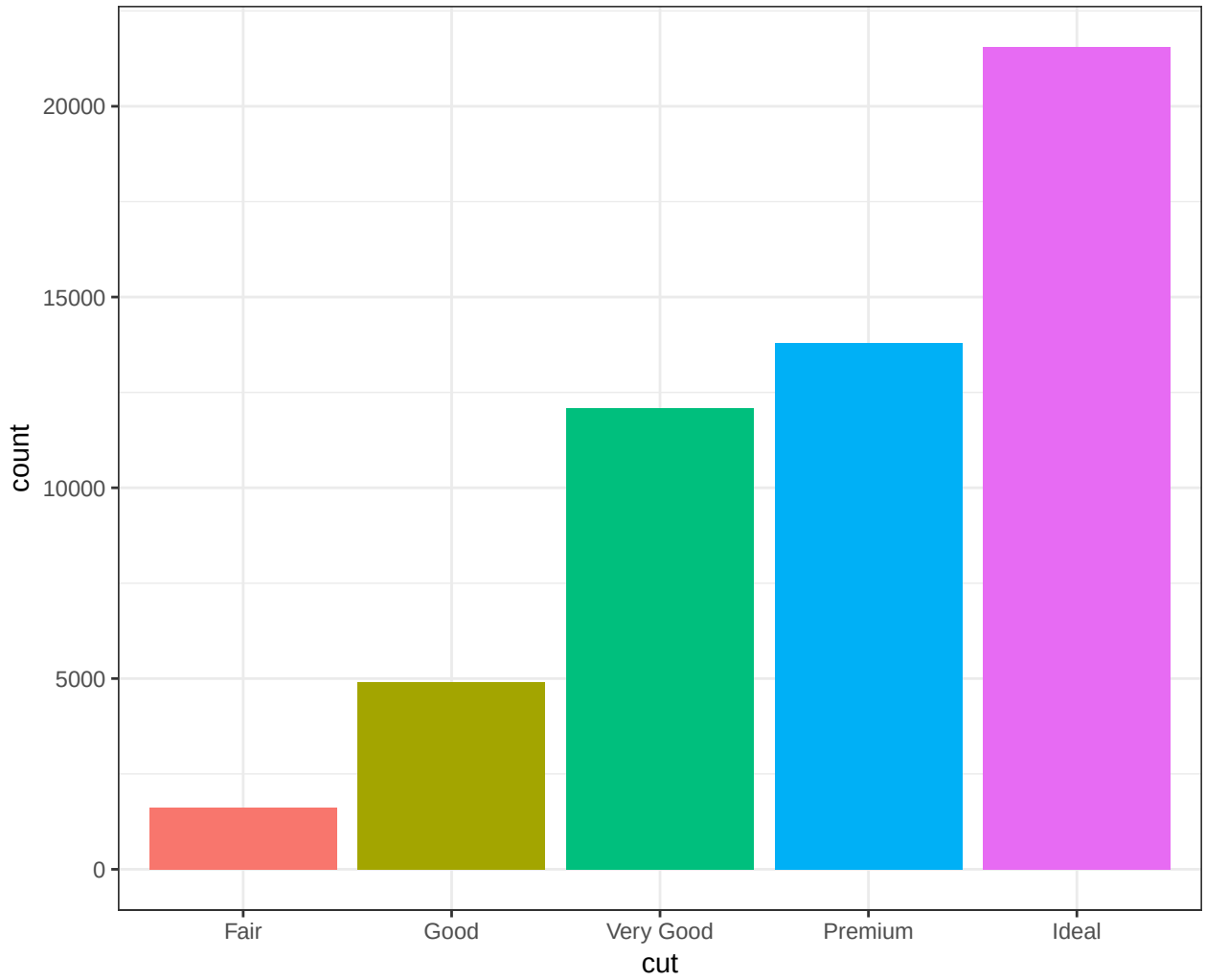
Here's how you can change the axis labels and give the plot a title:

```
> ggplot(data = mpg) +
+   geom_boxplot(mapping = aes(x = factor(cyl), y = hwy)) +
+   labs(title="Highway MPG by Cylinders",x="Cylinders",
+        y="Highway MPG")
```



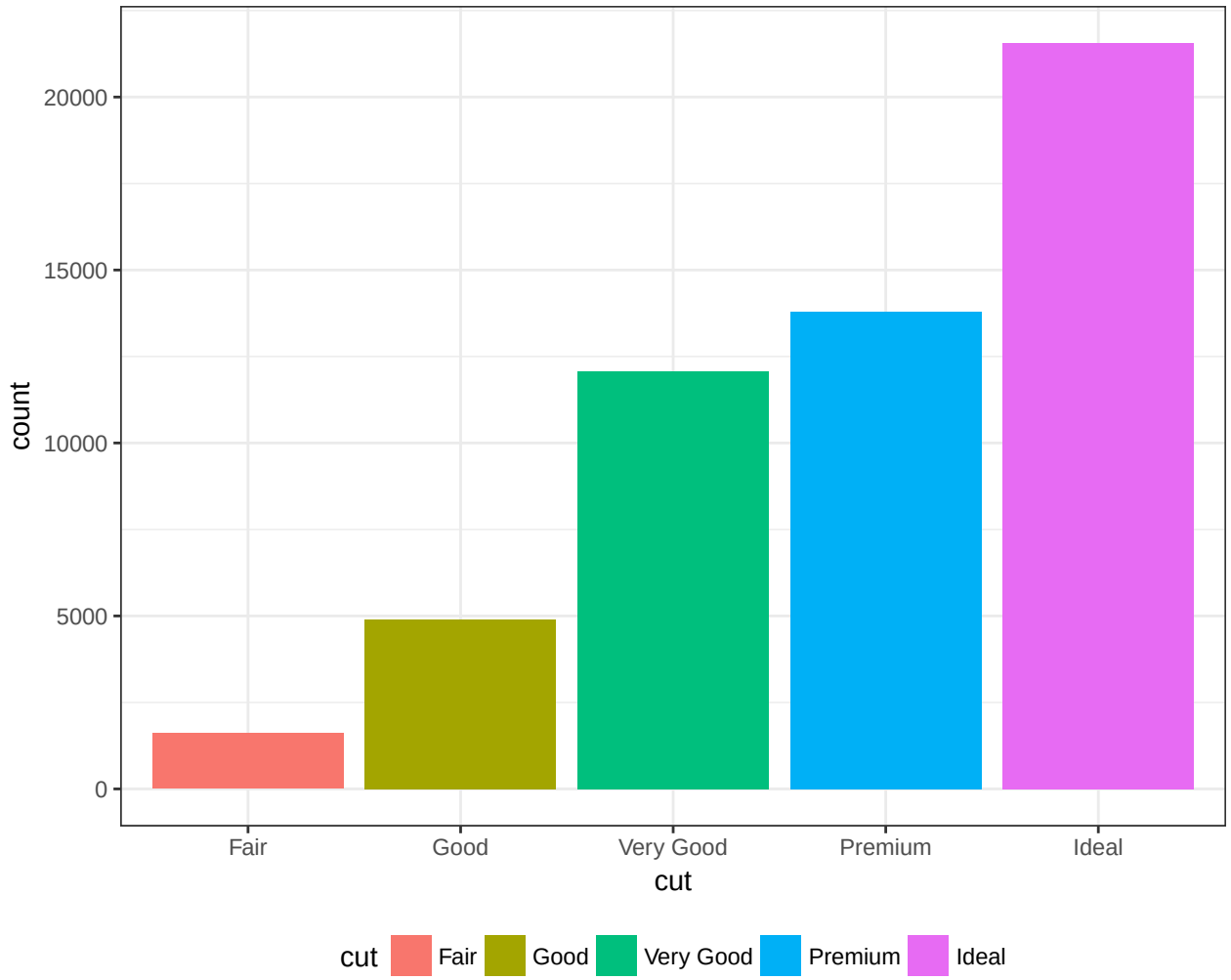
You can remove the legend to a plot by the following:

```
> ggplot(data = diamonds) +
+   geom_bar(mapping = aes(x = cut, fill = cut)) +
+   theme(legend.position="none")
```



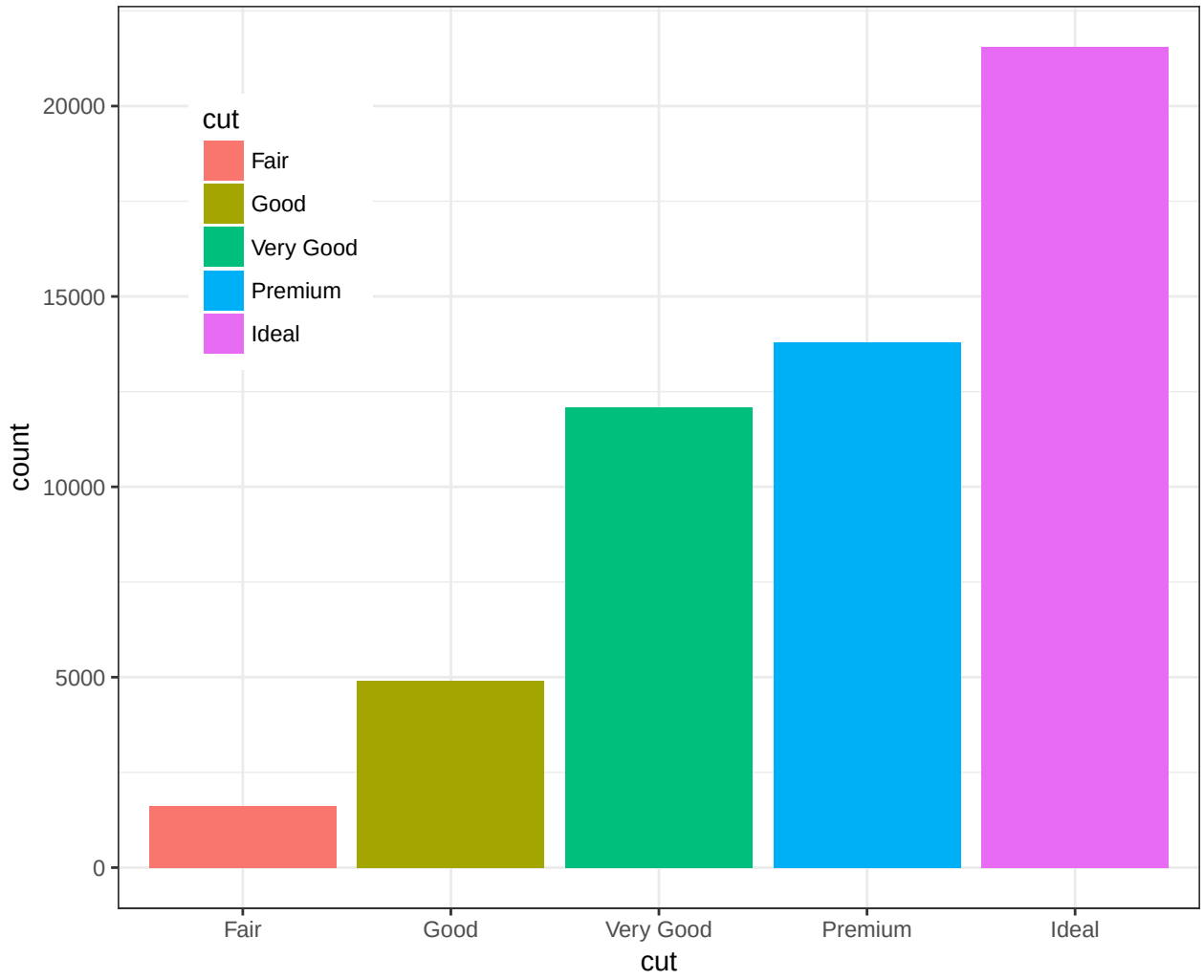
The legend can be placed on the “top”, “bottom”, “left”, or “right”:

```
> ggplot(data = diamonds) +
+   geom_bar(mapping = aes(x = cut, fill = cut)) +
+   theme(legend.position="bottom")
```



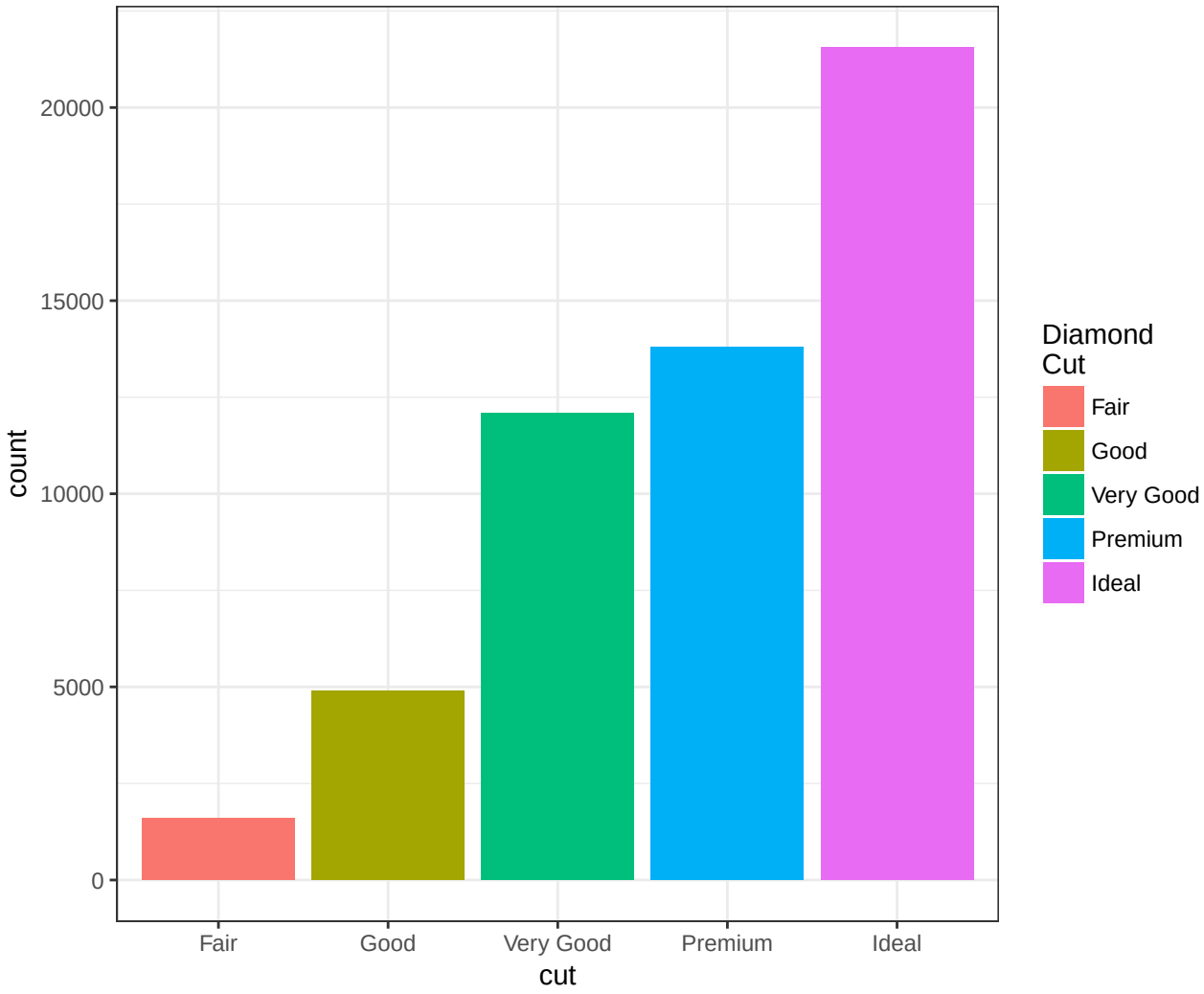
The legend can be moved inside the plot itself:

```
> ggplot(data = diamonds) +
+   geom_bar(mapping = aes(x = cut, fill = cut)) +
+   theme(legend.position=c(0.15,0.75))
```



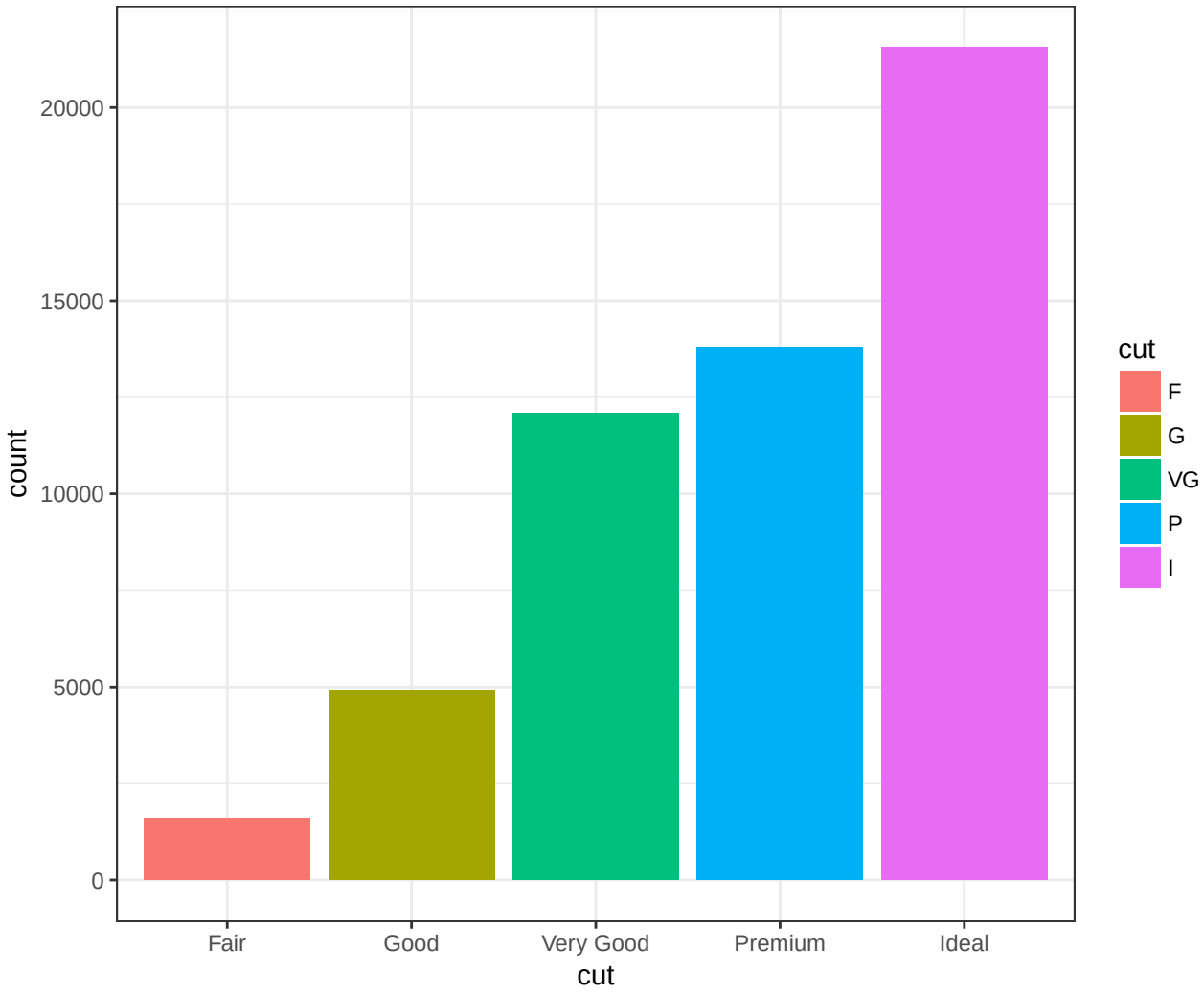
Change the name of the legend:

```
> ggplot(data = diamonds) +
+   geom_bar(mapping = aes(x = cut, fill = cut)) +
+   scale_fill_discrete(name="Diamond\nCut")
```



Change the labels within the legend:

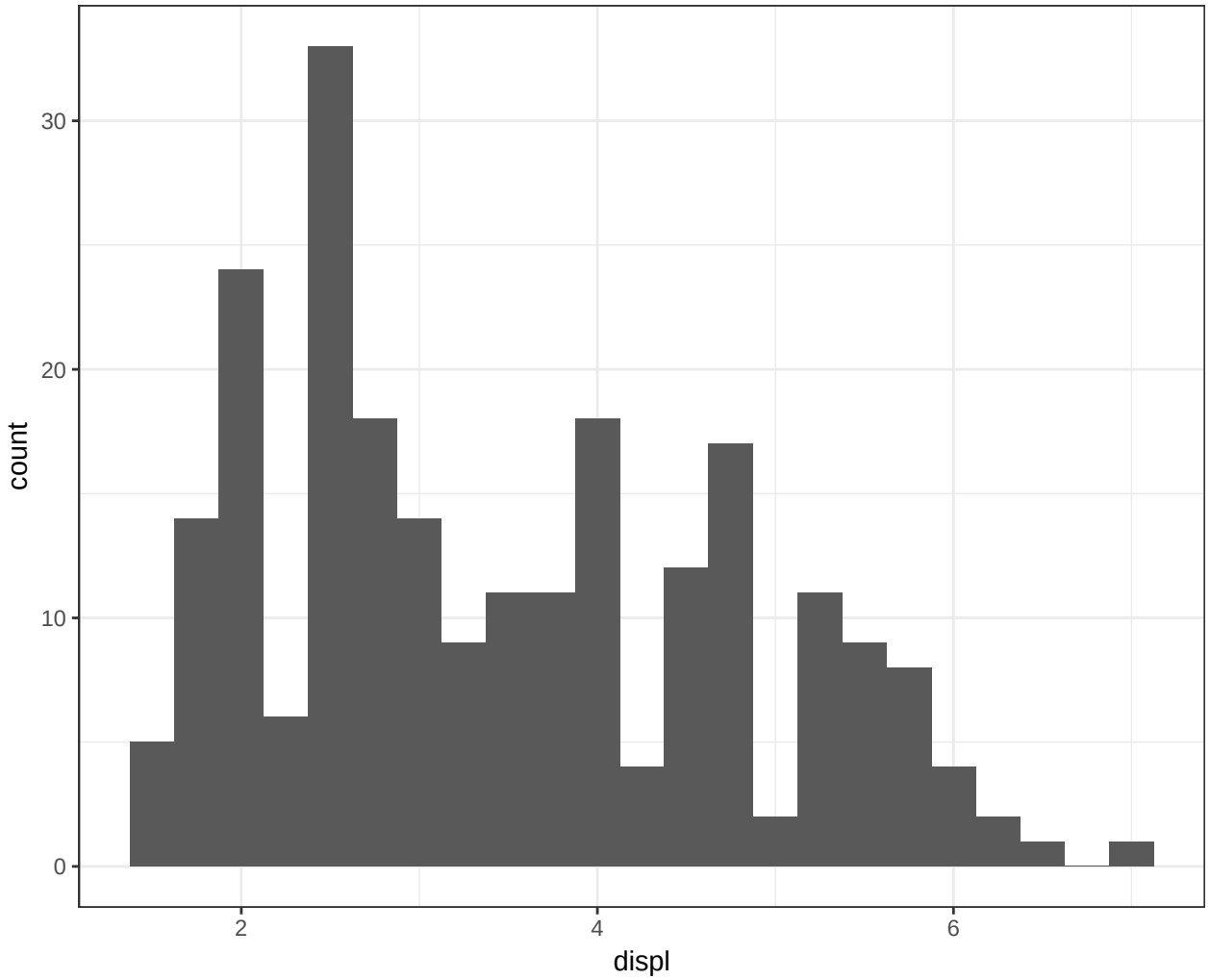
```
> ggplot(data = diamonds) +
+   geom_bar(mapping = aes(x = cut, fill = cut)) +
+   scale_fill_discrete(labels=c("F", "G", "VG", "P", "I"))
```



Facets

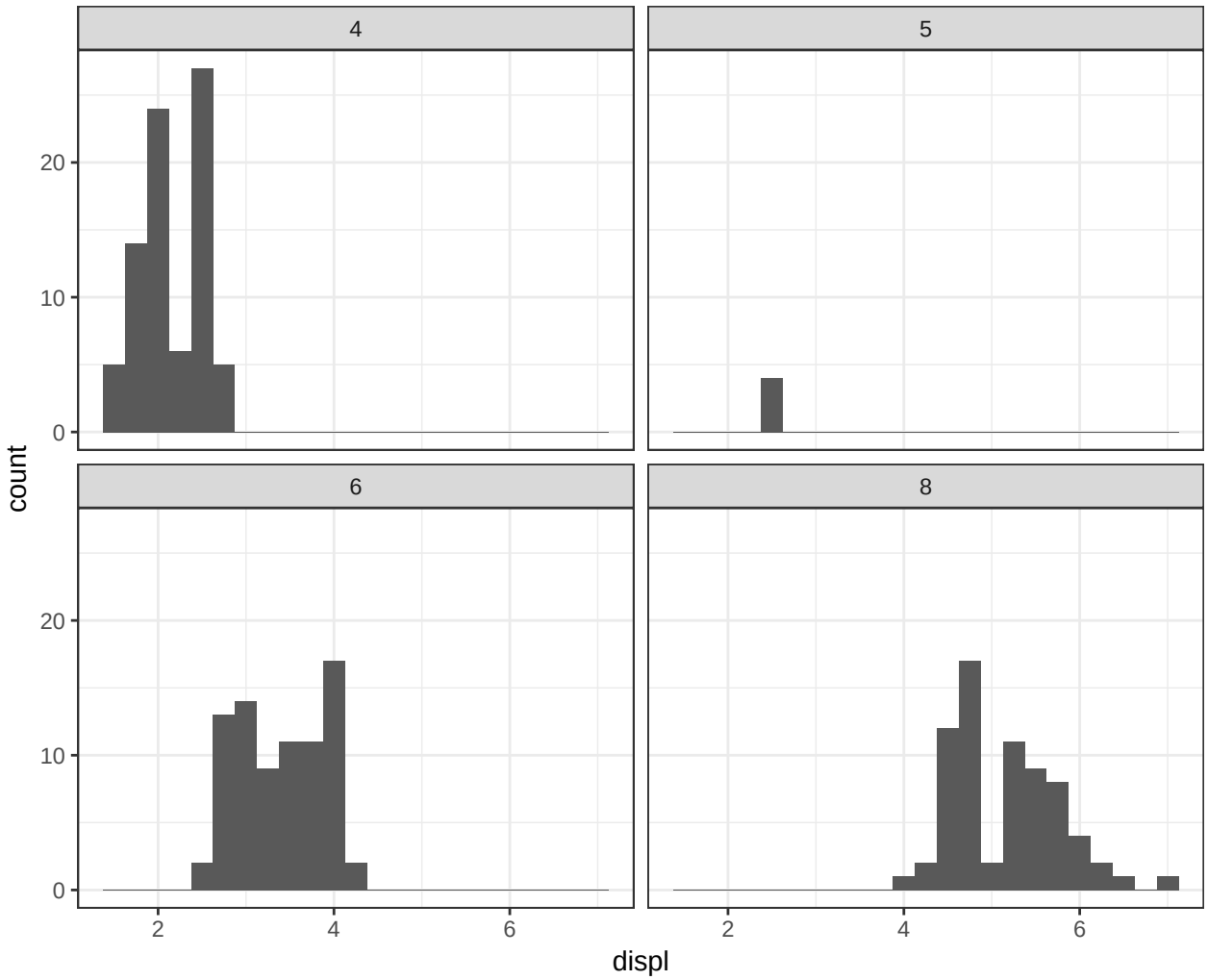
Here is the histogram of the `displ` variable from the `mpg` data set:

```
> ggplot(mpg) + geom_histogram(mapping=aes(x=displ),
+                              binwidth=0.25)
```



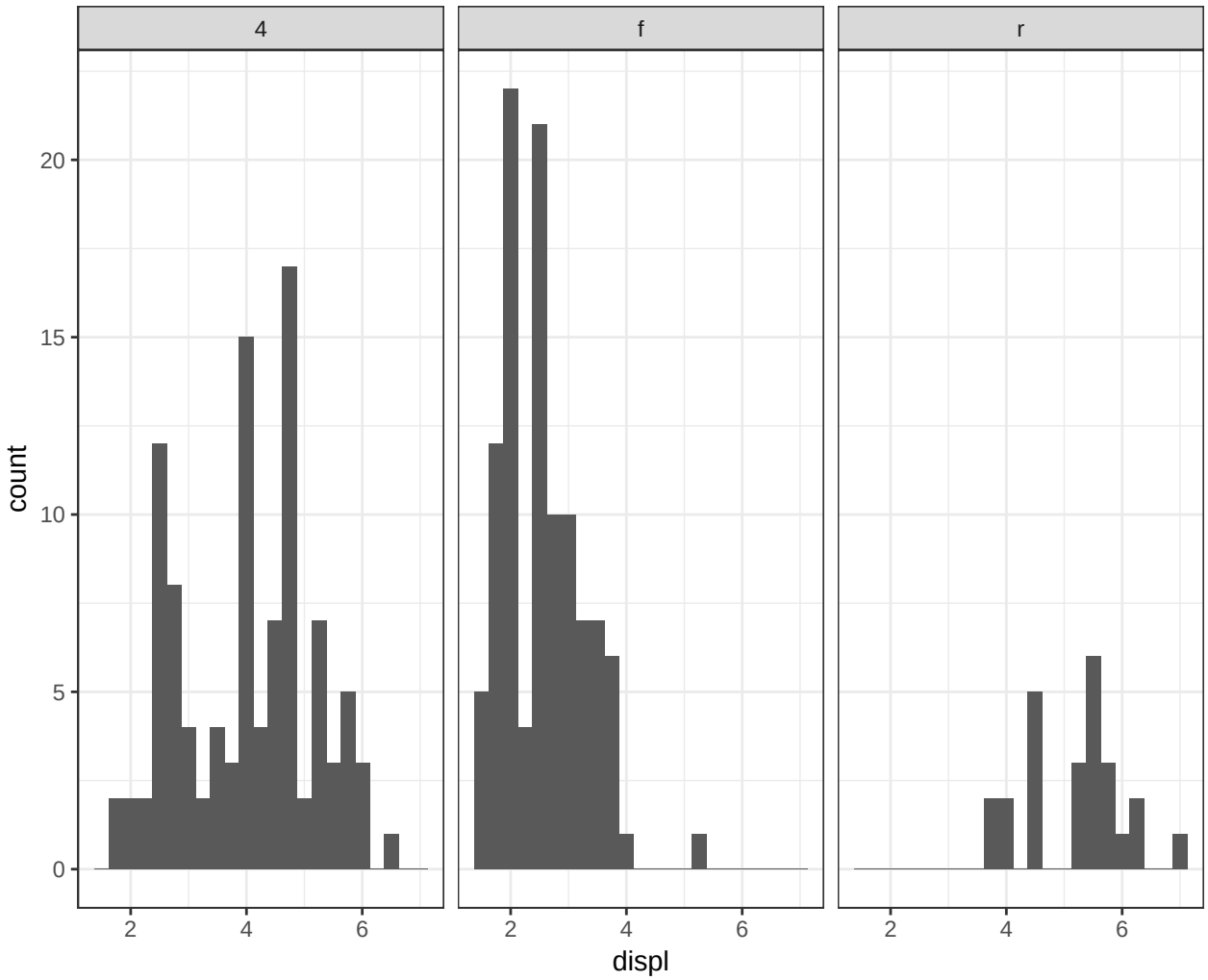
The `facet_wrap()` layer allows us to stratify the `displ` variable according to `cyl`, and show the histograms for the strata in an organized fashion:

```
> ggplot(mpg) +
+   geom_histogram(mapping=aes(x=displ), binwidth=0.25) +
+   facet_wrap(~ cyl)
```



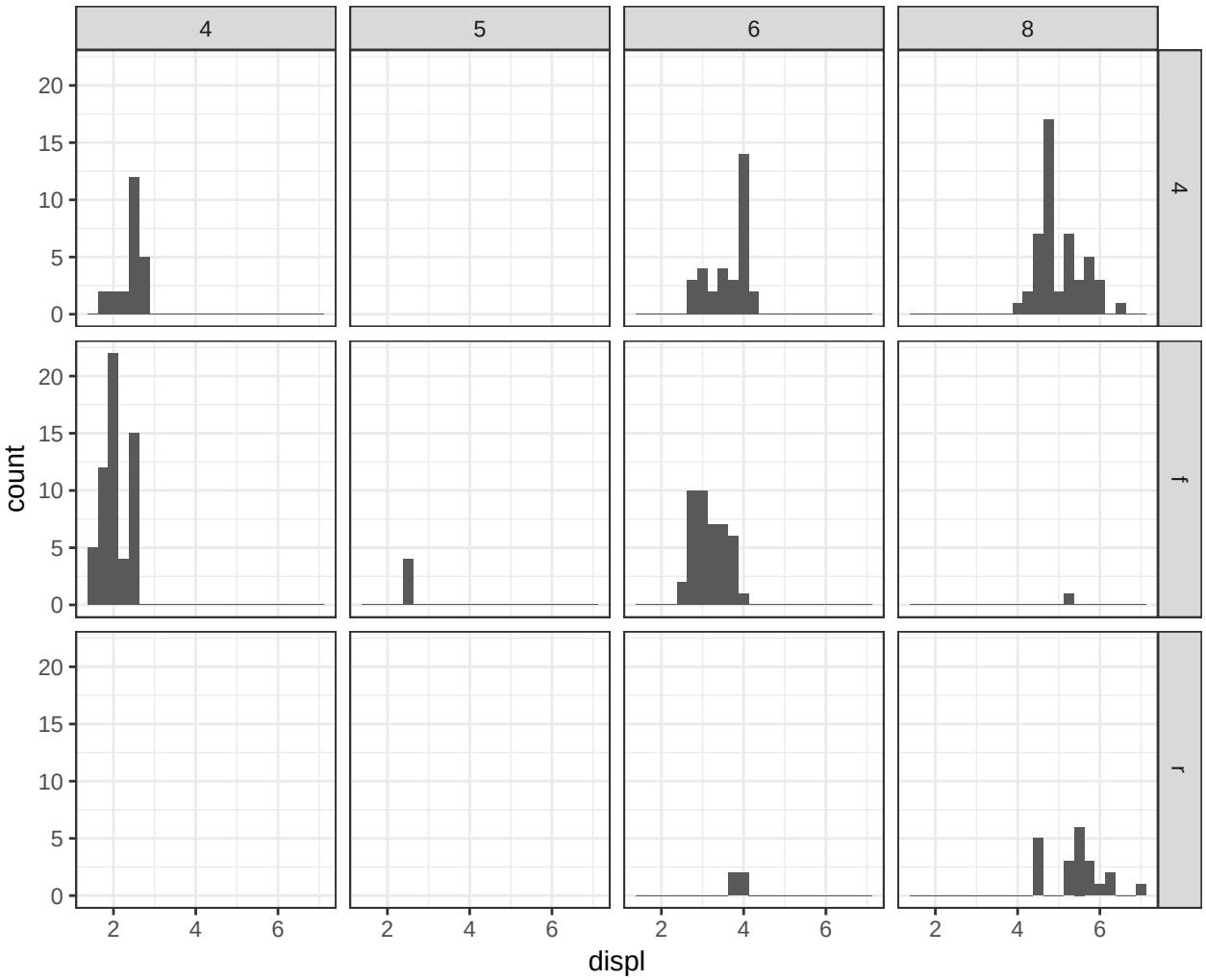
Here is `facet_wrap()` applied to `displ` startified by the `drv` variable:

```
> ggplot(mpg) +
+   geom_histogram(mapping=aes(x=displ), binwidth=0.25) +
+   facet_wrap(~ drv)
```



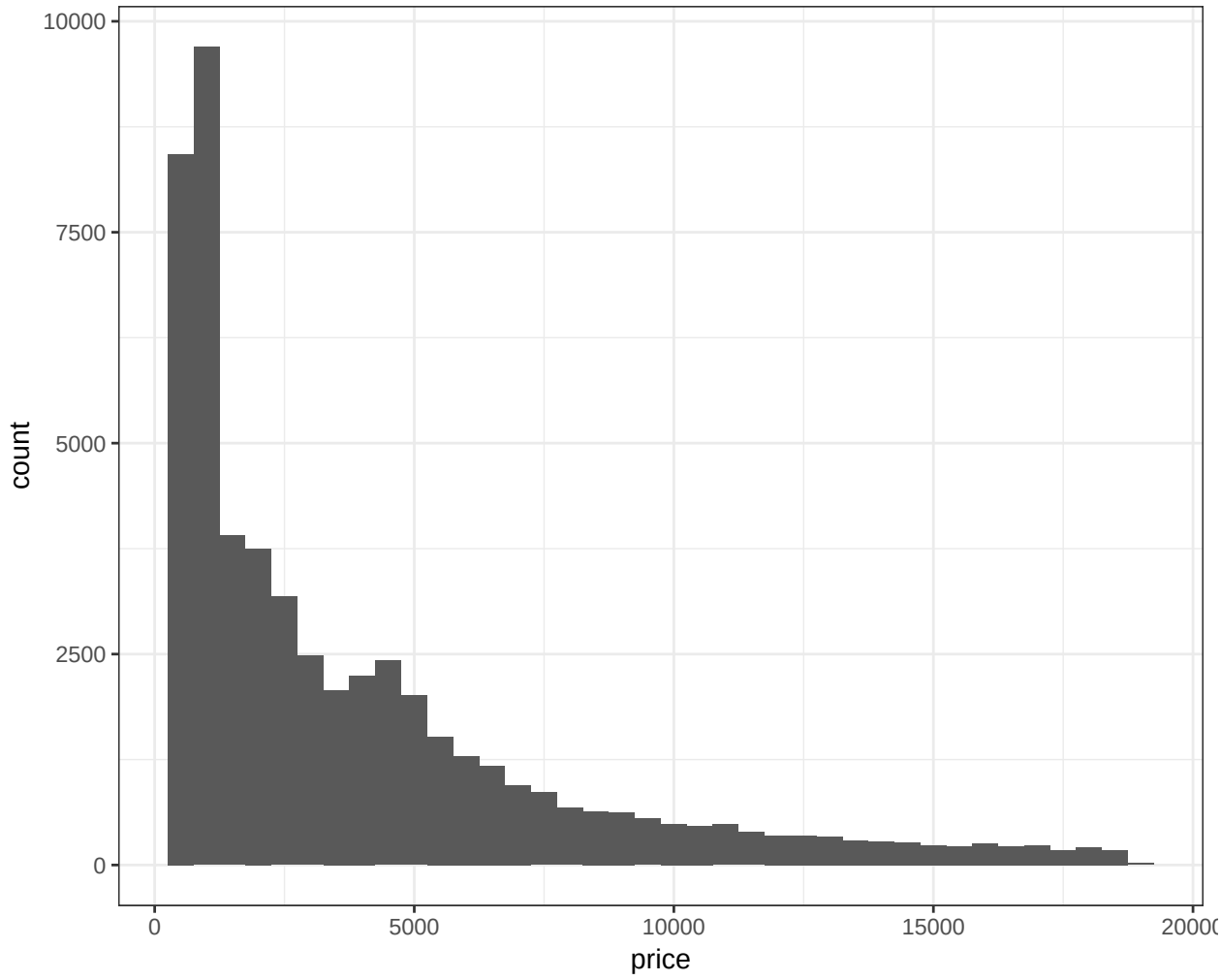
We can stratify by two variable simultaneously by using the `facet_grid()` layer:

```
> ggplot(mpg) +
+   geom_histogram(mapping=aes(x=displ), binwidth=0.25) +
+   facet_grid(drv ~ cyl)
```



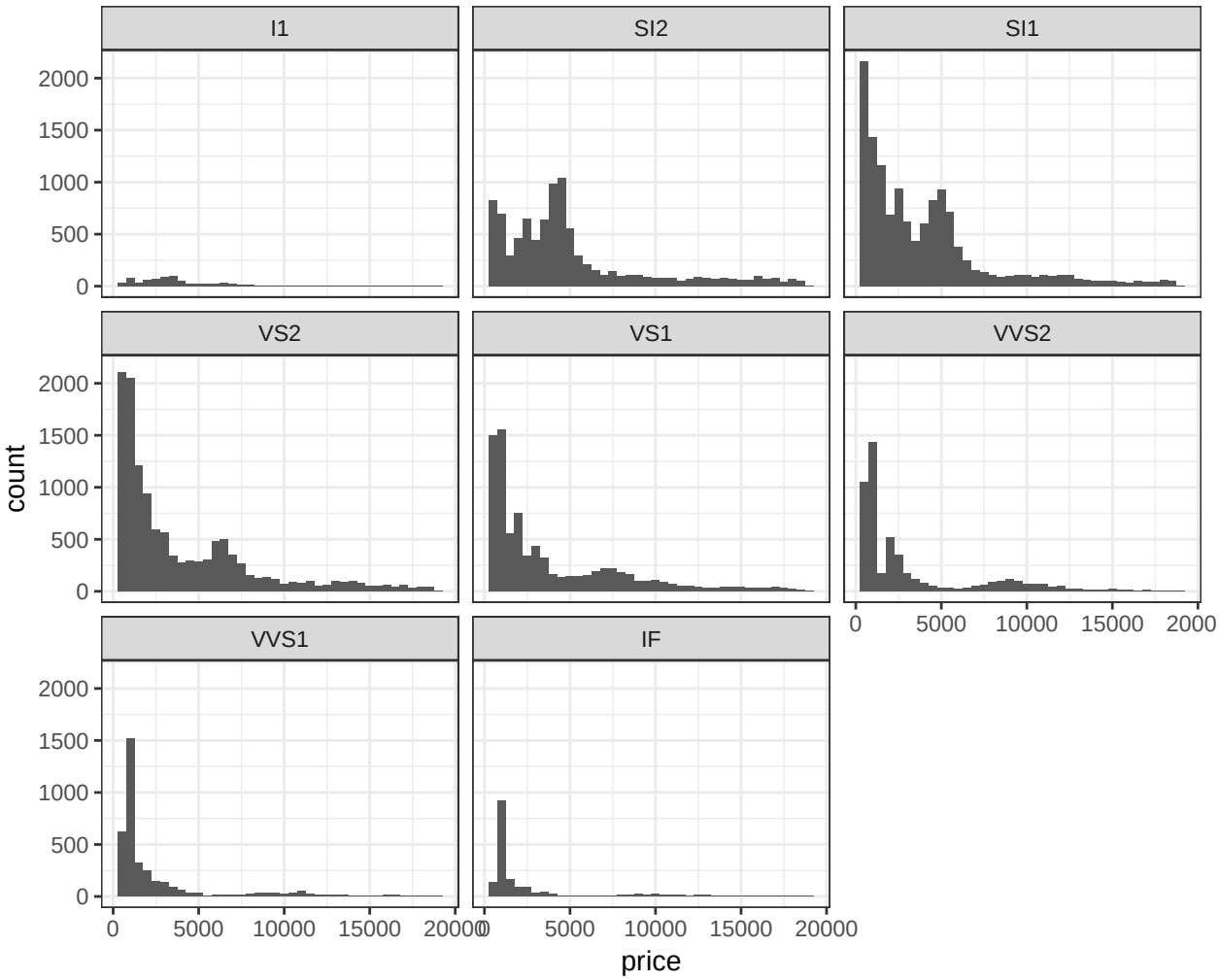
Let's carry out a similar faceting on the `diamonds` data over the next four plots:

```
> ggplot(diamonds) +
+   geom_histogram(mapping=aes(x=price), binwidth=500)
```



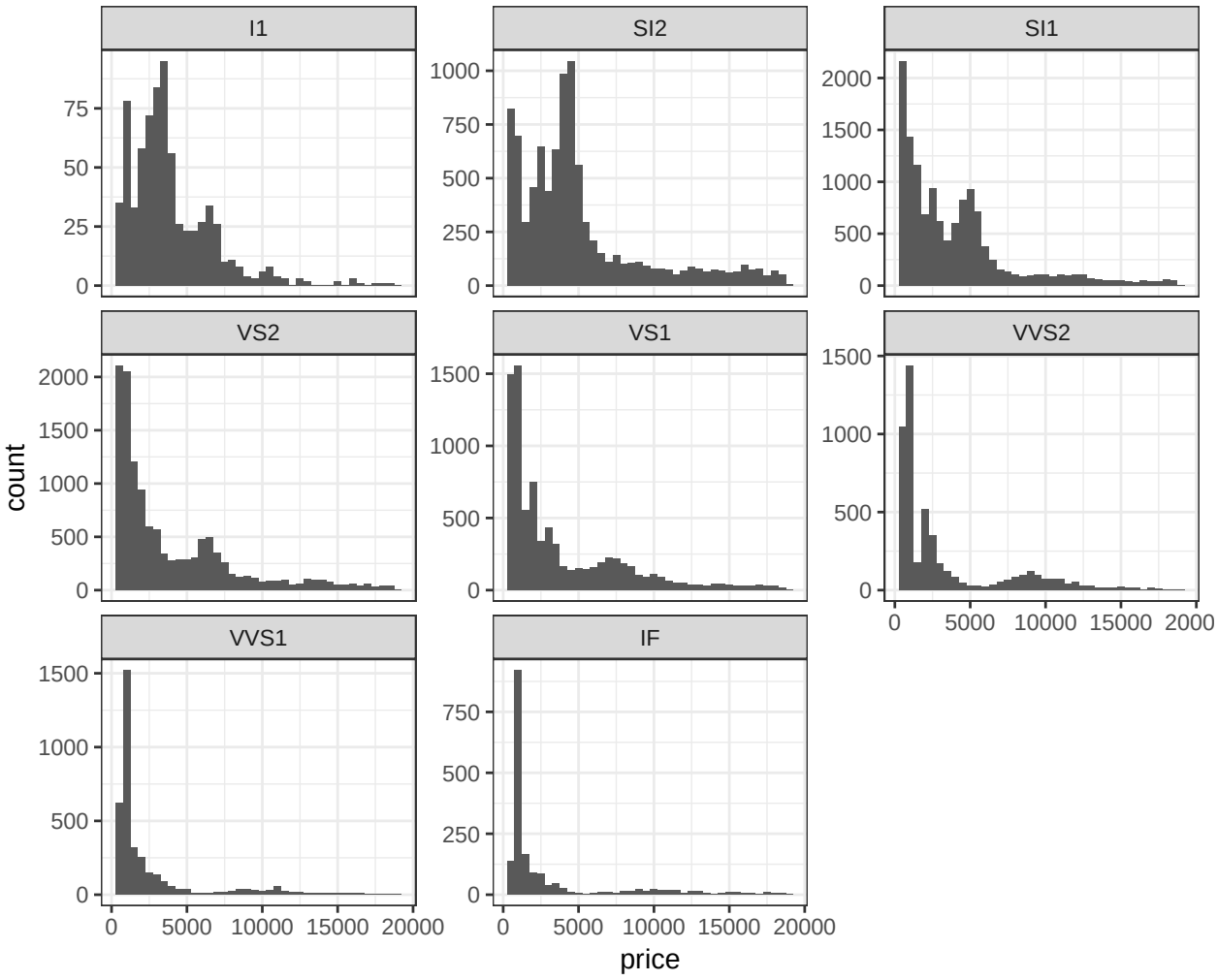
Stratify `price` by `clarity`:

```
> ggplot(diamonds) +
+   geom_histogram(mapping=aes(x=price), binwidth=500) +
+   facet_wrap(~ clarity)
```



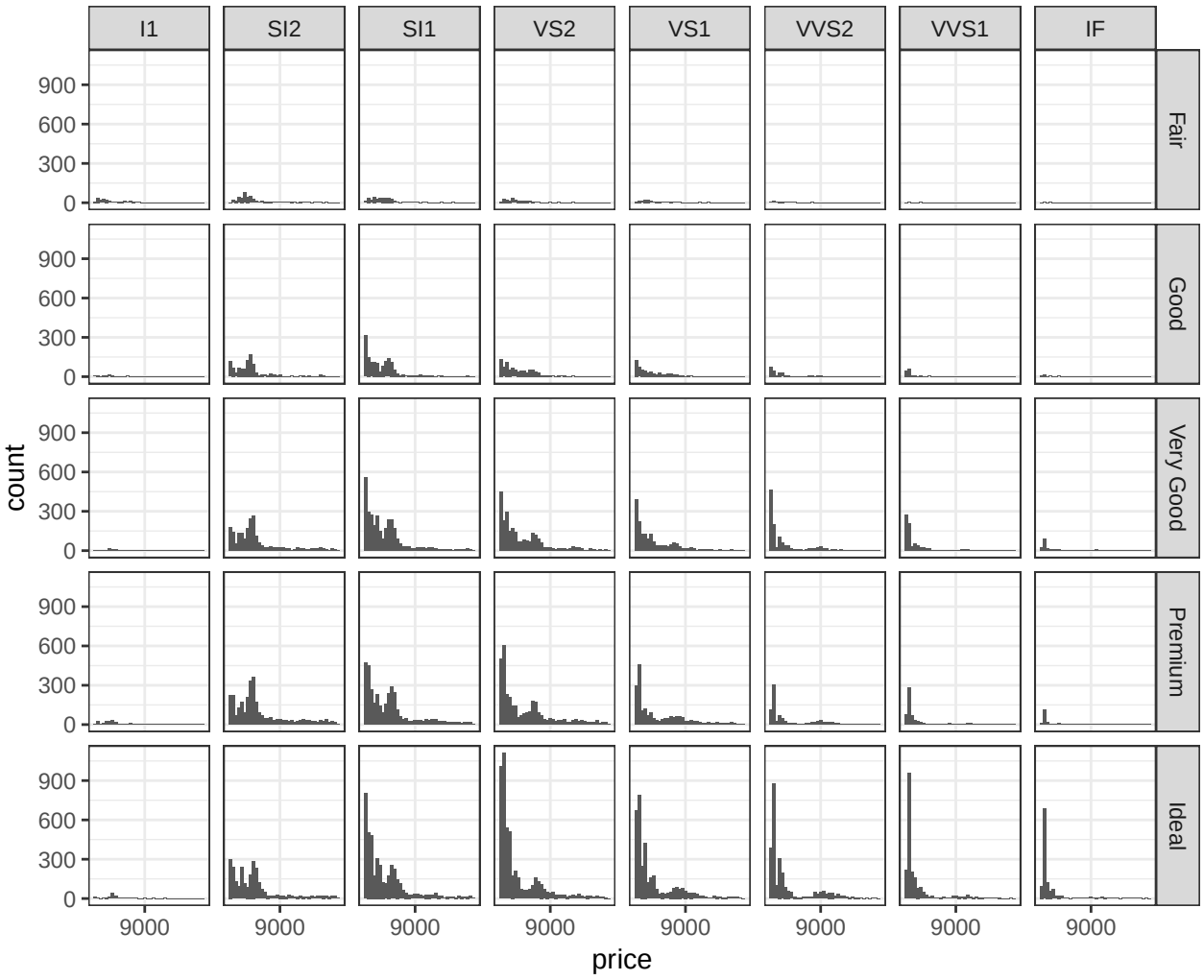
Stratify `price` by `clarity`, but allow each y-axis range to be different by including the `scale="free_y"` argument:

```
> ggplot(diamonds) +
+   geom_histogram(mapping=aes(x=price), binwidth=500) +
+   facet_wrap(~ clarity, scale="free_y")
```



Jointly stratify `price` by `cut` and `clarify`:

```
> ggplot(diamonds) +
+   geom_histogram(mapping=aes(x=price), binwidth=500) +
+   facet_grid(cut ~ clarity) +
+   scale_x_continuous(breaks=9000)
```



Colors

Finding Colors

- A list of named colors in R (e.g., "lightblue")
- RColorBrewer package
- The Crayola crayon colors from the `broman` package – use `brocolors(set="crayons")`
- Color blind palette:

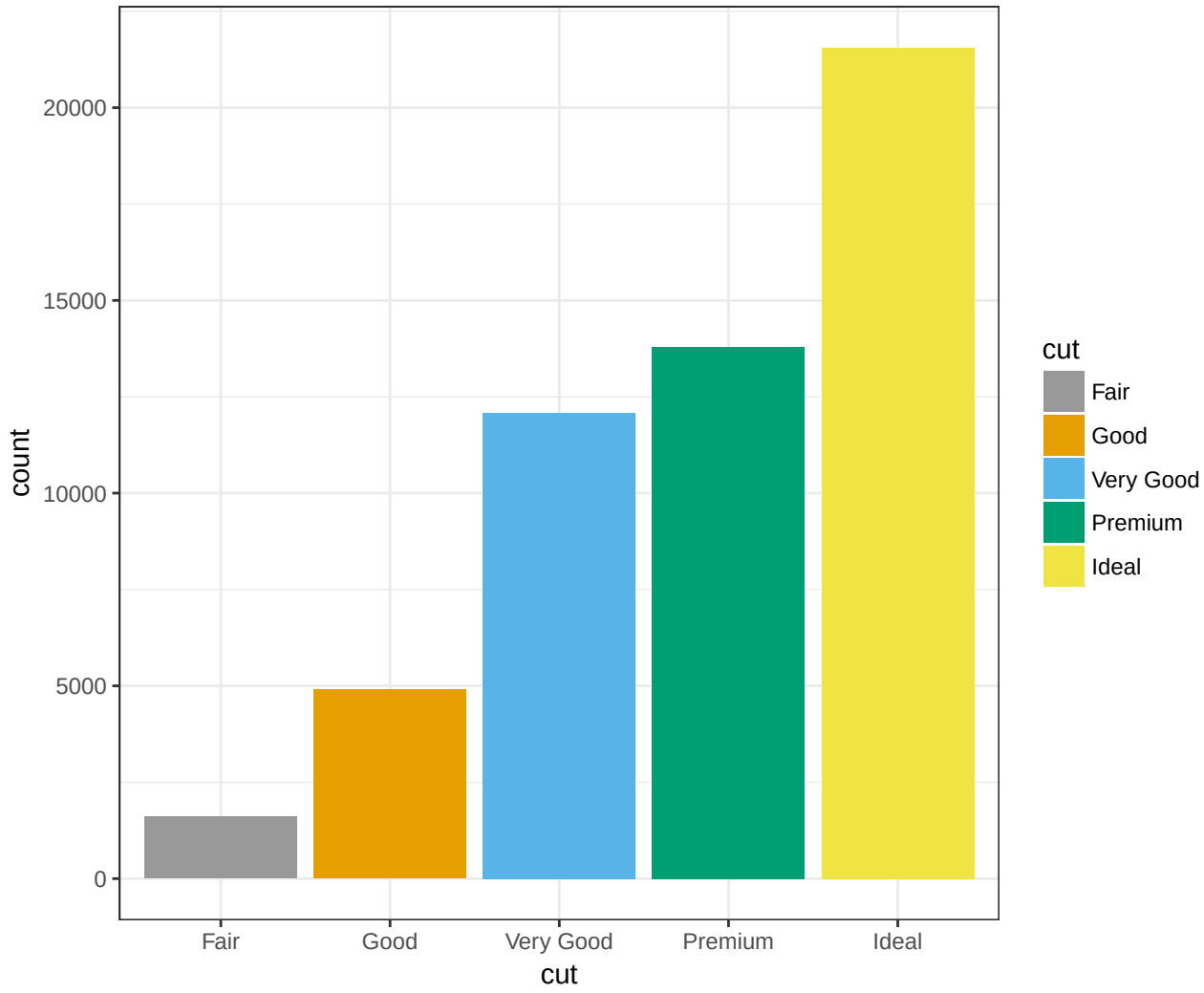
```
> cbPalette <- c("#999999", "#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2",
+                "#D55E00", "#CC79A7")
```

Some Useful Layers

- `scale_fill_manual()`
- `scale_color_manual()`
- `scale_fill_gradient()`
- `scale_color_gradient()`

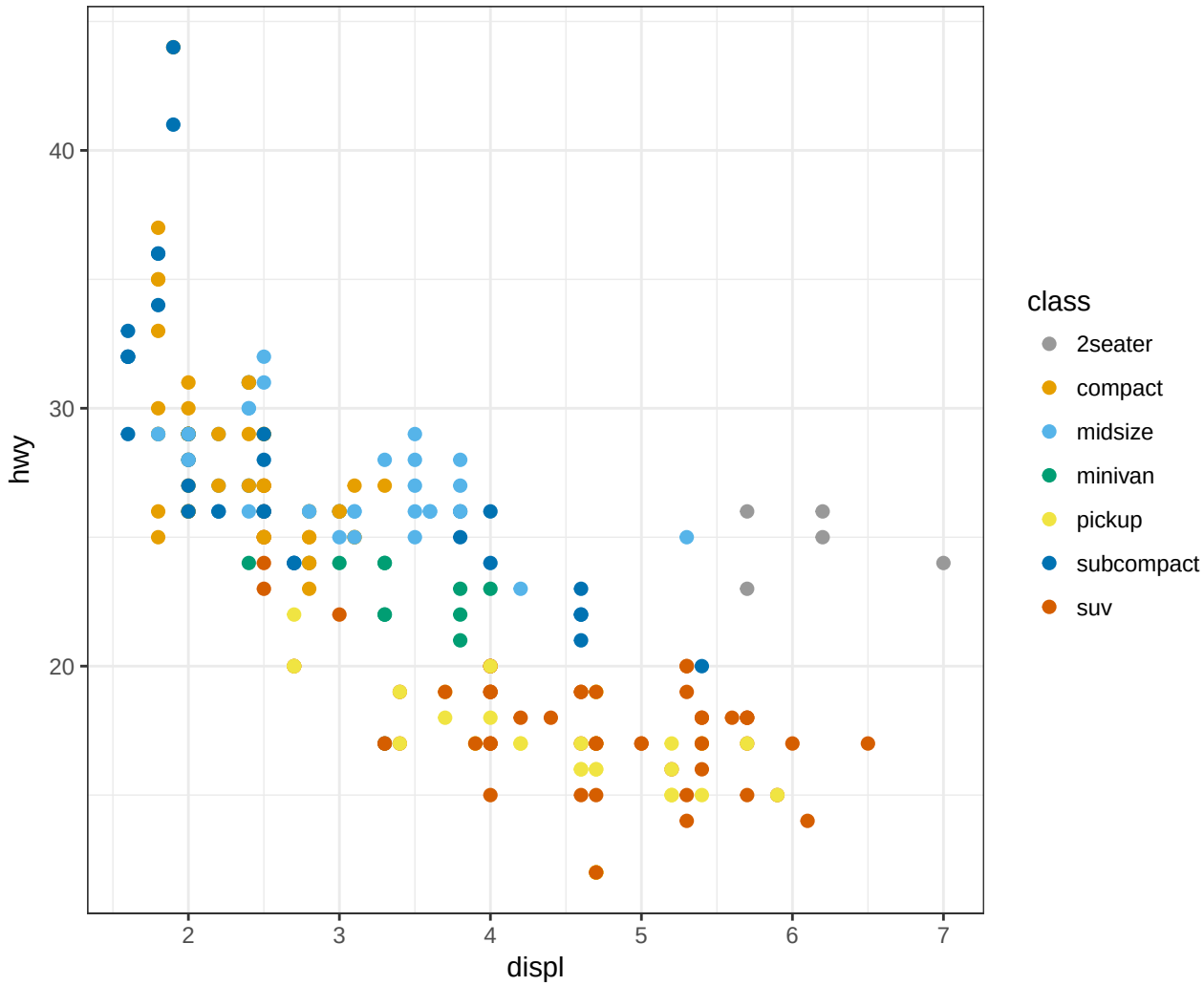
Manually determine colors to fill the barplot using the color blind palette defined above, `cbPalette`:

```
> ggplot(data = diamonds) +
+   geom_bar(mapping = aes(x = cut, fill = cut)) +
+   scale_fill_manual(values=cbPalette)
```



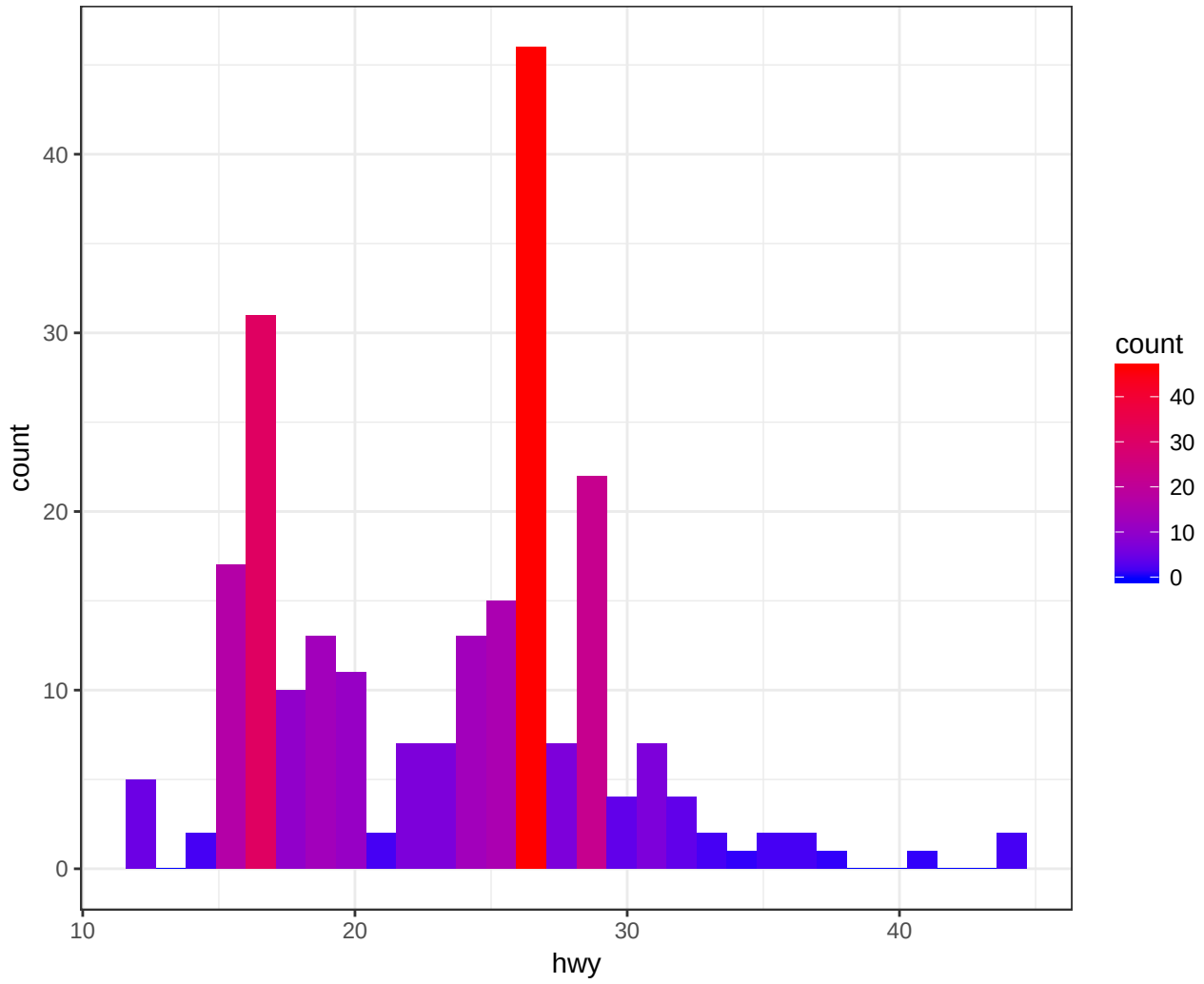
Manually determine point colors using the color blind palette defined above, `cbPalette`:

```
> ggplot(data = mpg) +
+   geom_point(mapping = aes(x = displ, y = hwy, color = class), size=2) +
+   scale_color_manual(values=cbPalette)
```



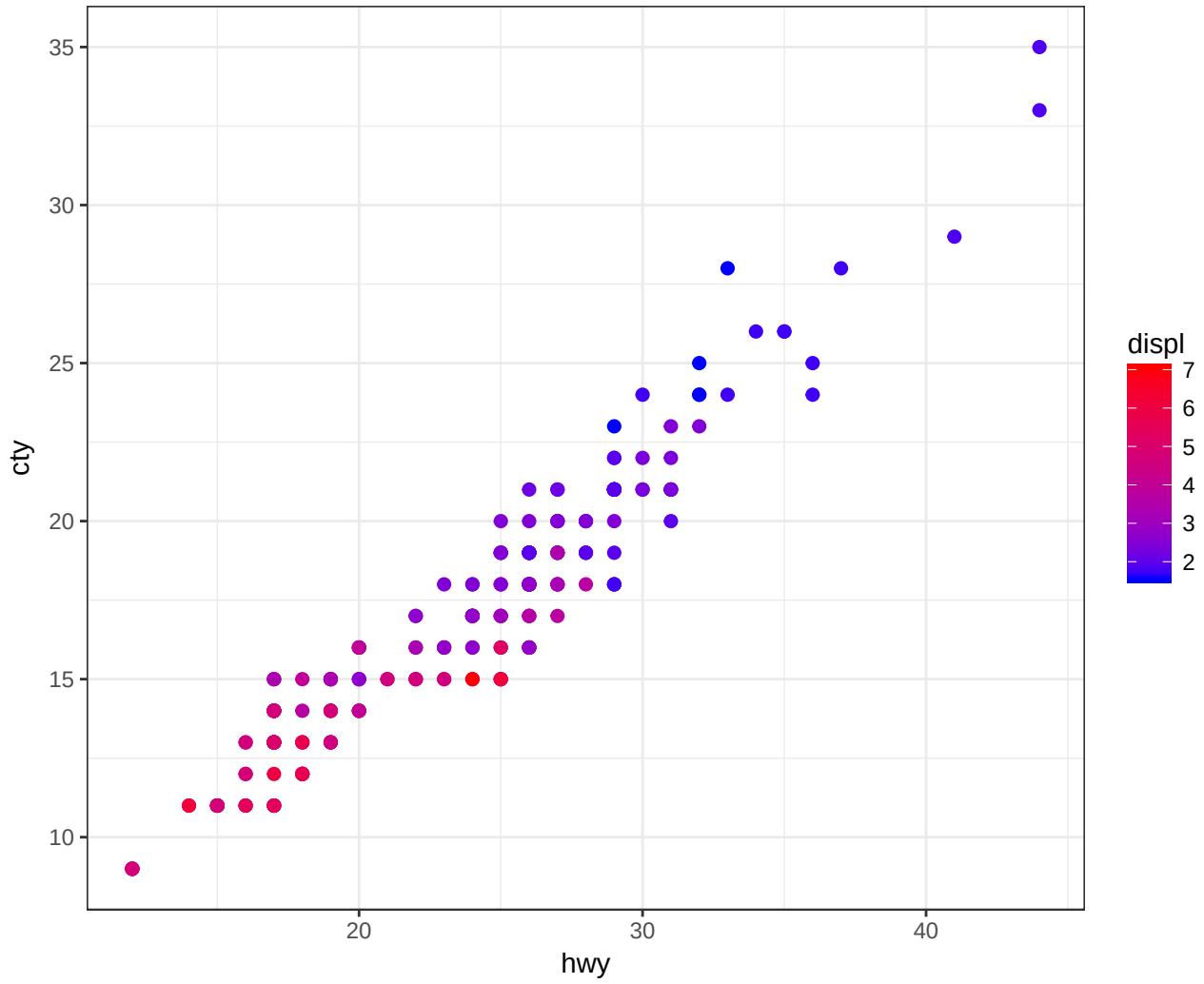
Fill the histogram bars using a color gradient by their counts, where we determine the endpoint colors:

```
> ggplot(data = mpg) +
+   geom_histogram(aes(x=hwy, fill=..count..)) +
+   scale_fill_gradient(low="blue", high="red")
```



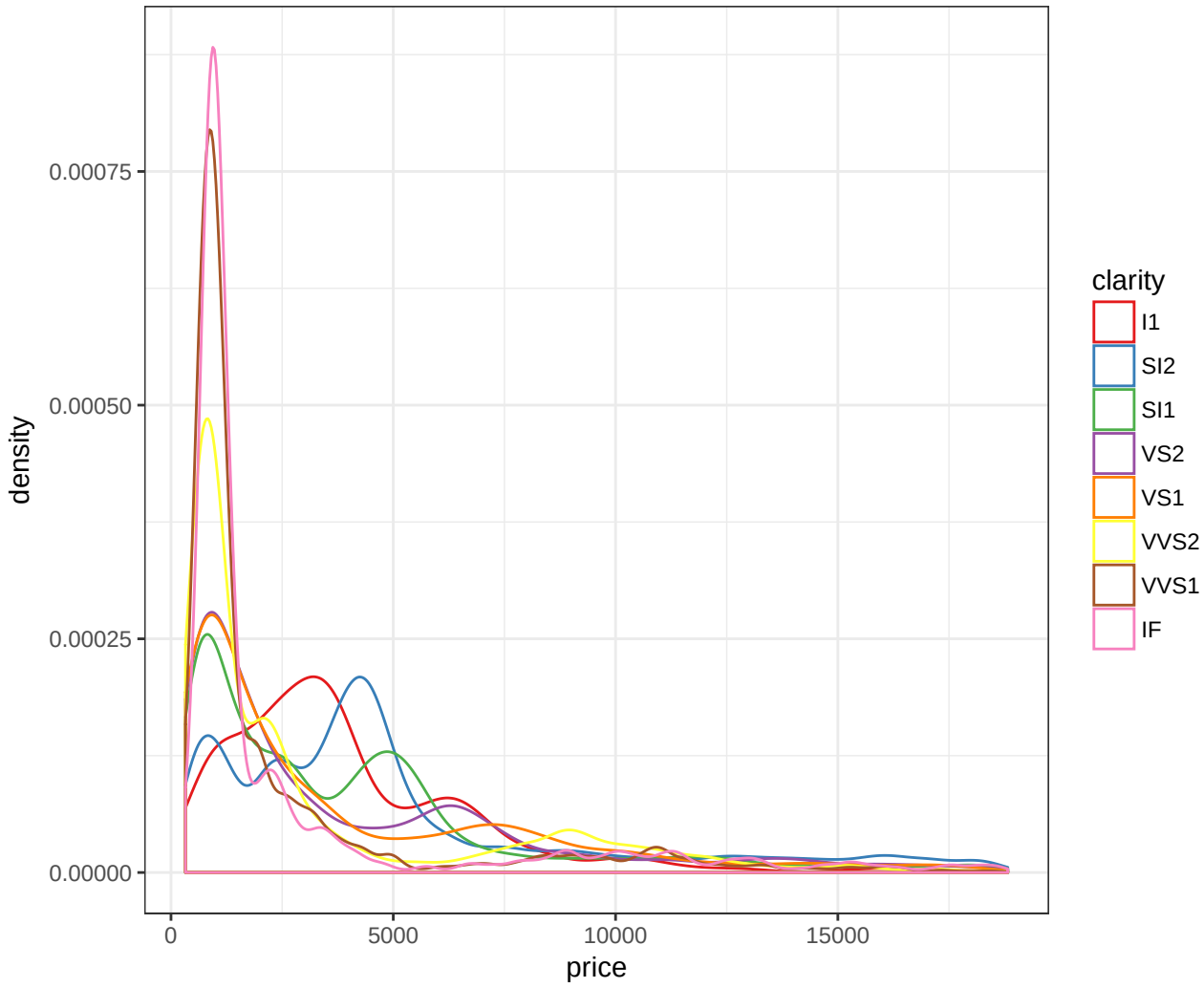
Color the points based on a gradient formed from the quantitative variable, `displ`, where we we determine the endpoint colors:

```
> ggplot(data = mpg) +
+   geom_point(aes(x=hwy, y=cty, color=displ), size=2) +
+   scale_color_gradient(low="blue", high="red")
```



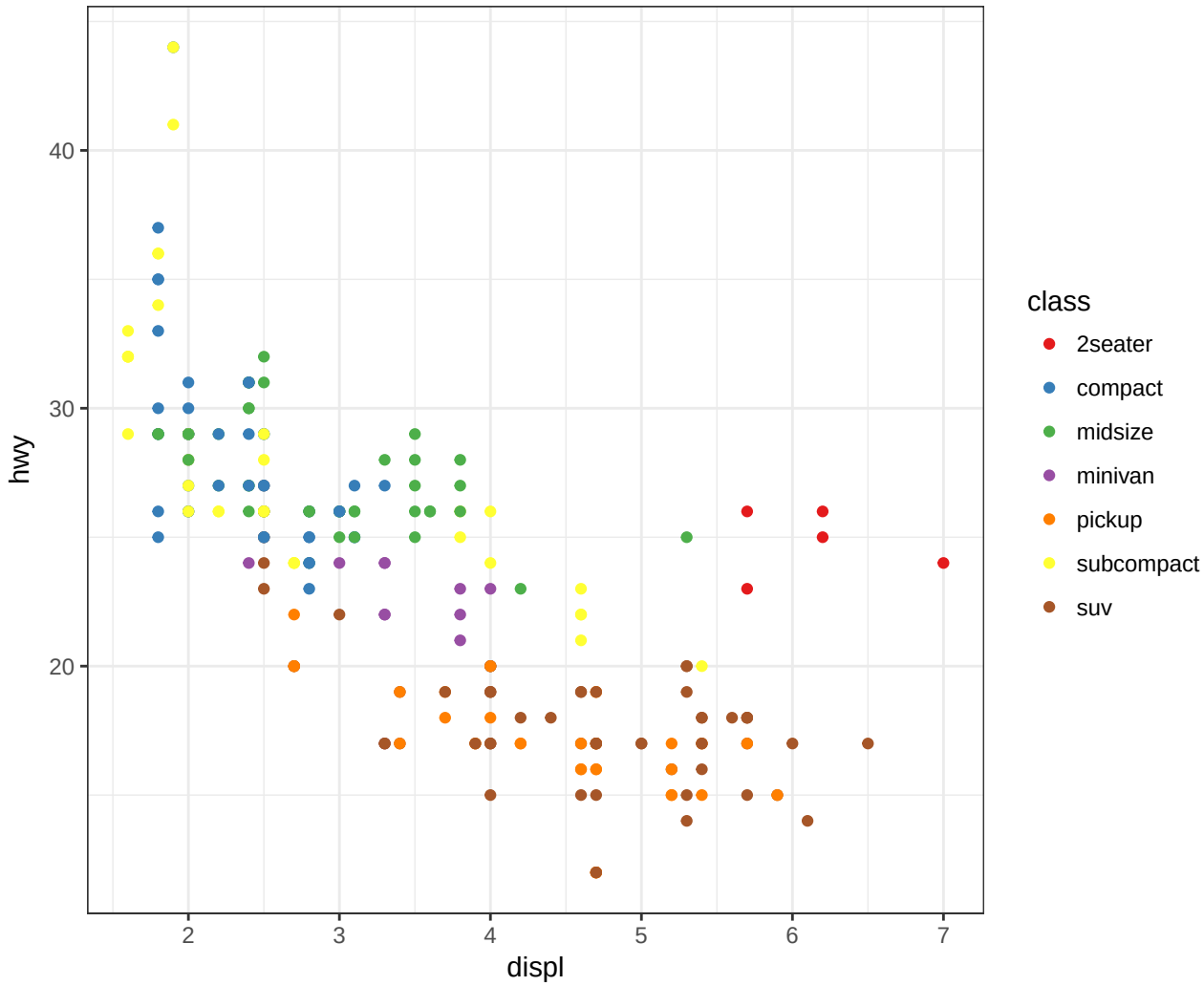
An example of using the palette "Set1" from the `RColorBrewer` package, included in `ggplot2`:

```
> ggplot(diamonds) +
+   geom_density(mapping = aes(x=price, color=clarity)) +
+   scale_color_brewer(palette = "Set1")
```



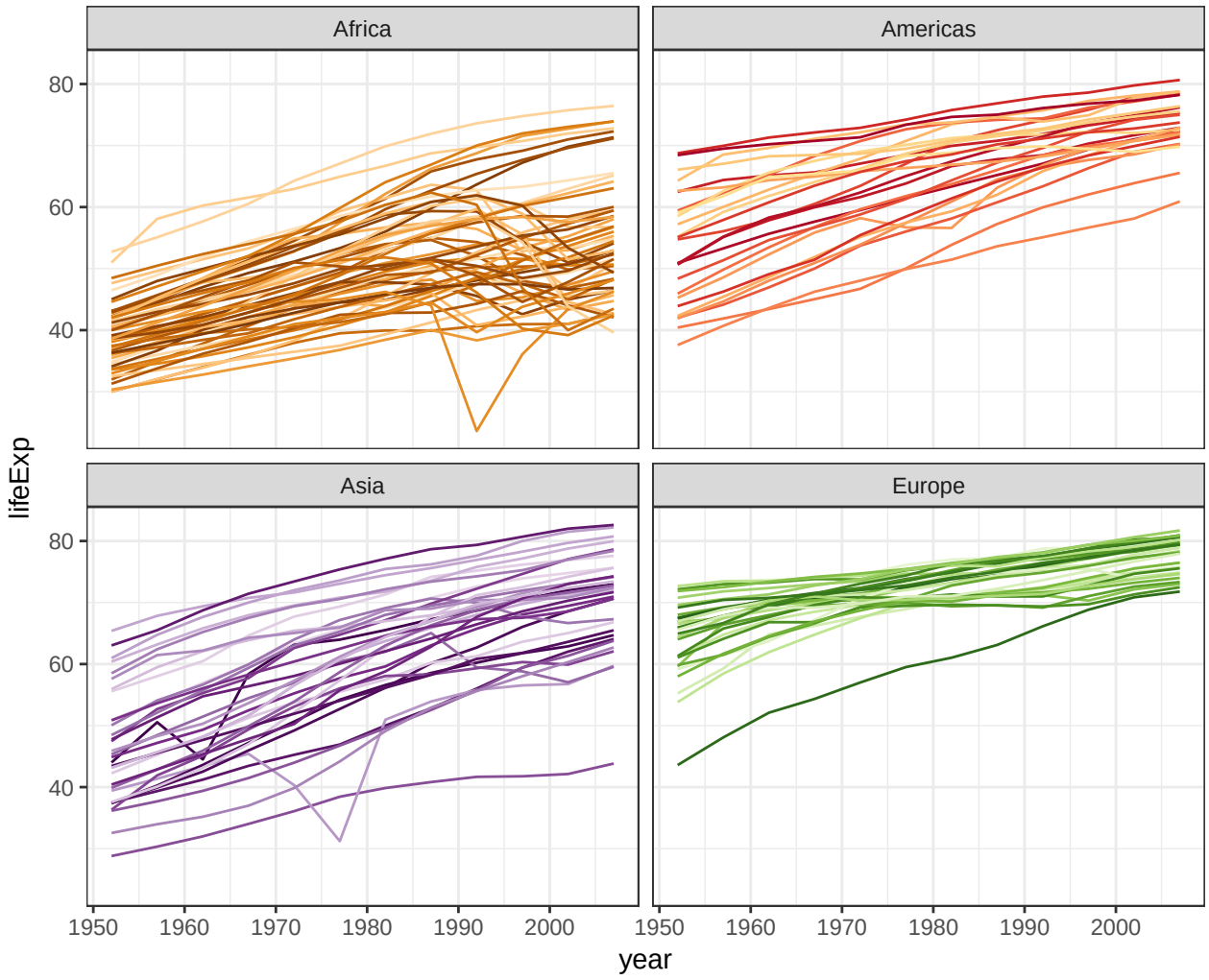
Another example of using the palette "Set1" from the `RColorBrewer` package, included in `ggplot2`:

```
> ggplot(data = mpg) +
+   geom_point(mapping = aes(x = displ, y = hwy, color = class)) +
+   scale_color_brewer(palette = "Set1")
```



The `gapminder` package comes with its own set of colors, `country_colors`.

```
> ggplot(subset(gapminder, continent != "Oceania"),
+        aes(x = year, y = lifeExp, group = country,
+            color = country)) +
+   geom_line(show.legend = FALSE) + facet_wrap(~ continent) +
+   scale_color_manual(values = country_colors)
```



Saving Plots

Saving Plots as Variables

Pieces of the plots can be saved as variables, which is particular useful to explortatory data analysis. These all produce the same plot:

```
> ggplot(data = mpg, mapping = aes(x = displ, y = hwy, color=drv)) +
+   geom_point() +
+   geom_smooth(se=FALSE)
```

```
> p <- ggplot(data = mpg, mapping = aes(x = displ, y = hwy, color=drv)) +
+   geom_point()
> p + geom_smooth(se=FALSE)
```

```
> p <- ggplot(data = mpg, mapping = aes(x = displ, y = hwy, color=drv))
> p +  geom_point() + geom_smooth(se=FALSE)
```

Try it yourself!

Saving Plots to Files

Plots can be saved to many formats using the `ggsave()` function. Here are some examples:

```
> p <- ggplot(data = mpg, mapping = aes(x = displ, y = hwy, color=drv)) +
+   geom_point() +
+   geom_smooth(se=FALSE)
> ggsave(filename="my_plot.pdf", plot=p) # saves PDF file
> ggsave(filename="my_plot.png", plot=p) # saves PNG file
```

Here are the arguments that `ggsave()` takes:

```
> str(ggsave)
function (filename, plot = last_plot(), device = NULL,
    path = NULL, scale = 1, width = NA, height = NA, units = c("in",
        "cm", "mm"), dpi = 300, limitsize = TRUE, ...)
```

Dynamic Visualization

Examples

Tools to dynamically interact with data visualizations (and calculations) are becoming increasingly common and straightforward to implement. Here are several examples:

- Shiny (see also, example from my lab)
- plotly
- ggvis
- animation
- gganimate

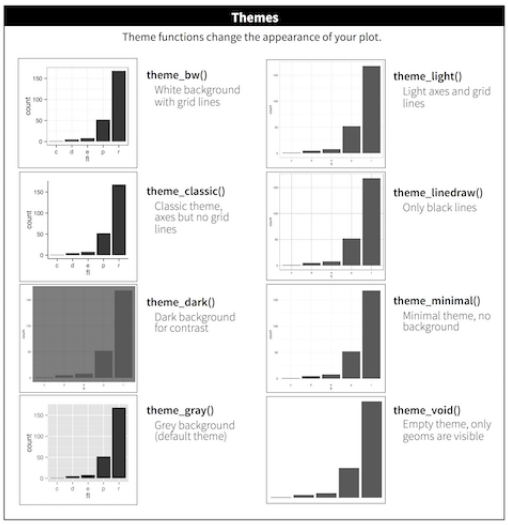
```
> p <- ggplot(gapminder) +
+         geom_point(aes(x=gdpPercap, y=lifeExp, size = pop,
+                    color = continent, frame = year)) +
+         scale_x_log10()
> gganimate(p)
```

```
> p <- ggplot(gapminder) +
+   geom_density(aes(x=lifeExp, color=as.factor(year),
+                    frame=year),
+                size=1.2) +
+   scale_color_discrete(name="year")
> gganimate(p)
```

```
> p <- ggplot(gapminder) +
+   geom_density(aes(x=lifeExp, color=as.factor(year),
+                    frame=year, cumulative = TRUE),
+                size=1.2) +
+   scale_color_discrete(name="year")
> gganimate(p)
```

Themes

Available Themes



From http://r4ds.had.co.nz/visualize.html. See also `ggthemes` package.

Setting a Theme

Globally:

```
> theme_set(theme_minimal())
```

Locally:

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

More Numerical Summaries

Measuring Symmetry

The **skewness** statistic measures symmetry of the data. It is calculated by:

$$\gamma = \frac{\sum_{i=1}^{n}(x_i - \overline{x})^3/n}{s^3}$$

A negative number is left-skewed, and a positive number is right-skewed.

Note: Use of n vs. $n-1$ may vary – check the code.

`skewness()` Function

In R, there is a function call `skewness()` from the `moments` package for calculating this statistic on data.

```
> library(moments)
> gapminder %>% filter(year==2007) %>% select(gdpPercap) %>%
+   skewness()
gdpPercap
 1.211228
> gapminder %>% filter(year==2007) %>% select(gdpPercap) %>%
+   log() %>% skewness()
 gdpPercap
-0.1524203
> rnorm(10000) %>% skewness()
[1] 0.01169526
```

Measuring Tails

The tails of a distribution are often described as being heavy or light depending on how slowly they descend.

This can be measured through statistic called **kurtosis**:

$$\kappa = \frac{\sum_{i=1}^{n}(x_i - \overline{x})^4/n}{s^4}$$

As with skewness γ, use of n vs $n-1$ may vary.

Excess Kurtosis

For a standard Normal distribution (mean 0 and standard deviation 1), the kurtosis is on average 3.

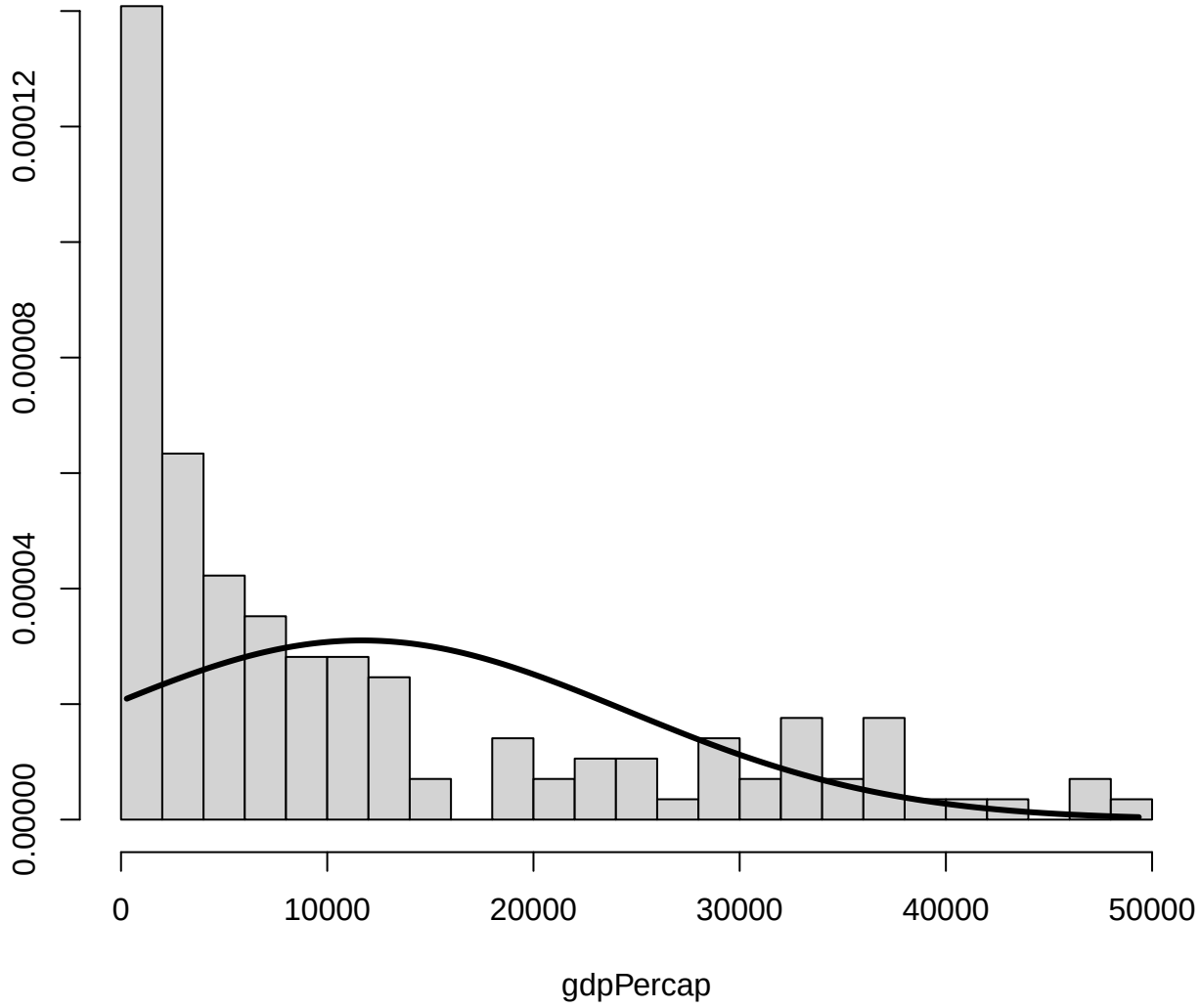
Therefore, a measure called "excess kurtosis" is defined to be $\kappa - 3$. A positive value implies heavier tails and a negative value implies lighter tails.

`kurtosis()` Function

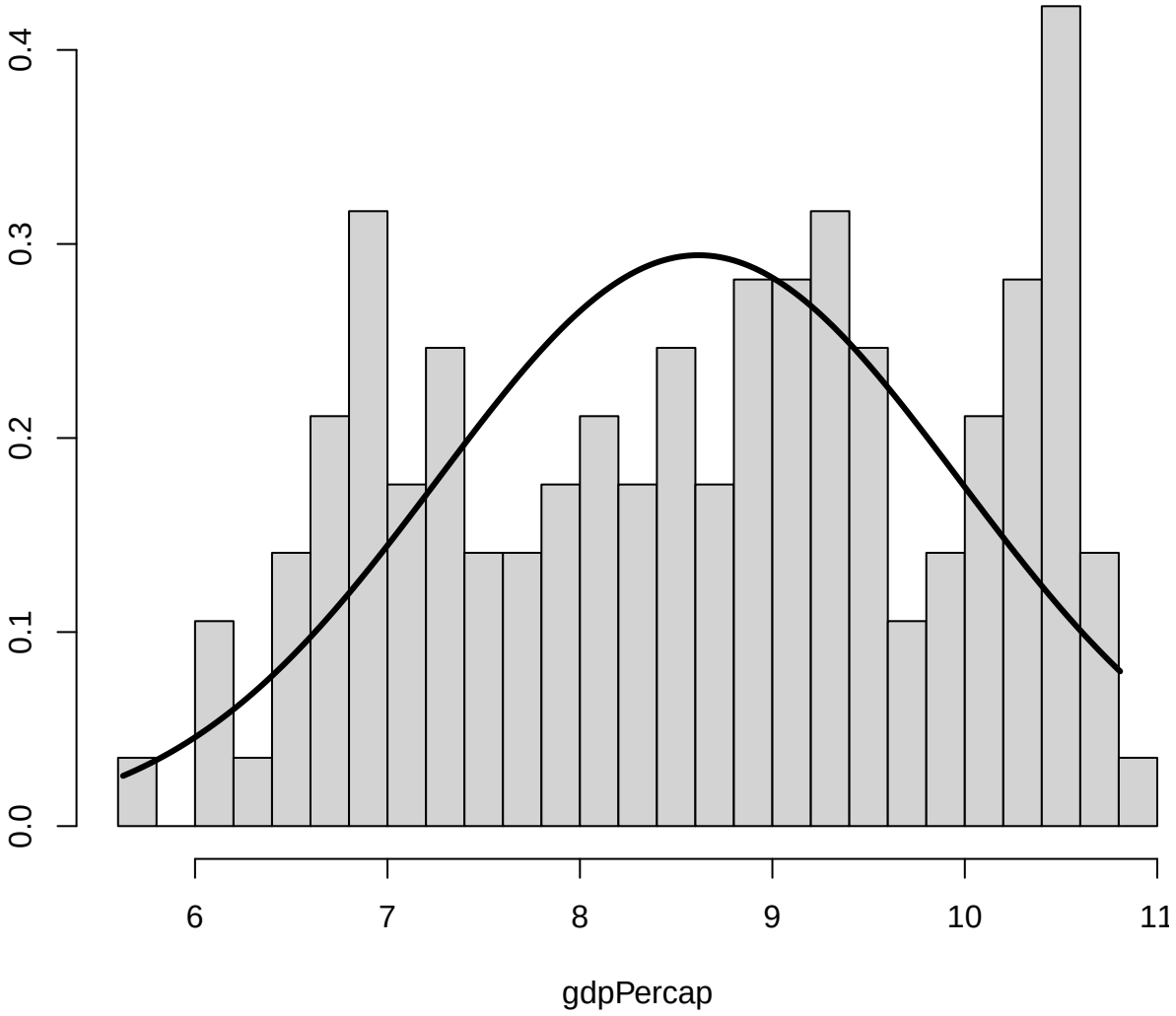
In R, there is a function call `kurtosis()` from the `moments` package for calculating this statistic on data.

```
> library(moments)
> gapminder %>% filter(year==2007) %>% select(gdpPercap) %>%
+   kurtosis()
gdpPercap
  3.29593
> gapminder %>% filter(year==2007) %>% select(gdpPercap) %>%
+   log() %>% kurtosis()
gdpPercap
 1.871608
> rnorm(10000) %>% kurtosis()
[1] 3.094407
```

Visualizing Skewness and Kurtosis



Visualizing Skewness and Kurtosis



Correlation

- It is often the case that two or more quantitative variables are measured on each unit of observation (such as an individual).
- We are then often interested in characterizing how pairs of variables are associated or how they vary together.
- A common measure that is used is called "correlation", which is most well suited for measuring linear associations

Pearson Correlation

Suppose we observe n pairs of data $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$. Their sample correlation is

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \quad (1)$$

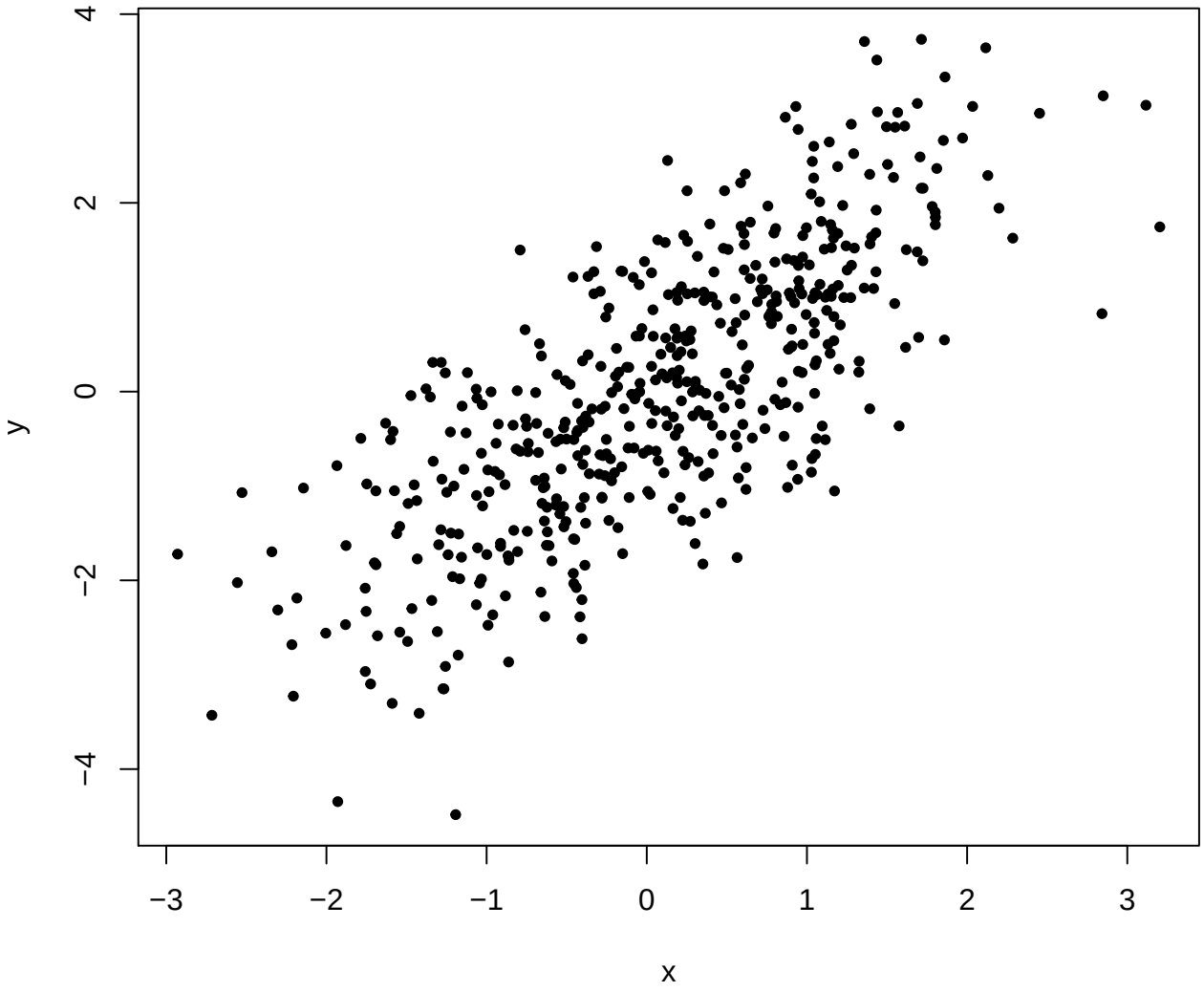
$$= \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{(n-1)s_x s_y} \quad (2)$$

where s_x and s_y are the sample standard deviations of each measured variable.

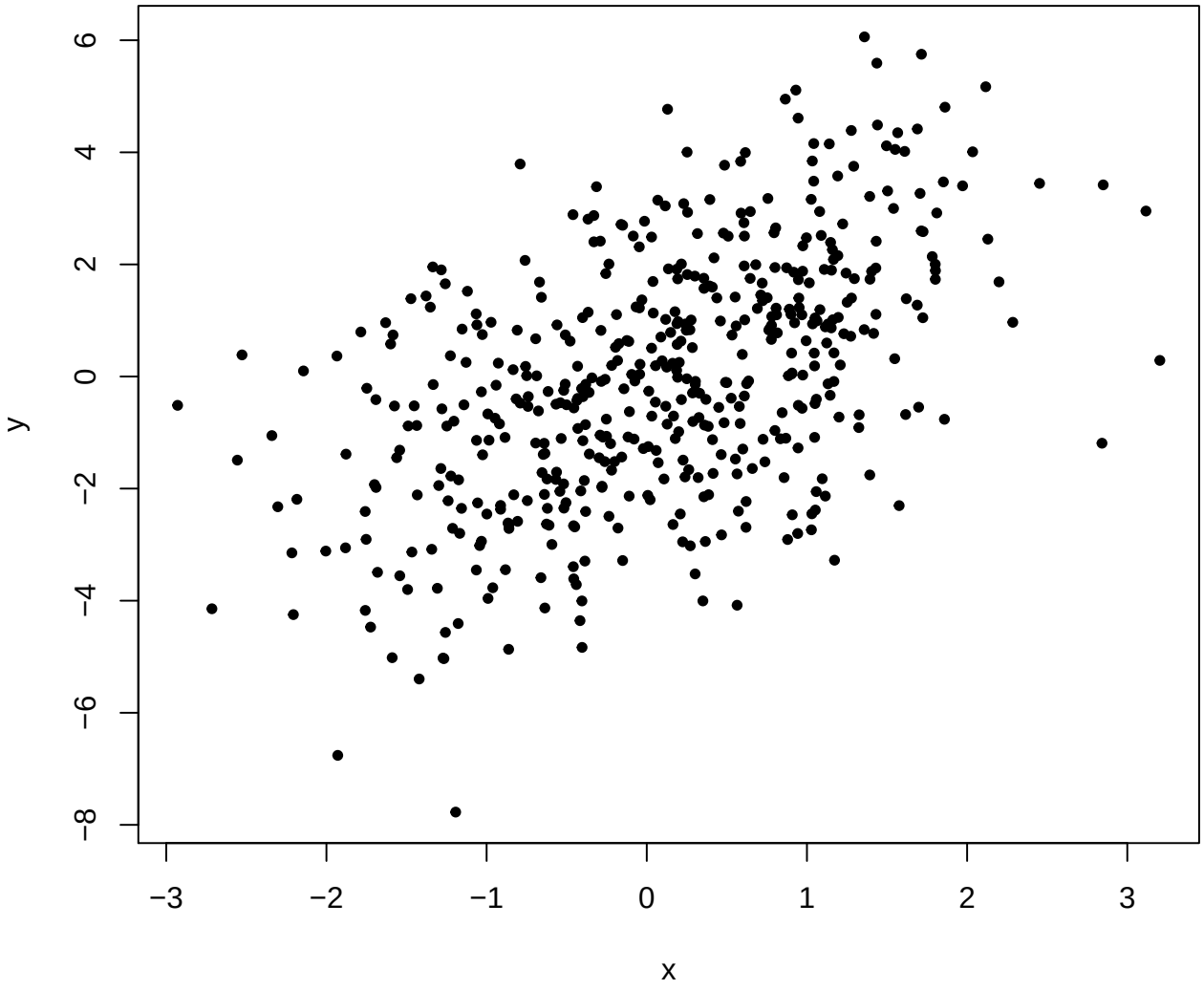
Spearman Correlation

- There are other ways to measure correlation that are less reliant on linear trends in covariation and are also more robust to outliers.
- Specifically, one can convert each measured variable to ranks by size (1 for the smallest, n for the largest) and then use a formula for correlation designed for these ranks.
- One popular measure of rank-based correlation is the Spearman correlation.

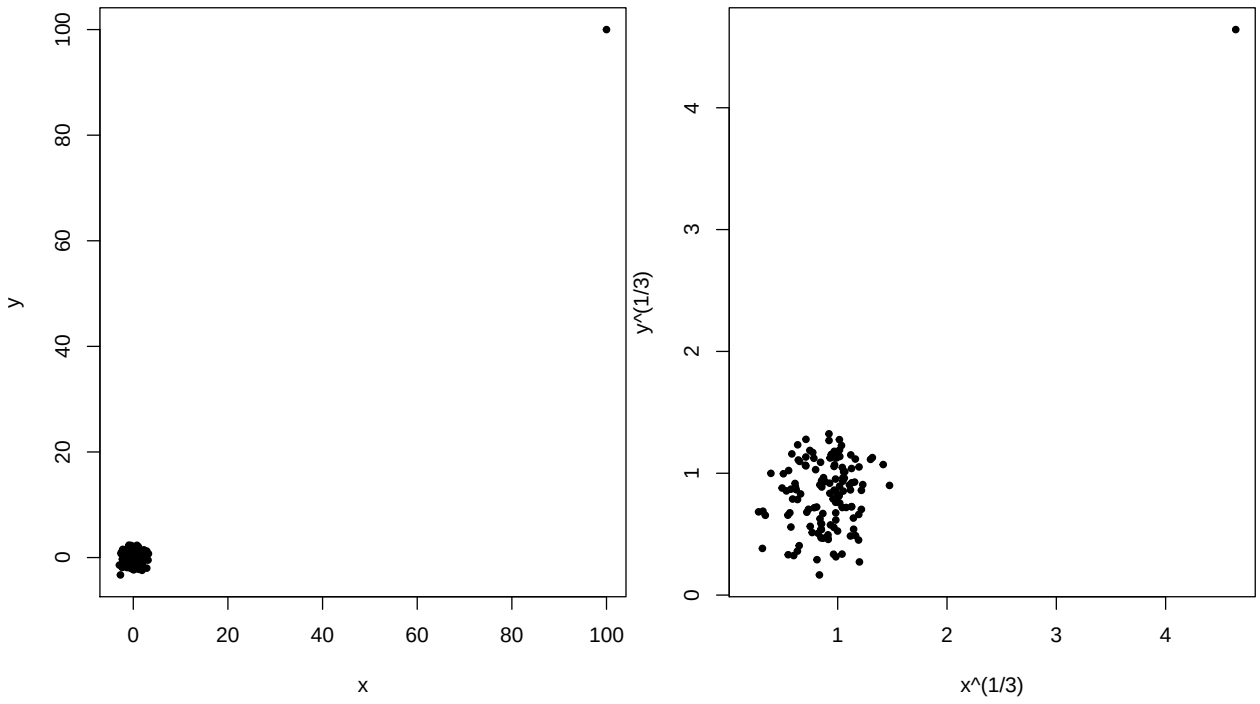
```
> x <- rnorm(500)
> y <- x + rnorm(500)
> cor(x, y, method="pearson")
[1] 0.7542651
> cor(x, y, method="spearman")
[1] 0.7499555
```




```
> x <- rnorm(500)
> y <- x + rnorm(500, sd=2)
> cor(x, y, method="pearson")
[1] 0.5164903
> cor(x, y, method="spearman")
[1] 0.5093092
```




```
> x <- c(rnorm(499), 100)
> y <- c(rnorm(499), 100)
> cor(x, y, method="pearson")
[1] 0.9528564
> cor(x, y, method="spearman")
[1] -0.02133551
```



Quantile-Quantile Plots

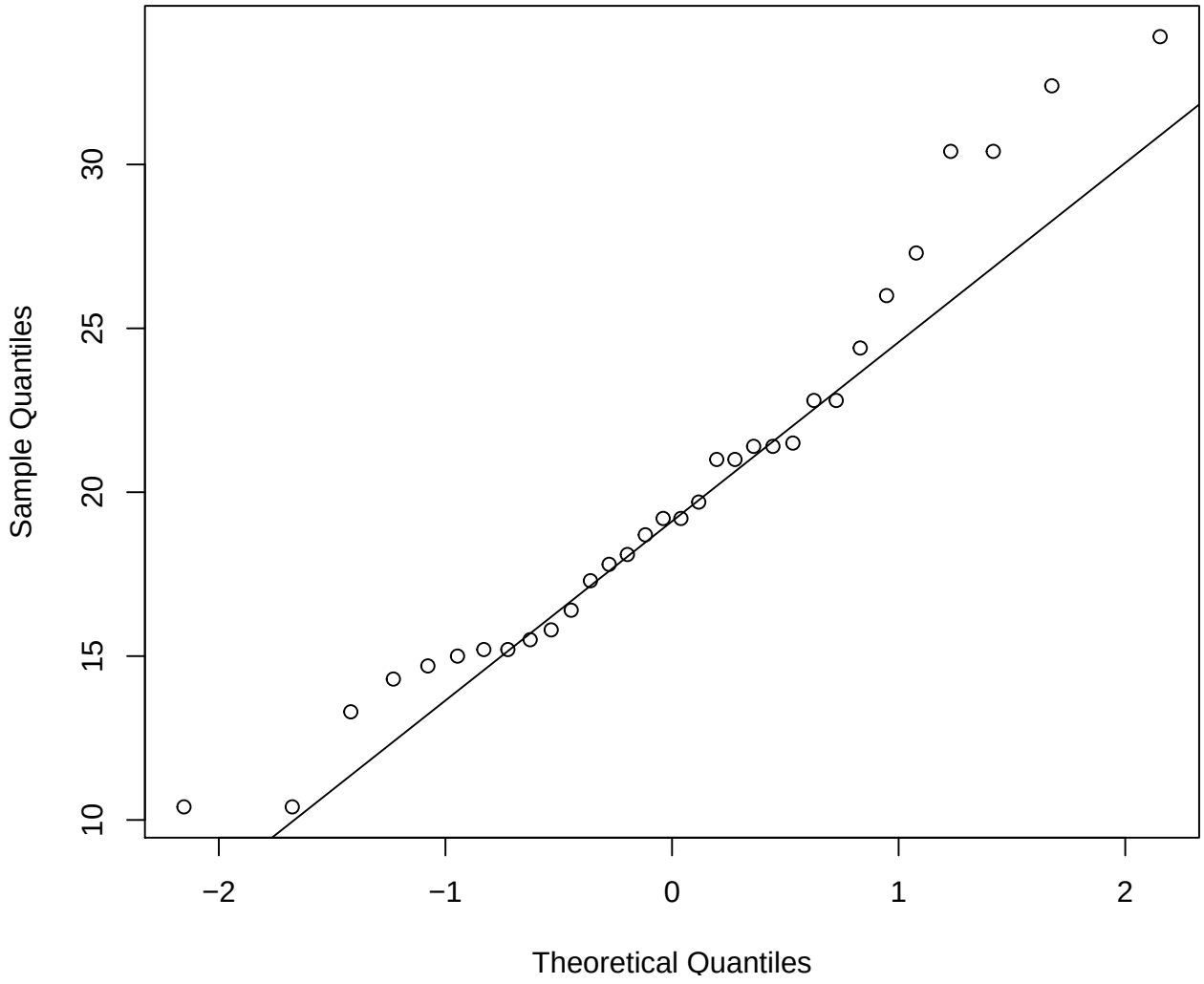
Quantile-quantile plots display the quantiles of:

1. two samples of data
2. a sample of data vs a theoretical distribution

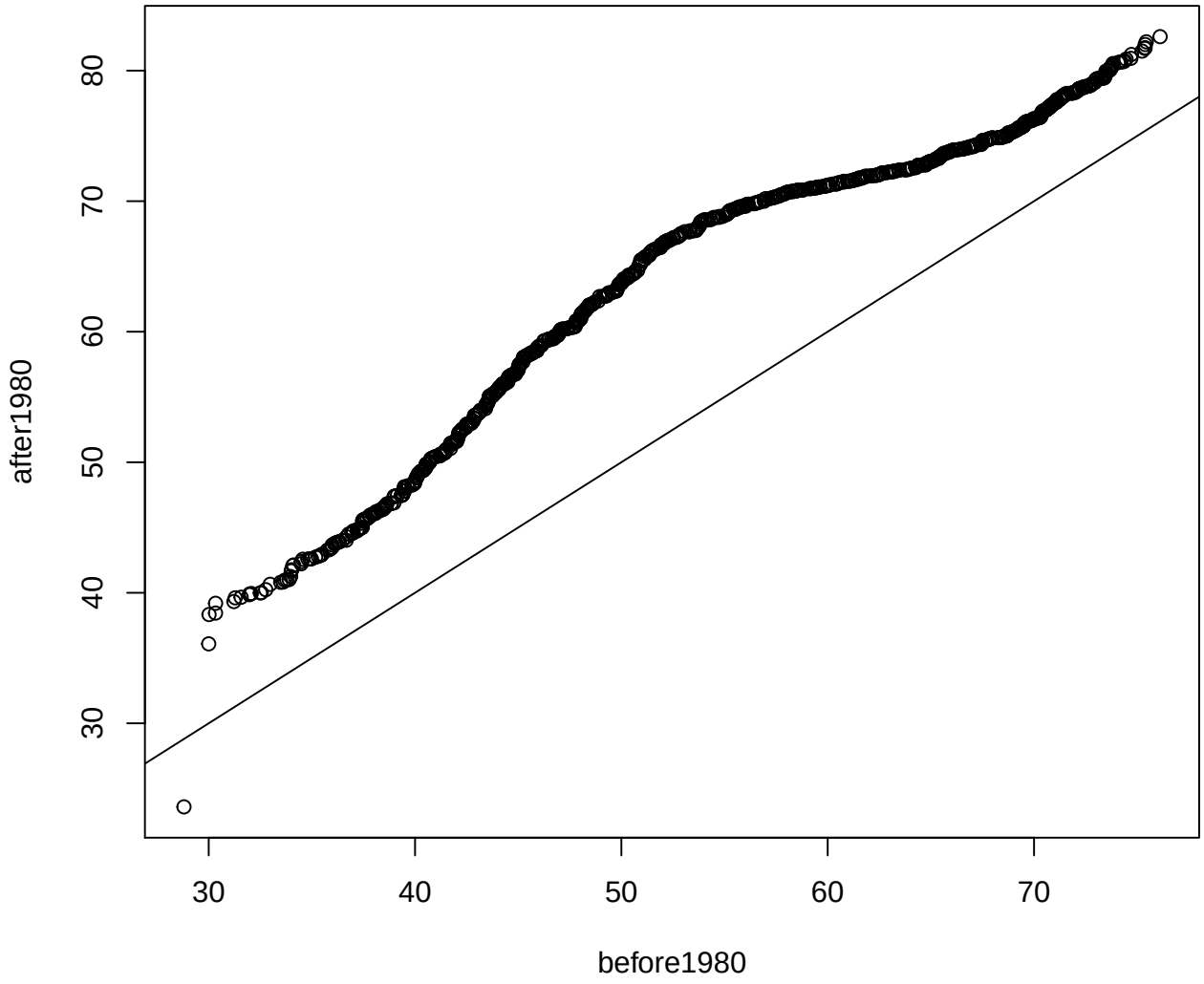
The first type allows one to assess how similar the distributions are of two samples of data.

The second allows one to assess how similar a sample of data is to a theoretical distribution (often Normal with mean 0 and standard deviation 1).

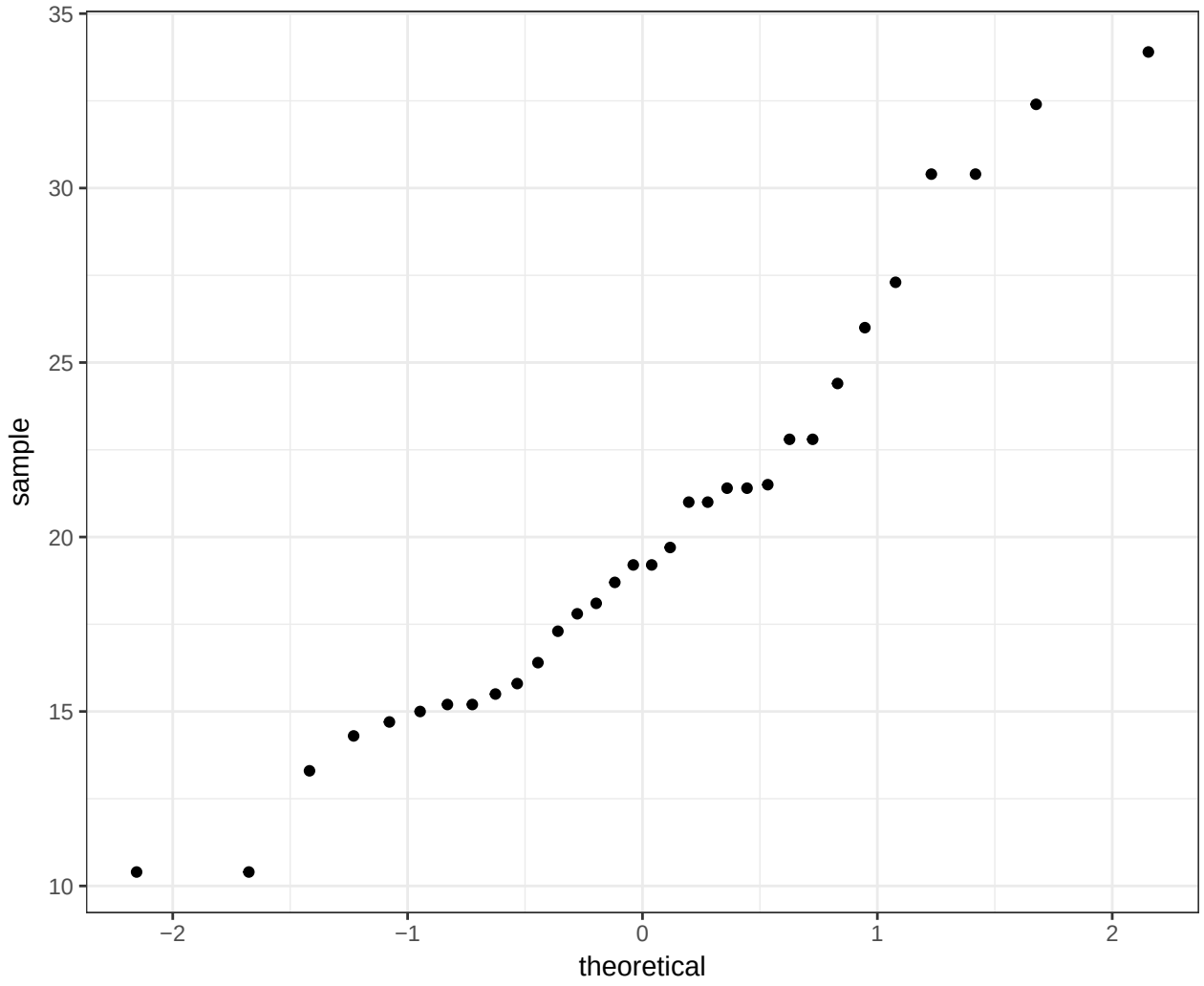
```
> qqnorm(mtcars$mpg, main=" ")
> qqline(mtcars$mpg) # line through Q1 and Q3
```



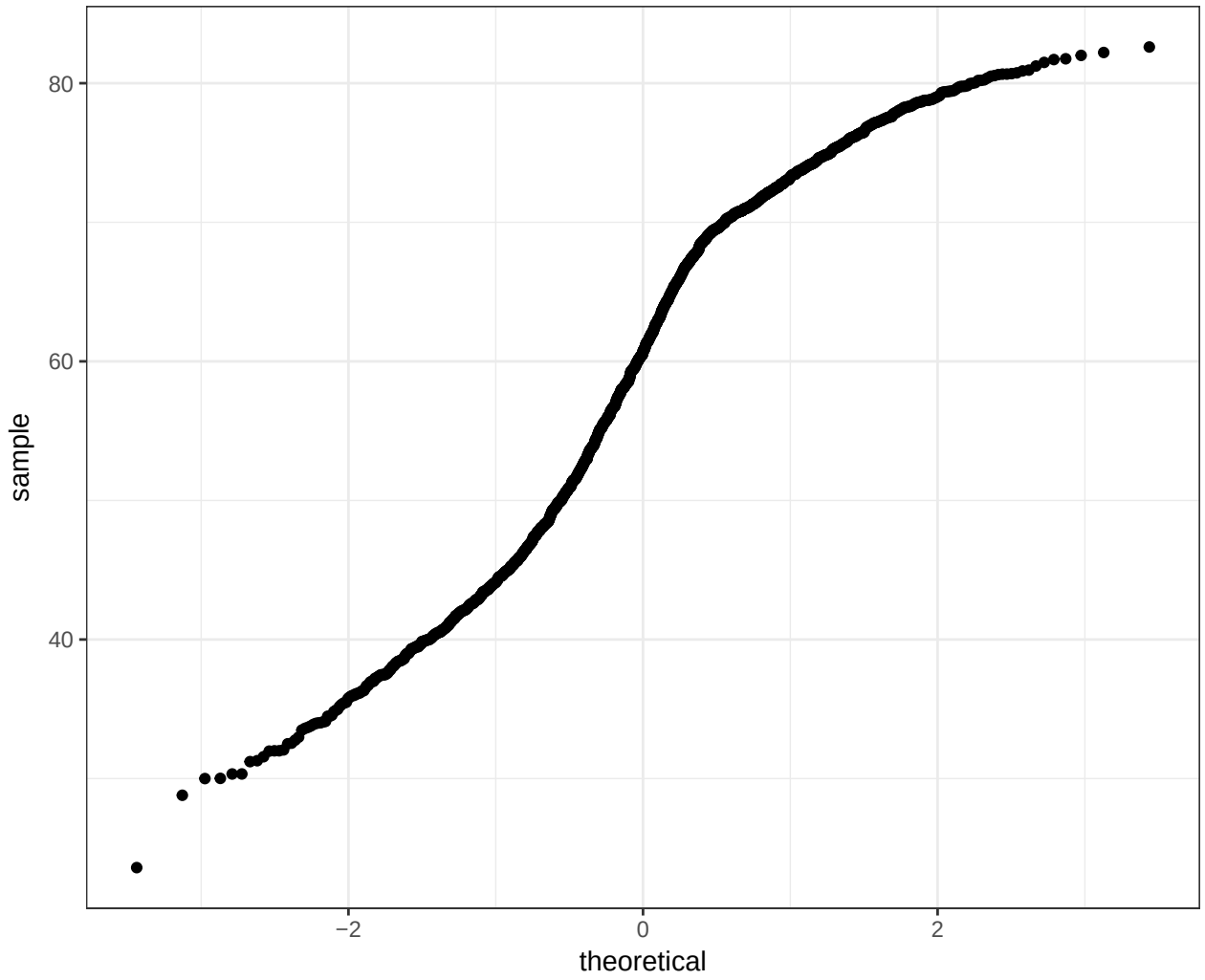

```
> before1980 <- gapminder %>% filter(year < 1980) %>%
+   select(lifeExp) %>% unlist()
> after1980 <- gapminder %>% filter(year > 1980) %>%
+   select(lifeExp) %>% unlist()
> qqplot(before1980, after1980); abline(0,1)
```



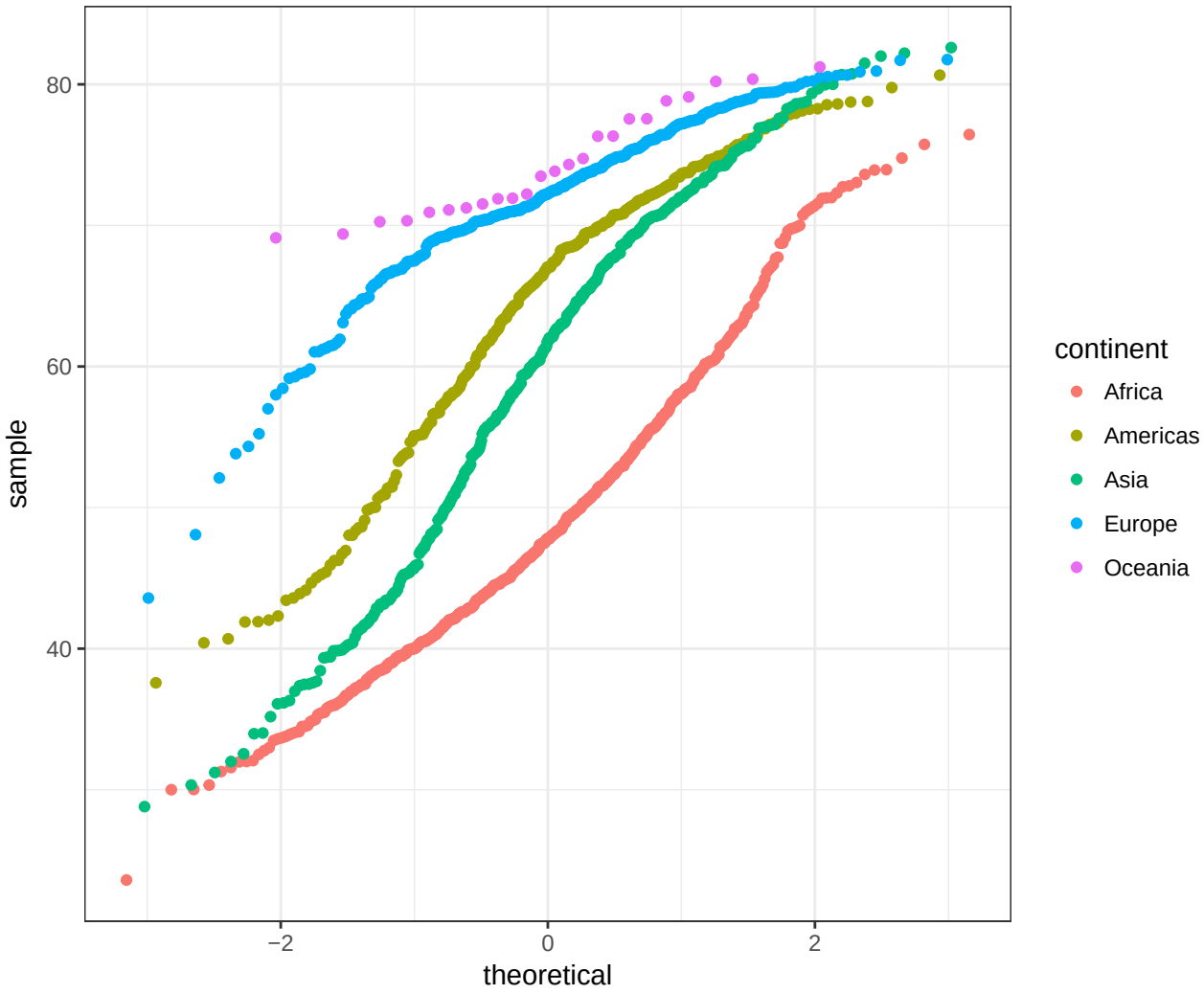

```
> ggplot(mtcars) + stat_qq(aes(sample = mpg))
```




```
> ggplot(gapminder) + stat_qq(aes(sample=lifeExp))
```




```
> ggplot(gapminder) +
+   stat_qq(aes(sample=lifeExp, color=continent))
```



Extras

Source

License

Source Code

Session Information

```
> sessionInfo()
R version 3.3.2 (2016-10-31)
Platform: x86_64-apple-darwin13.4.0 (64-bit)
Running under: macOS Sierra 10.12.3

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
```

```
attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods
[7] base

other attached packages:
 [1] moments_0.14    hexbin_1.27.1   babynames_0.2.1
 [4] gapminder_0.2.0 gganimate_0.1   animation_2.4
 [7] dplyr_0.5.0     purrr_0.2.2     readr_1.0.0
[10] tidyr_0.6.1     tibble_1.2      ggplot2_2.2.1
[13] tidyverse_1.1.1 knitr_1.15.1    magrittr_1.5
[16] devtools_1.12.0

loaded via a namespace (and not attached):
 [1] Rcpp_0.12.9         RColorBrewer_1.1-2 highr_0.6
 [4] plyr_1.8.4          forcats_0.2.0      tools_3.3.2
 [7] digest_0.6.12       lubridate_1.6.0    jsonlite_1.2
[10] evaluate_0.10       memoise_1.0.0      nlme_3.1-131
[13] gtable_0.2.0        lattice_0.20-34    psych_1.6.12
[16] DBI_0.5-1           yaml_2.1.14        parallel_3.3.2
[19] haven_1.0.0         xml2_1.1.1         withr_1.0.2
[22] stringr_1.1.0       httr_1.2.1         hms_0.3
[25] rprojroot_1.2       grid_3.3.2         R6_2.2.0
[28] readxl_0.1.1        foreign_0.8-67     rmarkdown_1.3
[31] modelr_0.1.0        reshape2_1.4.2     codetools_0.2-15
[34] backports_1.0.5     scales_0.4.1       htmltools_0.3.5
[37] rvest_0.3.2         assertthat_0.1     mnormt_1.5-5
[40] colorspace_1.3-2    labeling_0.3       stringi_1.1.2
[43] lazyeval_0.2.0      munsell_0.4.3      broom_0.4.2
```