Lecture 4: Generating 2D graphics with R

October 12, 2016

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- Intro to `ggplot2` package
- Comparison with base-graphics
- Geometric objects and aesthetics
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- Scales
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Installation

```
install.packages("ggplot2")
install.packages("ggrepel")
install.packages("gridExtra")
library(ggplot2)
library(ggrepel)
library(gridExtra)
```

Intro to `ggplot2` package

What is `ggplot2`?

> "*`ggplot2` is **a plotting system for R, based on the grammar of graphics**. 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"[1].*

[1] http://ggplot2.org/

Advantages of `ggplot2`

- Graphics are defined at **a high level of abstraction**.
- Plots are broken down into **layers**.
- The package is **flexible** and offers extensive **customization** options.
- The **documentation** is well-written.
- `ggplot2` has a large user base => **it's easy find to help**.

Weaknesses of `ggplot2`

You should not or cannot use `ggplot2` for:

- 3D graphics
  - use `rgl` or `ggplot2 + plotly` instead,
- graph/network plots with nodes and edges
  - use `igraph` instead
- interactive graphics:
  - use `ggvis`, `plotly` instead

What is a grammar of graphics?

- It is a concept **coined by Leland Wilkinson in 2005**.
- An **abstraction** which facilitates reasoning and communicating graphics.
- `ggplot2` is **a layered grammar of graphics** which allow users to

independently specify the building blocks of a plot and combine them to create just a any kind of graphical display

Building blocks of a `ggplot2` graphs

- data
- aesthetic mapping
- geometric objects
- statistical transformations
- scales
- coordinate system
- positioning adjustments
- faceting

`ggplot()` function

- `ggplot()` is used to **initialize the basic graph structure**.
- It **cannot produce a plot** alone by itself.
- Instead, we need to **add extra components** to generate a graph.
- You need to **specify different parts** of a plot, and *add them all together* using an + operator.

The structure of ggplot object

```
ggplot(data = <default data set>,
aes(x = <default x axis variable>,
y = <default y axis variable>,
... <other default aesthetic mappings>),
... <other plot defaults>) +

geom_<geom type>(aes(size = <size variable for this geom>,
... <other aesthetic mappings>),
data = <data for this point geom>,
stat = <statistic string or function>,
position = <position string or function>,
color = <"fixed color specification">,
... <other arguments, possibly passed to the _stat_ function) +

scale_<aesthetic>_<type>(name = <"scale label">,
breaks = <where to put tick marks>,
labels = <labels for tick marks>,
... <other options for the scale>) +

theme(plot.background = element_rect(fill = "gray"),
... <other theme elements>)
```

Comparison with base-graphics

ggplot2 compared to base graphics is

- more verbose for **simple / out of the box** graphics
- less verbose for **complex / custom** graphics
- uses a different system for **adding plot elements** instead of calling new functions.
- more details on why to use `ggplot2` over base plot can be found in this blog.

Example 1: History of unemployment

`ggplot2` has a built-in **`economics`** dataset, which inclides time series data on unemployment from 1967 to 2015.

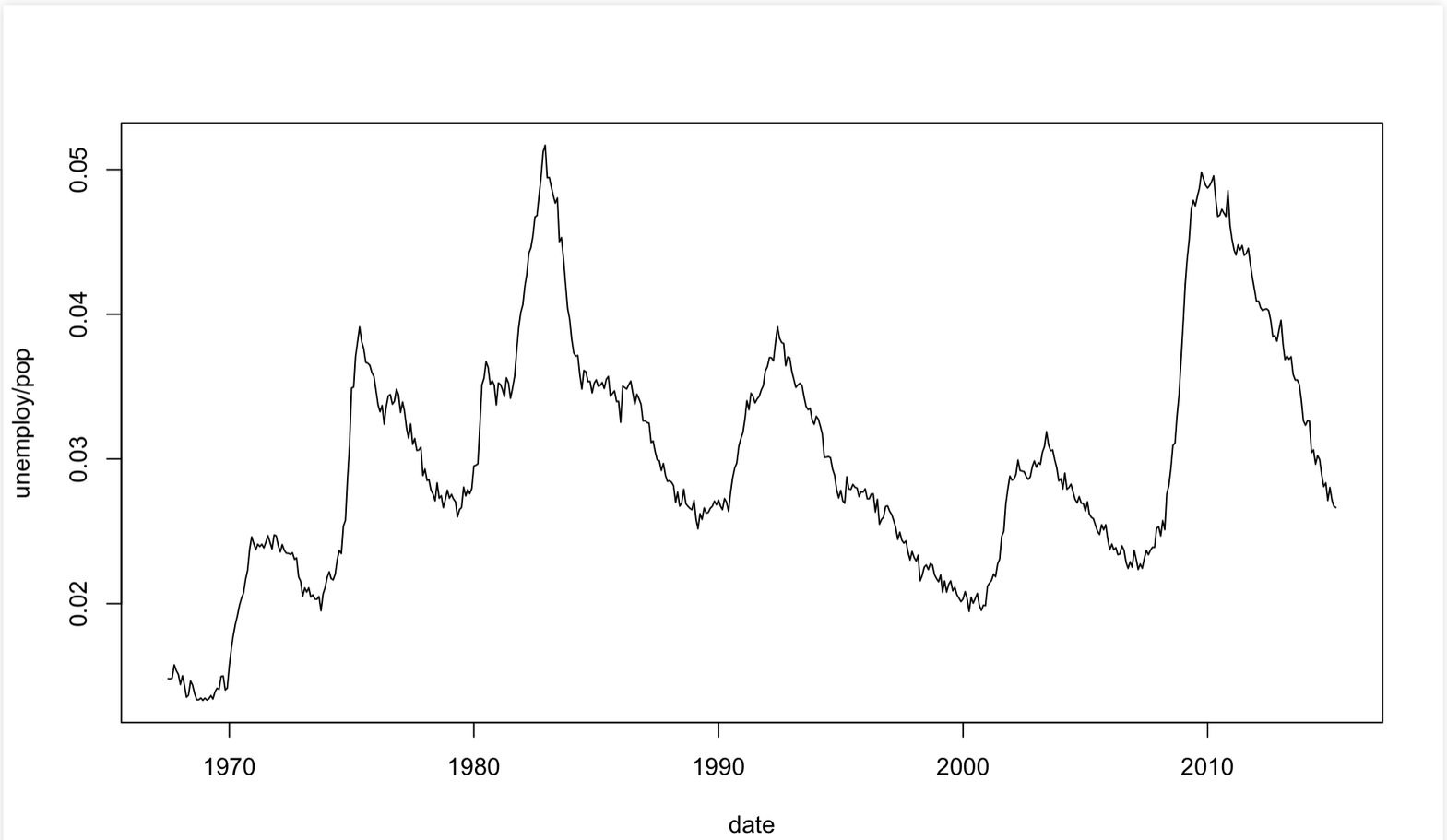
```
economics
```

```
## # A tibble: 574 x 6
## date pce pop psavert uempmed unemploy
## <date> <dbl> <int> <dbl> <dbl> <int>
## 1 1967-07-01 507.4 198712 12.5 4.5 2944
## 2 1967-08-01 510.5 198911 12.5 4.7 2945
## 3 1967-09-01 516.3 199113 11.7 4.6 2958
## 4 1967-10-01 512.9 199311 12.5 4.9 3143
## 5 1967-11-01 518.1 199498 12.5 4.7 3066
## 6 1967-12-01 525.8 199657 12.1 4.8 3018
## 7 1968-01-01 531.5 199808 11.7 5.1 2878
## 8 1968-02-01 534.2 199920 12.2 4.5 3001
## 9 1968-03-01 544.9 200056 11.6 4.1 2877
## 10 1968-04-01 544.6 200208 12.2 4.6 2709
## # ... with 564 more rows
```

```
economics <- mutate(economics, unemp_rate = unemploy/pop)
```

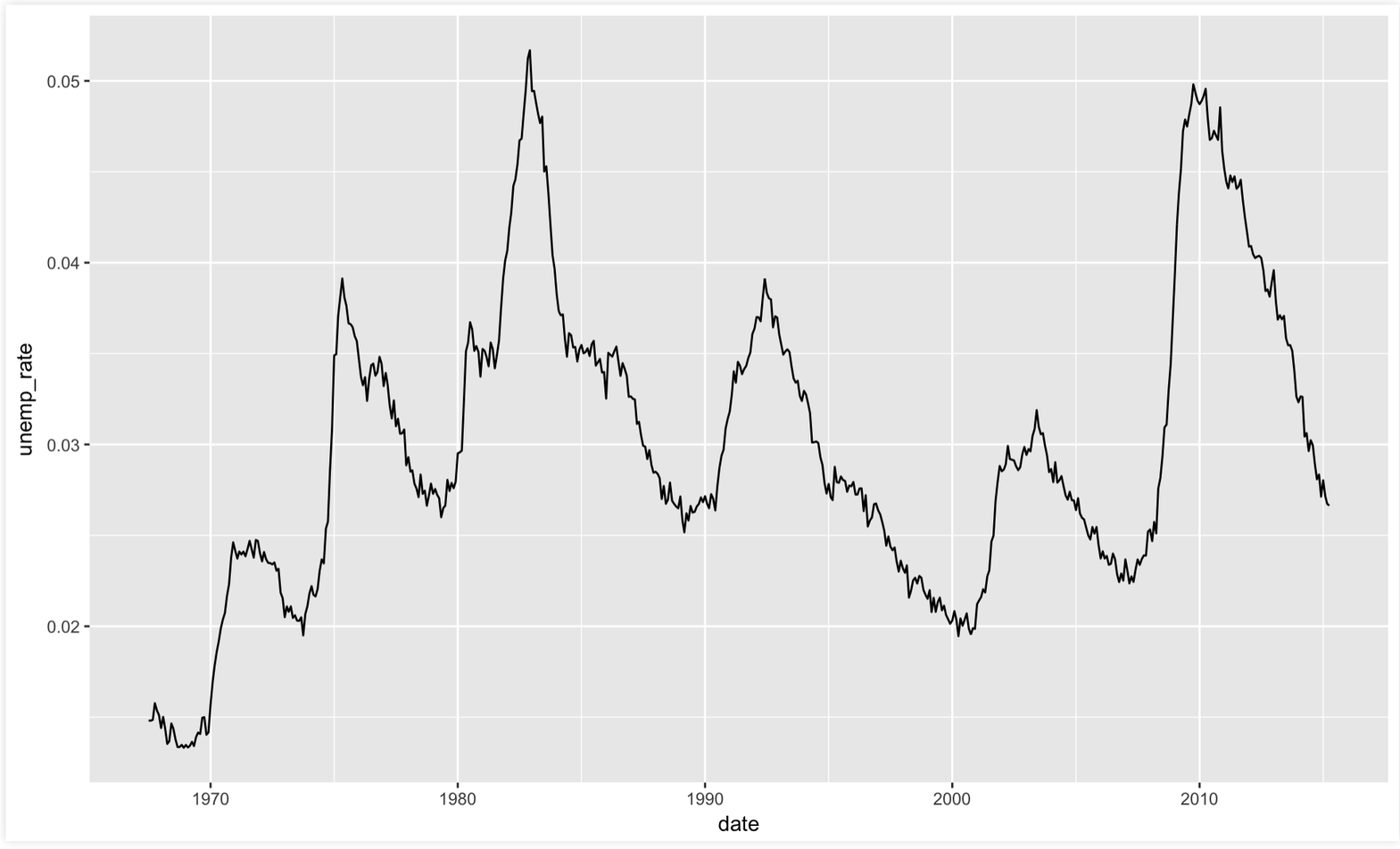
R base graphics

```
plot(unemploy/pop ~ date, data = economics, type = "l")
```



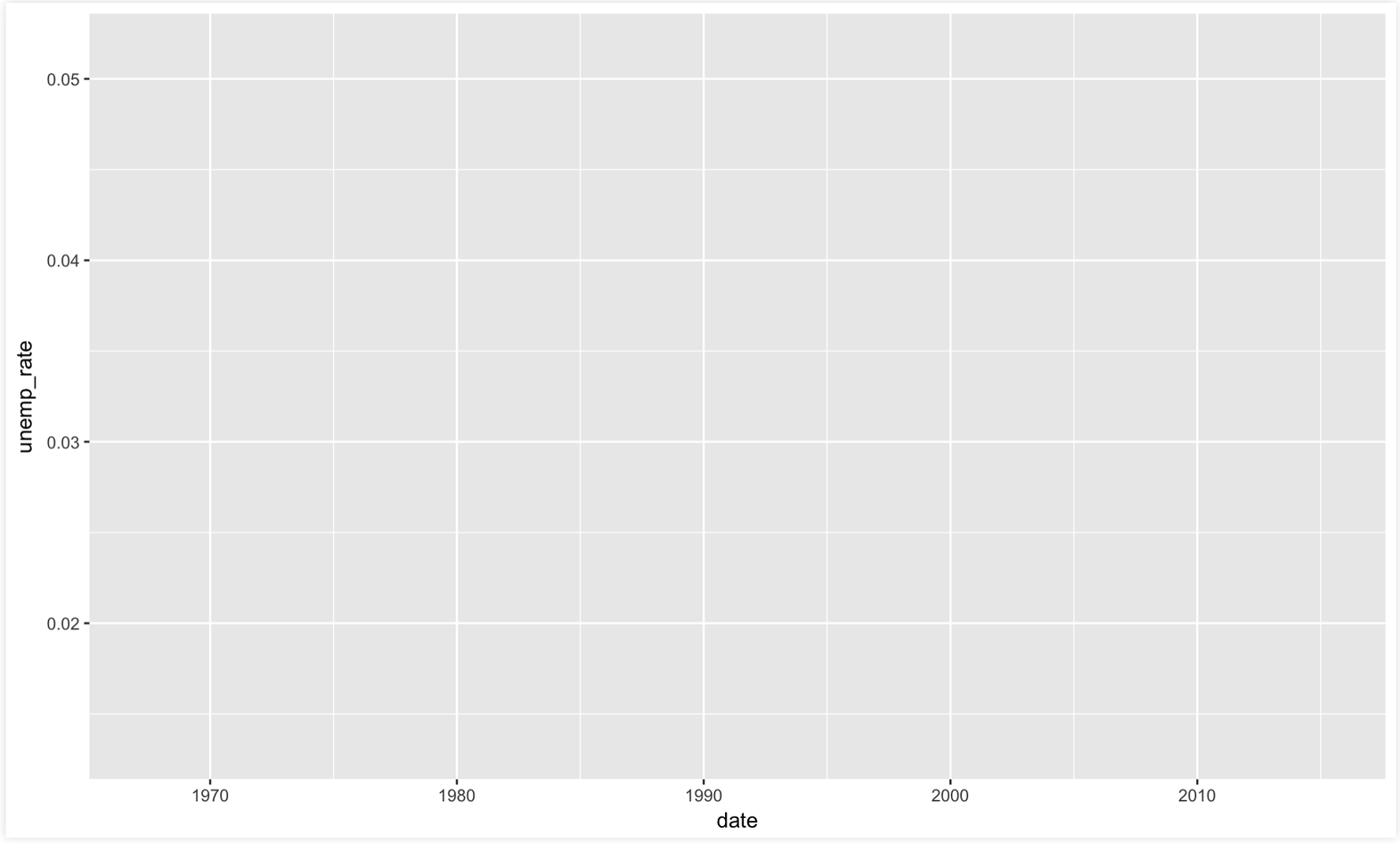
ggplot2 package

```
library(ggplot2)
ggplot(data = economics, aes(x = date, y = unemp_rate)) + geom_line()
```



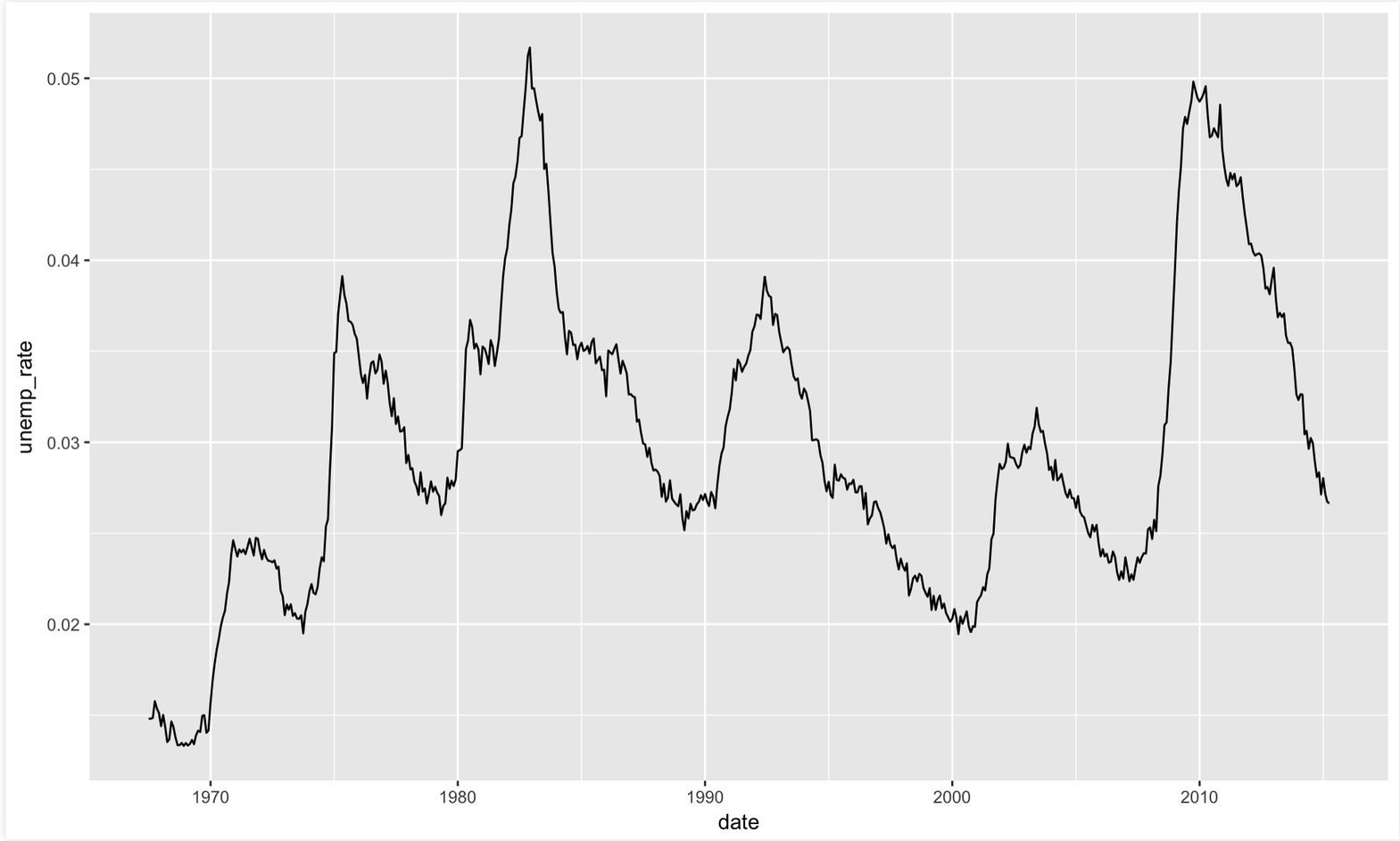
ggplot() by itself does not plot the data

```
ggplot(data = economics, aes(x = date, y = unemp_rate))
```



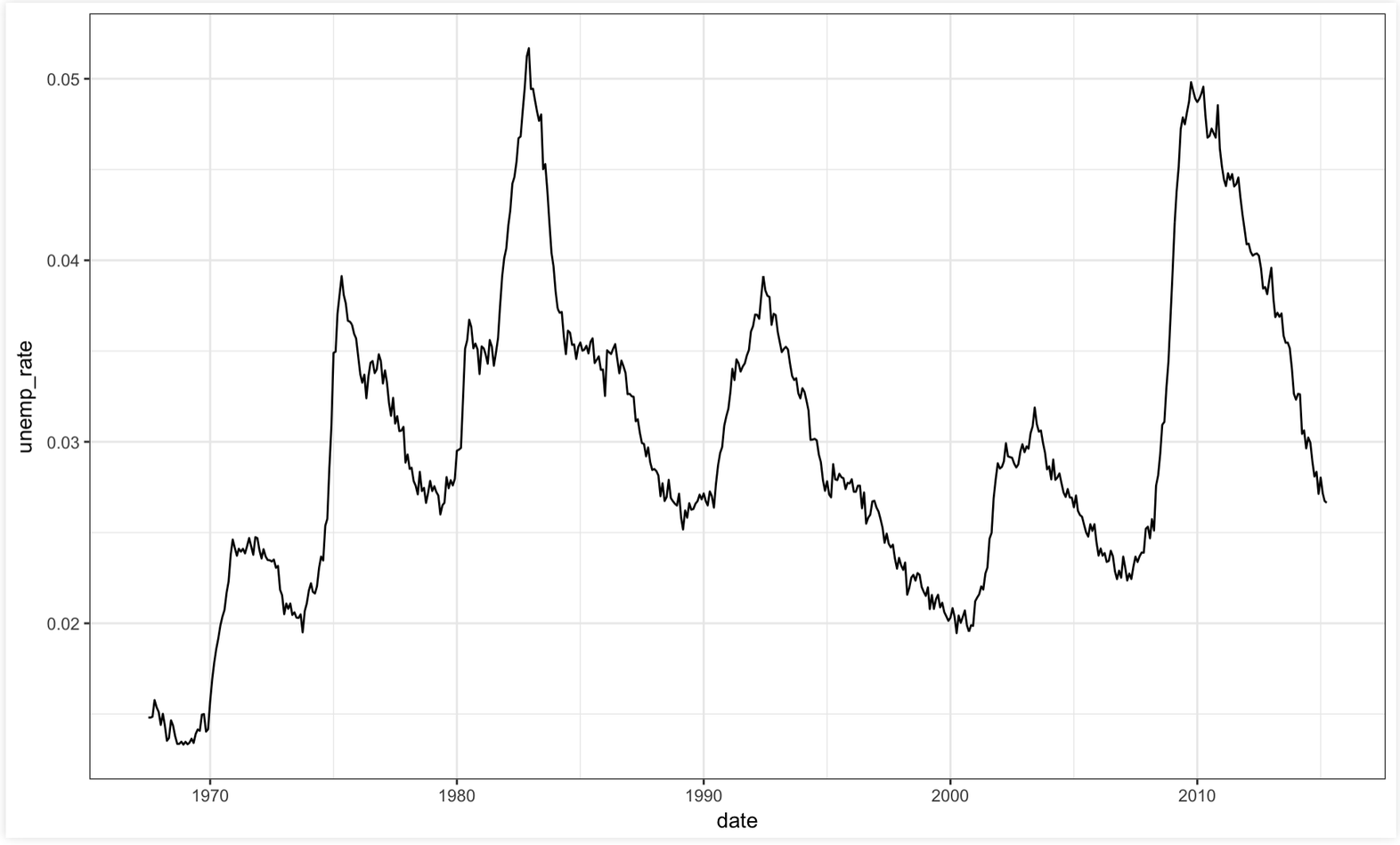
You need to add a line-layer

```
ggplot(data = economics, aes(x = date, y = unemp_rate)) + geom_line()
```



Change the background color to white

```
ggplot(data = economics, aes(x = date, y = unemp_rate)) +
geom_line() + theme_bw()
```



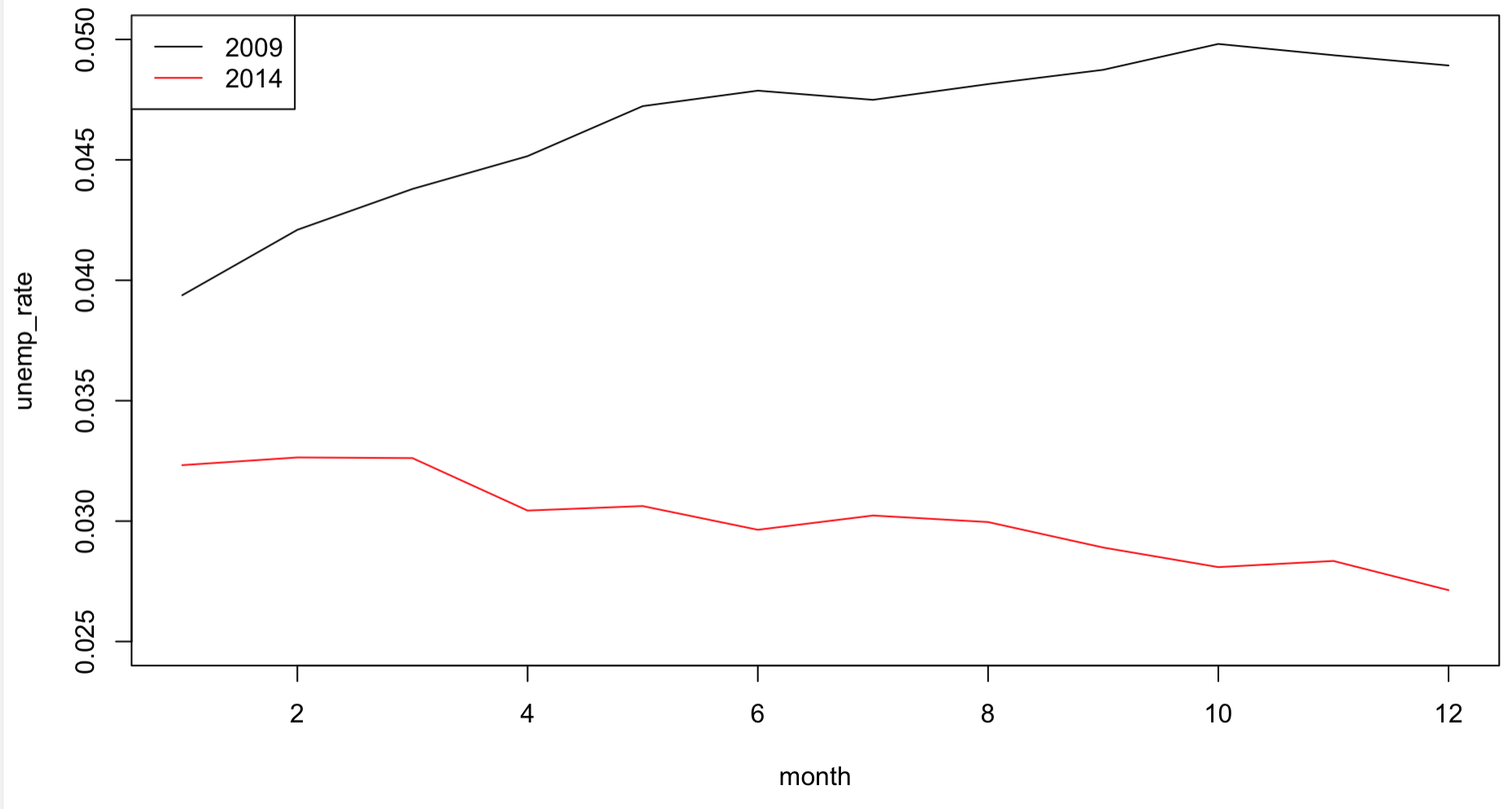
What about comparing 2009 to 2014?

```
# Add new variables for plotting
economics <- economics %>%
mutate(month = as.numeric(format(date, format="%m")),
year = as.numeric(format(date, format="%Y")))
economics %>% select(date, month, year, unemp_rate)
```

```
## # A tibble: 574 x 4
## date month year unemp_rate
## <date> <dbl> <dbl> <dbl>
## 1 1967-07-01 7 1967 0.01481541
## 2 1967-08-01 8 1967 0.01480562
## 3 1967-09-01 9 1967 0.01485589
## 4 1967-10-01 10 1967 0.01576933
## 5 1967-11-01 11 1967 0.01536858
## 6 1967-12-01 12 1967 0.01511592
## 7 1968-01-01 1 1968 0.01440383
## 8 1968-02-01 2 1968 0.01501100
## 9 1968-03-01 3 1968 0.01438097
## 10 1968-04-01 4 1968 0.01353093
## # ... with 564 more rows
```

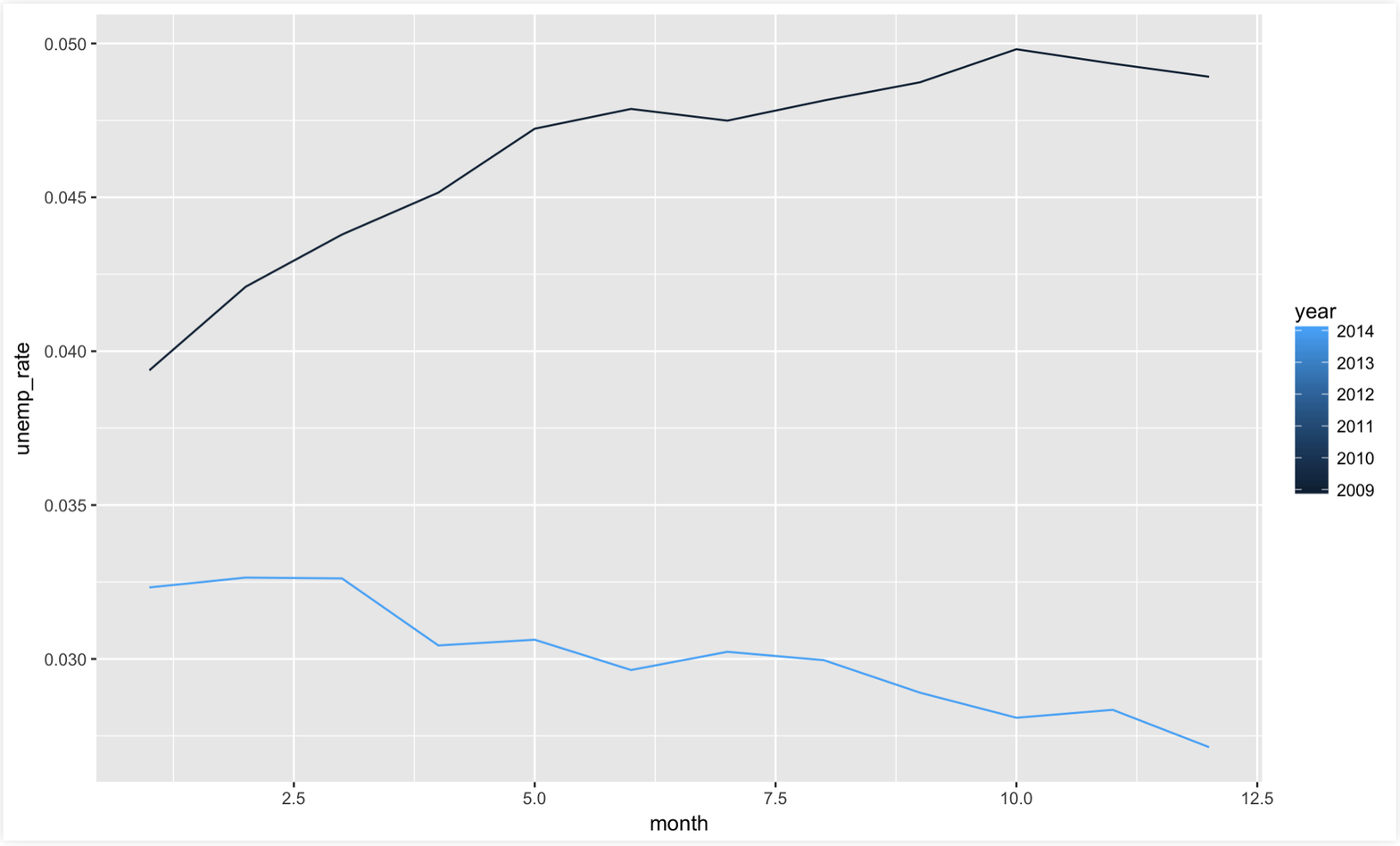
Using base graphics

```
data09 <- subset(economics, year == 2009)
data14 <- subset(economics, year == 2014)
plot(unemp_rate ~ month, data = data09, ylim = c(0.025, 0.05), type = "l")
lines(unemp_rate ~ month, data = data14, col = "red")
legend("topleft", c("2009", "2014"), col = c("black", "red"), lty = c(1,1))
```

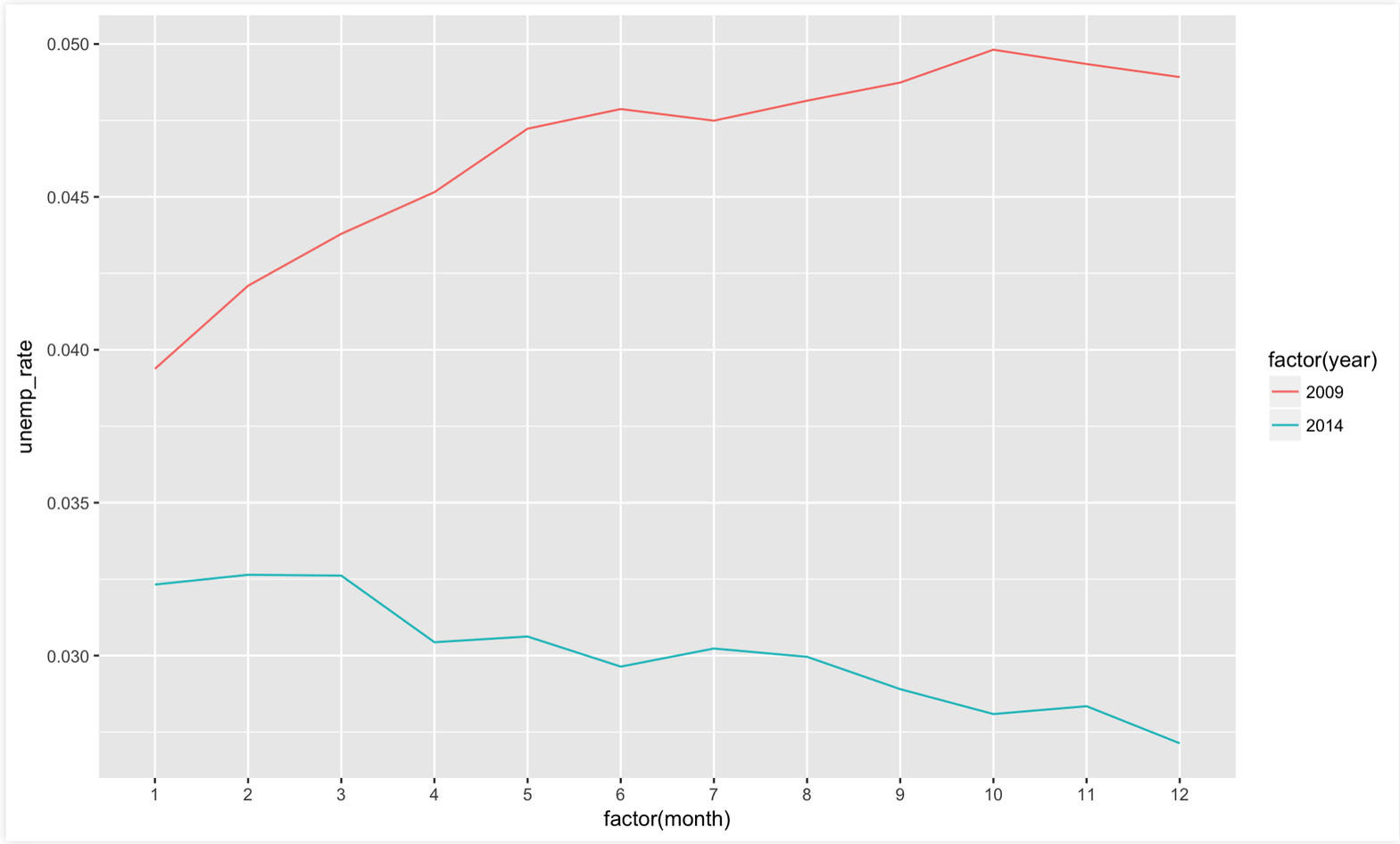


Using ggplot2

```
data2009_2014 <- subset(economics, year %in% c(2014, 2009))
ggplot(data = data2009_2014, aes(x = month, y = unemp_rate)) +
geom_line(aes(group = year, color = year)) # No need to specify a legend
```

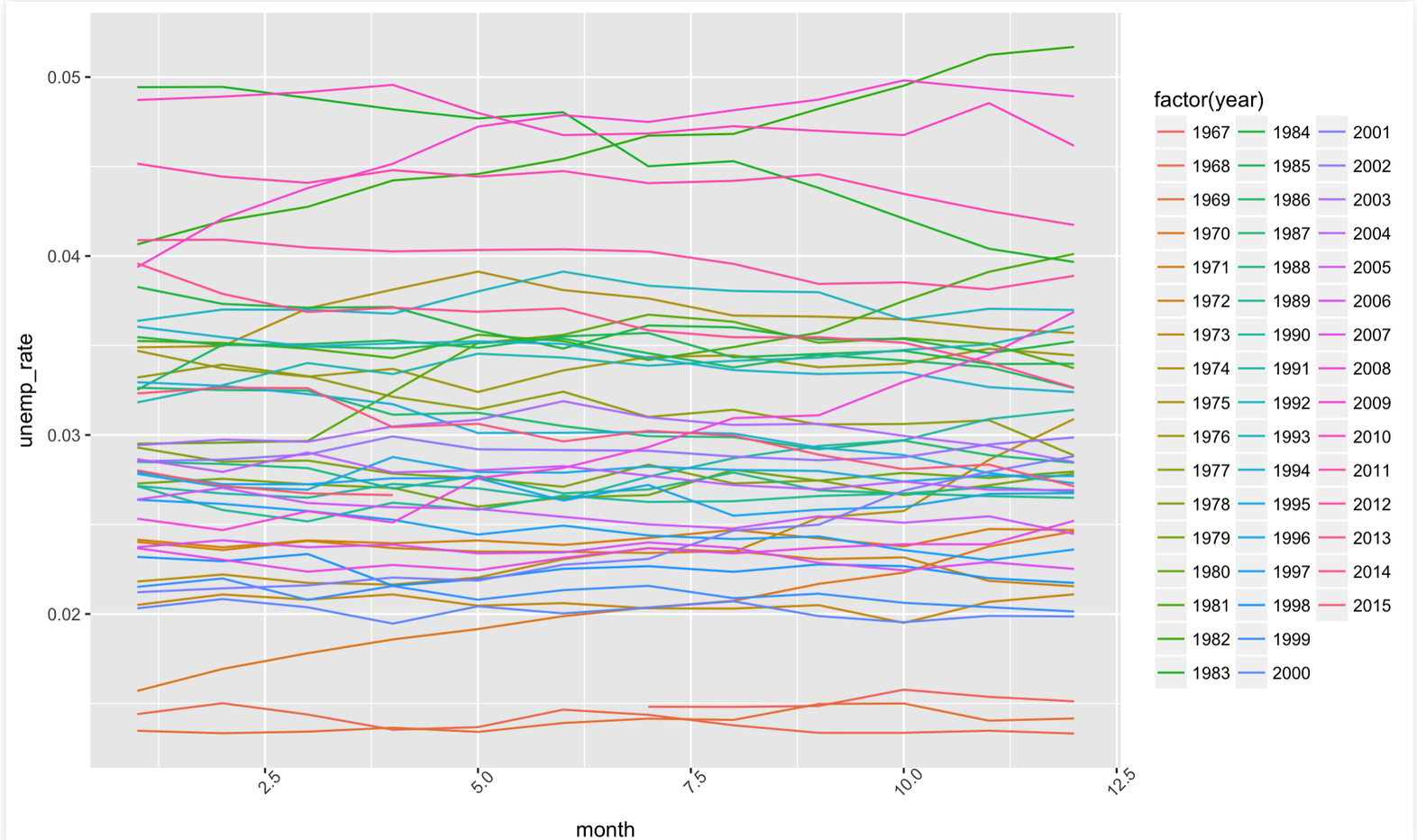


```
ggplot(data = data2009_2014, aes(x = factor(month), y = unemp_rate)) +
geom_line(aes(group = year, color = factor(year)))
```



Plotting all the years together is easy

```
ggplot(data = economics, aes(x = month, y = unemp_rate)) +
geom_line(aes(group = year, color = factor(year))) +
theme(axis.text.x = element_text(angle = 45))
```



Example 2: diamonds dataset

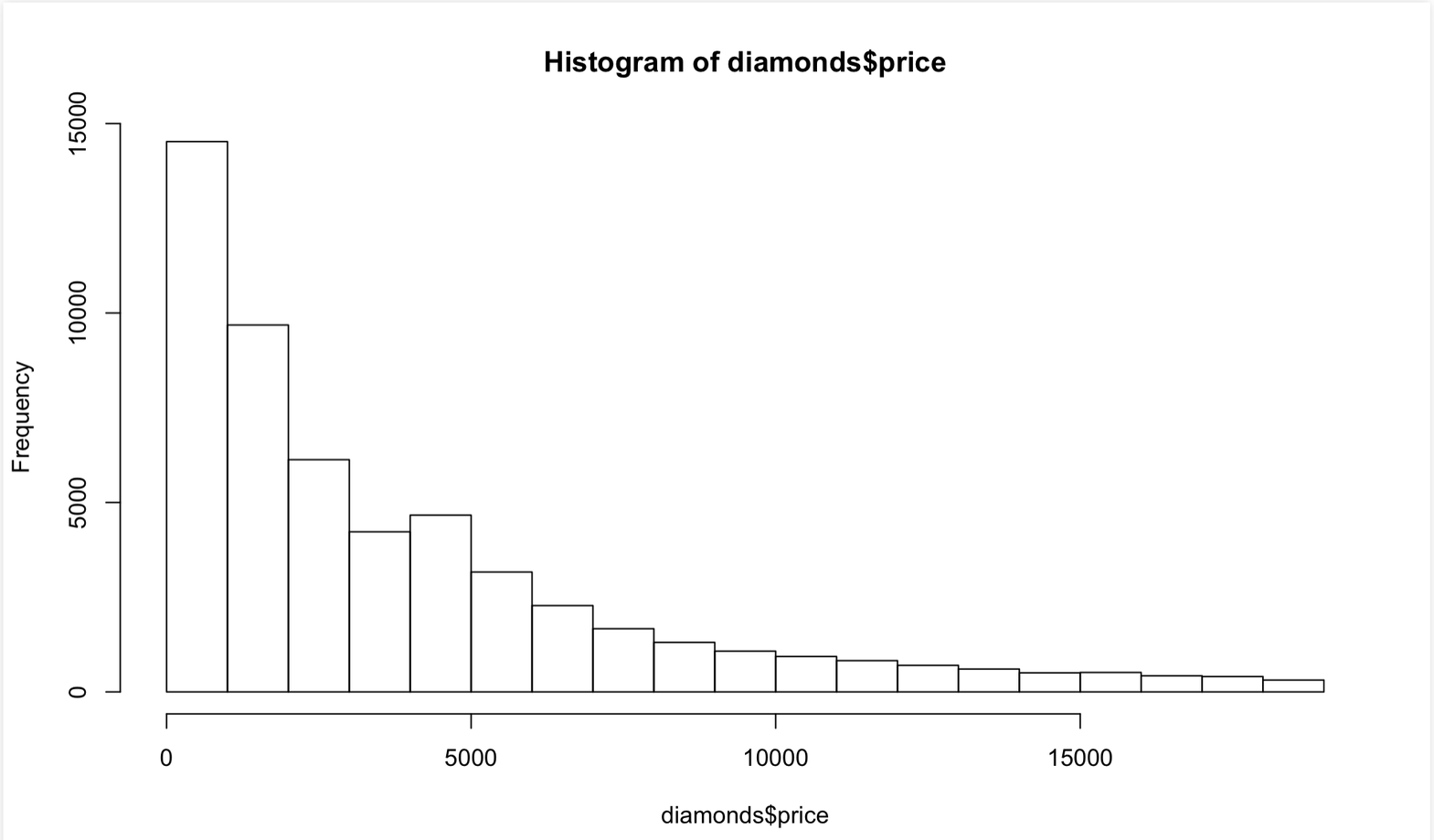
The dataset contains the prices and other attributes of almost 54,000 diamonc
You can call `?diamonds` to learn more about the available attributes.

```
diamonds
```

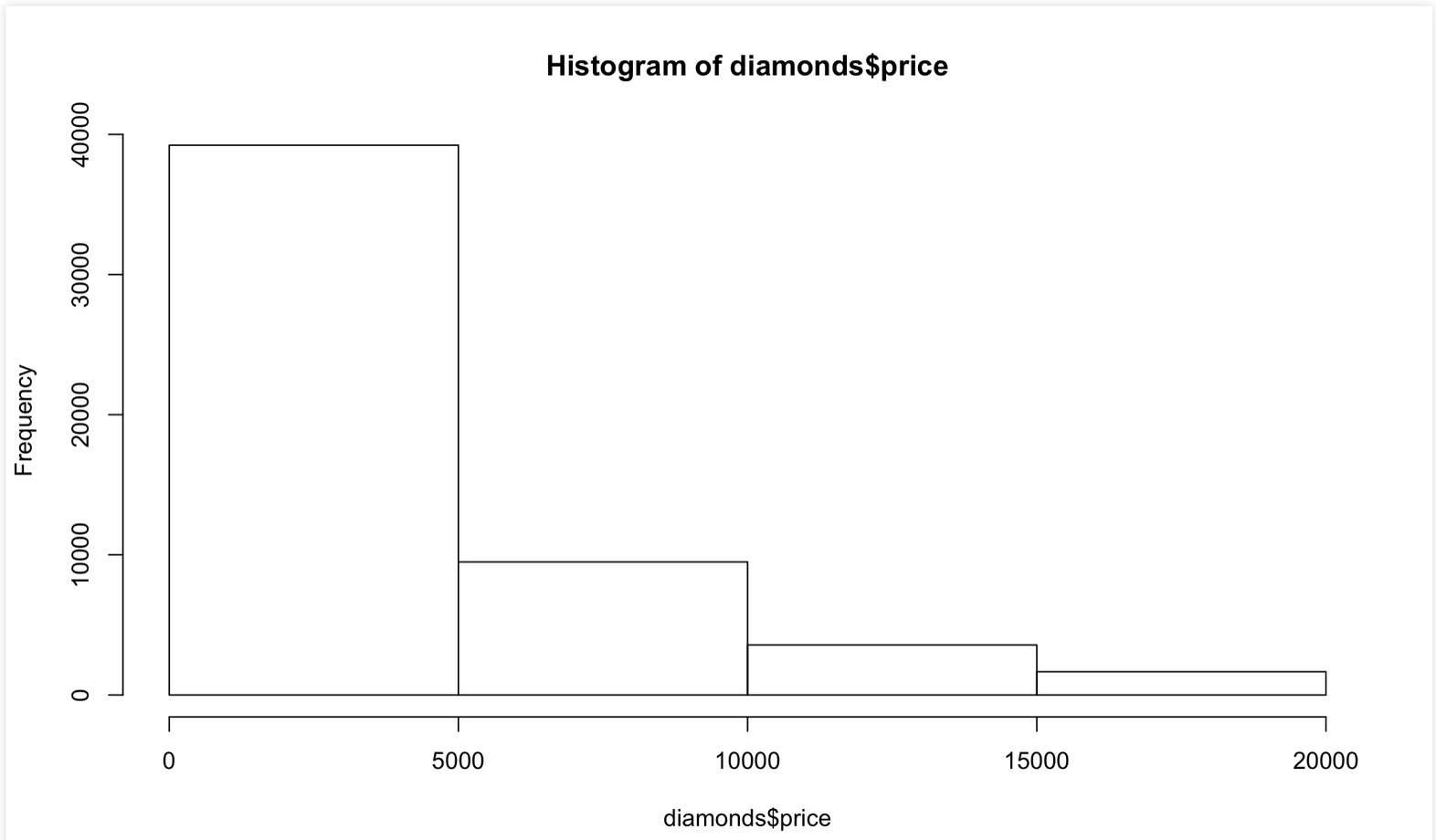
```
## # A tibble: 53,940 x 10
## carat cut color clarity depth table price x y z
## <dbl> <ord> <ord> <ord> <dbl> <dbl> <int> <dbl> <dbl> <dbl>
## 1 0.23 Ideal E SI2 61.5 55 326 3.95 3.98 2.43
## 2 0.21 Premium E SI1 59.8 61 326 3.89 3.84 2.31
## 3 0.23 Good E VS1 56.9 65 327 4.05 4.07 2.31
## 4 0.29 Premium I VS2 62.4 58 334 4.20 4.23 2.63
## 5 0.31 Good J SI2 63.3 58 335 4.34 4.35 2.75
## 6 0.24 Very Good J VVS2 62.8 57 336 3.94 3.96 2.48
## 7 0.24 Very Good I VVS1 62.3 57 336 3.95 3.98 2.47
## 8 0.26 Very Good H SI1 61.9 55 337 4.07 4.11 2.53
## 9 0.22 Fair E VS2 65.1 61 337 3.87 3.78 2.49
## 10 0.23 Very Good H VS1 59.4 61 338 4.00 4.05 2.39
## # ... with 53,930 more rows
```

Distribution of the diamonds prices with base graphics

```
hist(diamonds$price)
```



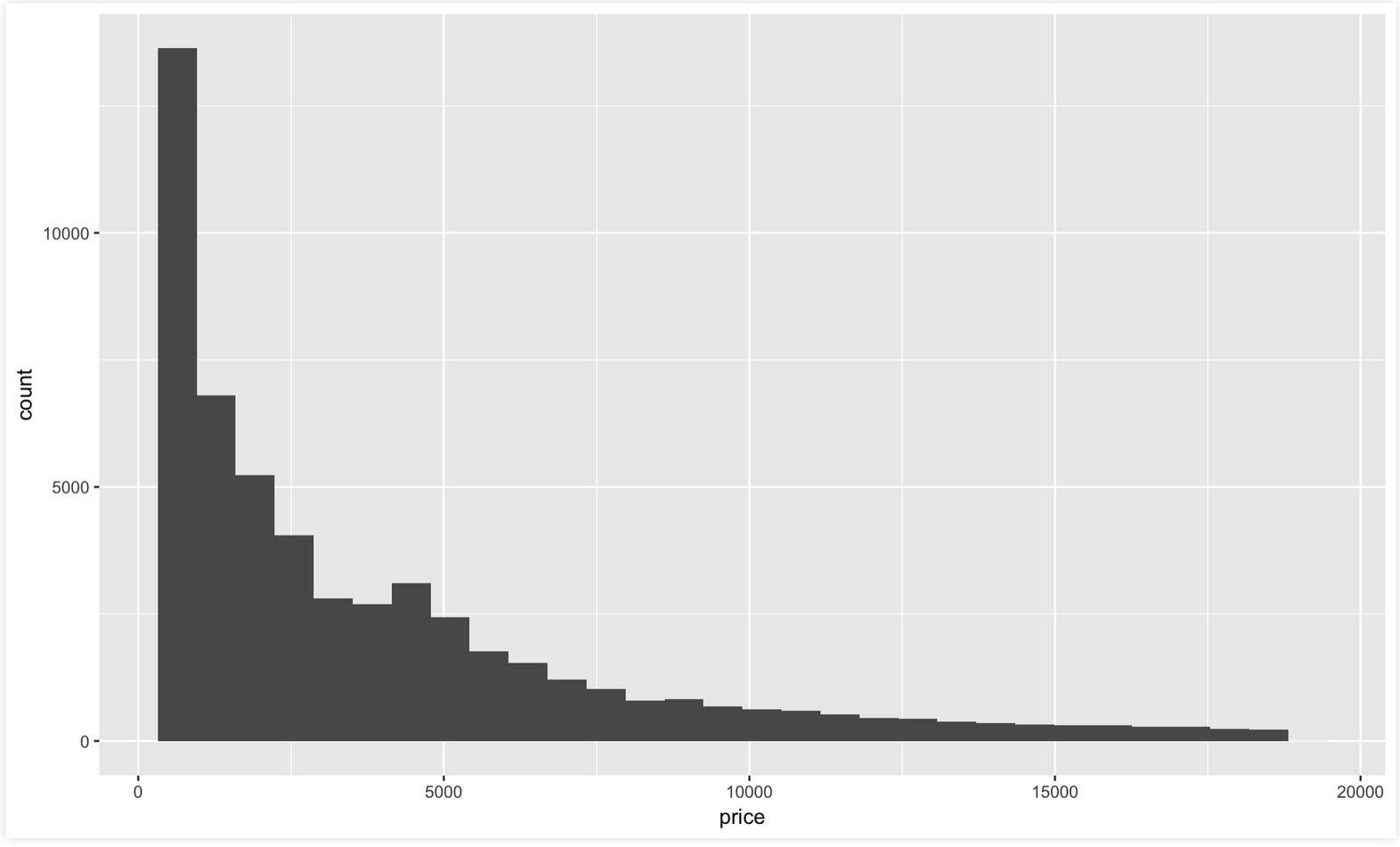
```r
# breaks can be a vector, a function or a single number
hist(diamonds$price, breaks = 5)
```



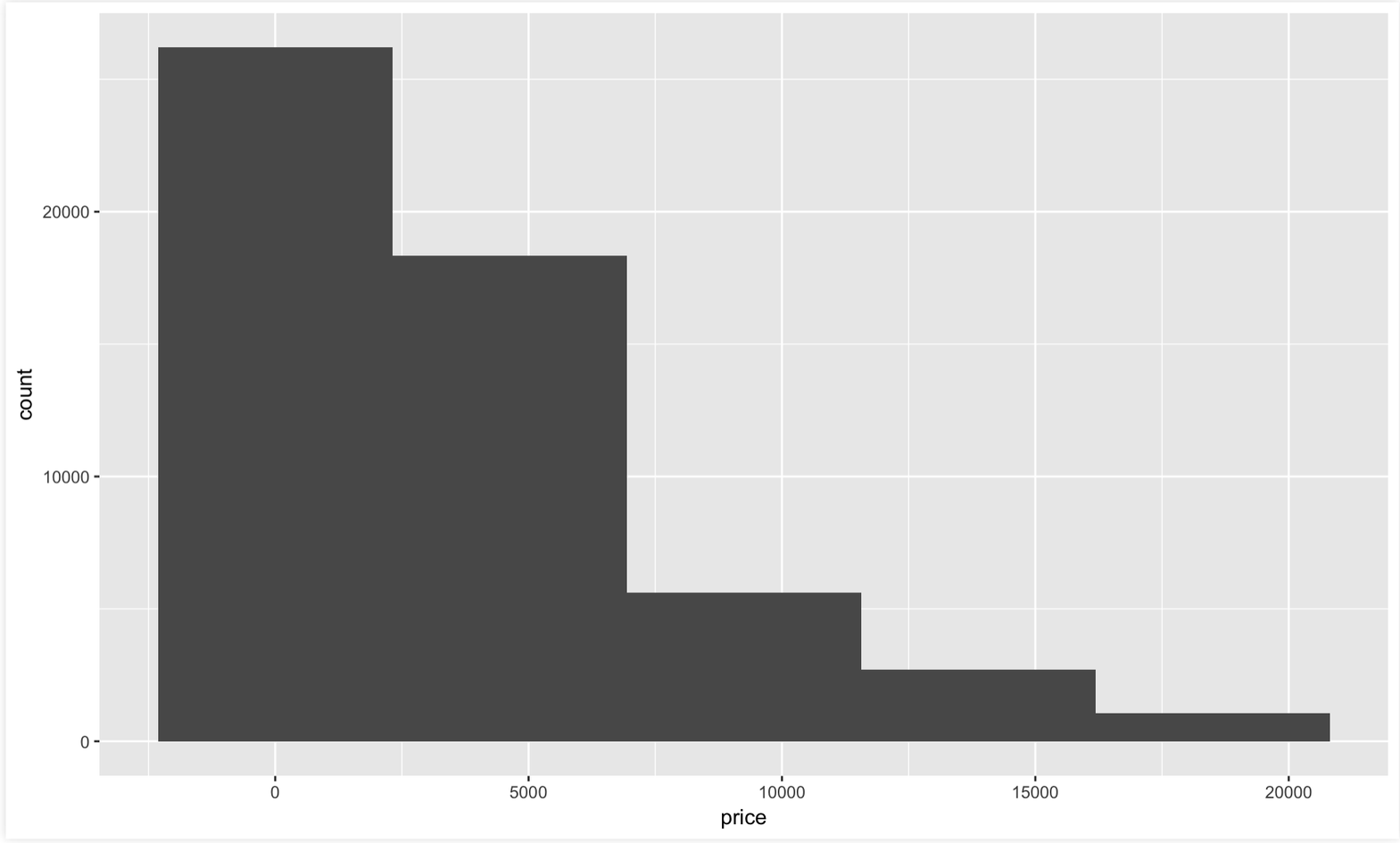
Histograms with ggplot2

```
ggplot(diamonds, aes(x = price)) + geom_histogram()
```

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



```r
# you can set bins= or binwidths =
ggplot(diamonds, aes(x = price)) + geom_histogram(bins = 5)
```



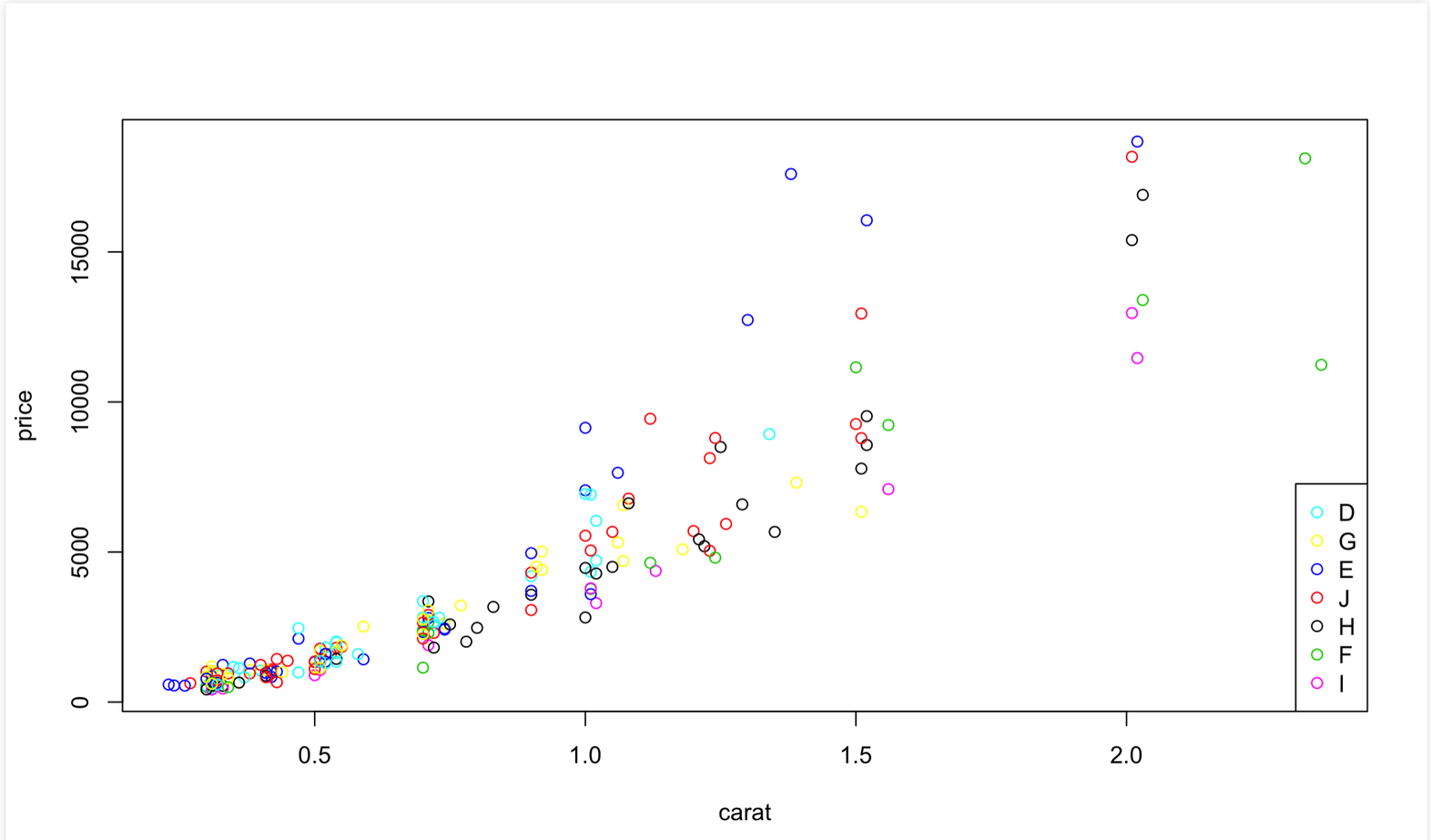
Subset the data

- We select a random subset of the data to use for plotting the relationship between the weights (carat = 200 mg) and prices ($) of diamonds

```
set.seed(12345) # Make the sample reproducible
dsmall <- diamonds[sample(nrow(diamonds), 200), ]
```

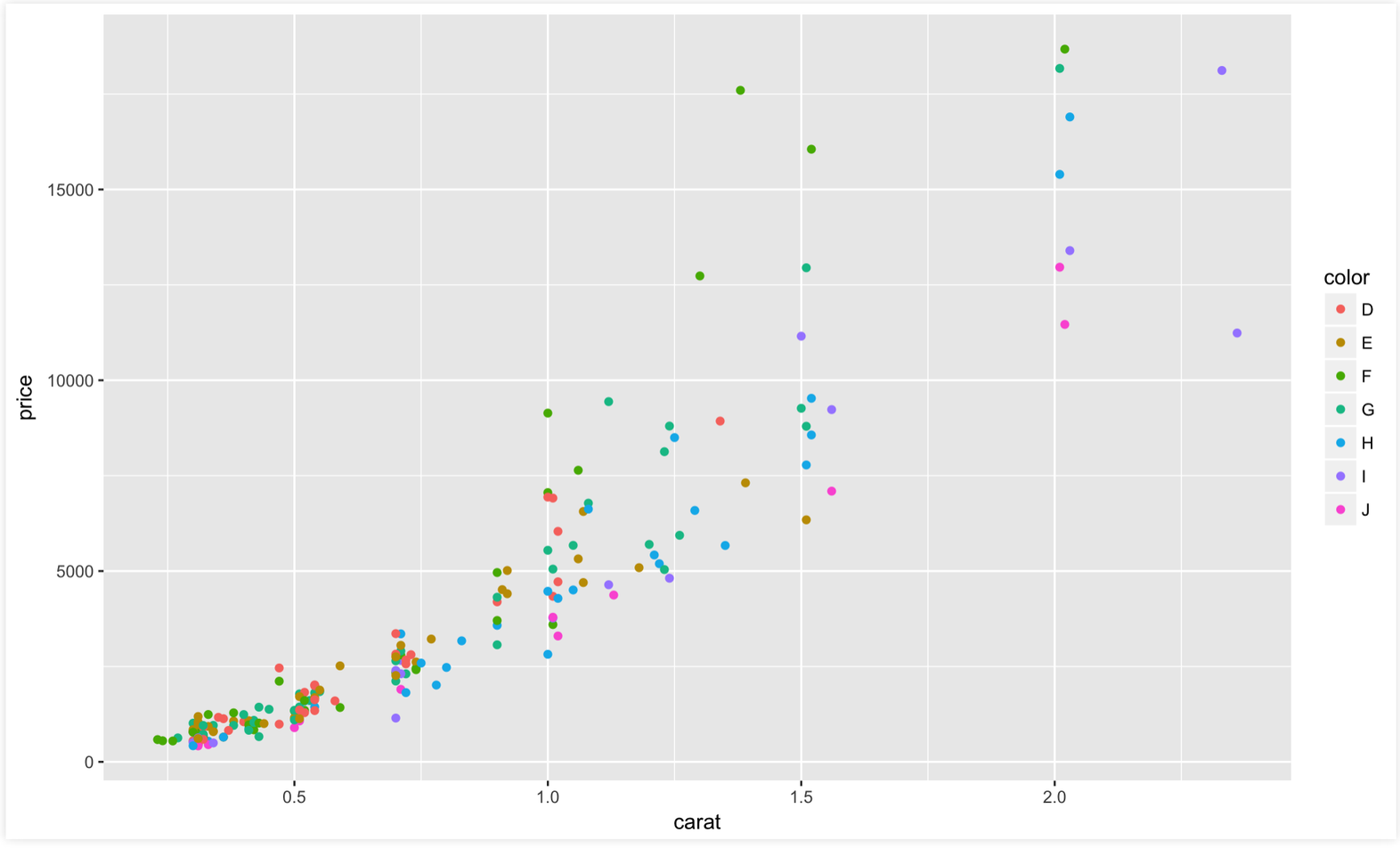
Scatter plot with base graphics

```
colorMap <- data.frame(row.names = unique(dsmall$color),
color = rainbow(length(unique(dsmall$color))))
plot(price ~ carat, data = dsmall, col = colorMap[dsmall$color, "color"])
legend(x = 'bottomright', legend = rownames(colorMap), col = colorMap$color, pch = 1)
```



Scatter plot with ggplot2

```
ggplot(data = dsmall, aes(x = carat, y = price, color = color)) +
geom_point()
```



Geometric objects and aesthetics

Geometic objects - actual items on the plot

- points (`geom_point()`, used for scatter plots)
- lines (`geom_line()`, used for time series, trend lines, etc.)
- boxplot (`geom_boxplot()` used for, well, boxplots!)

There is no upper limit to how many geom objects you can use. You can add a ge
objects to a plot using an + operator.

To get a list of available geometric objects use the following:

```
help.search("geom_", package = "ggplot2")
```

Aesthetic mapping

- In ggplot an **aesthetic mapping**, defined with aes(), describes how variables are mapped to visual properties or aesthetics.
- For example, we might map weight to x weigth, height to y price, and cut to color for the diamonds dataset.
- The details of the mapping are described by the scales.

Examples of aesthetics are:

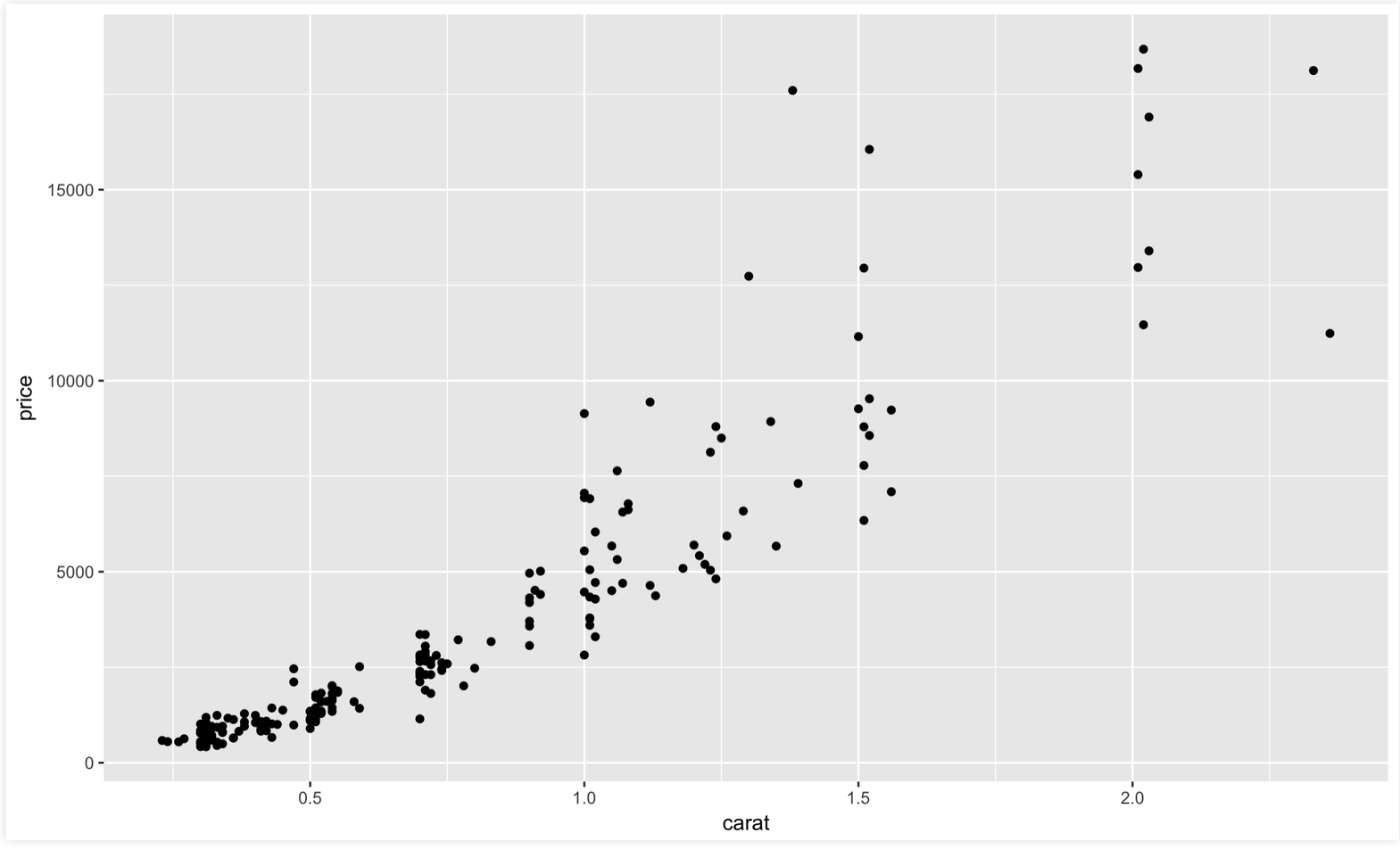
- position (i.e., on the x and y axes)
- shape
- linetype
- size
- color (“outside” color)
- fill (“inside” color)

Each type of geom objects accepts only a subset of aesthetics.

Refer to the geom help pages to see what mappings each geom accepts.

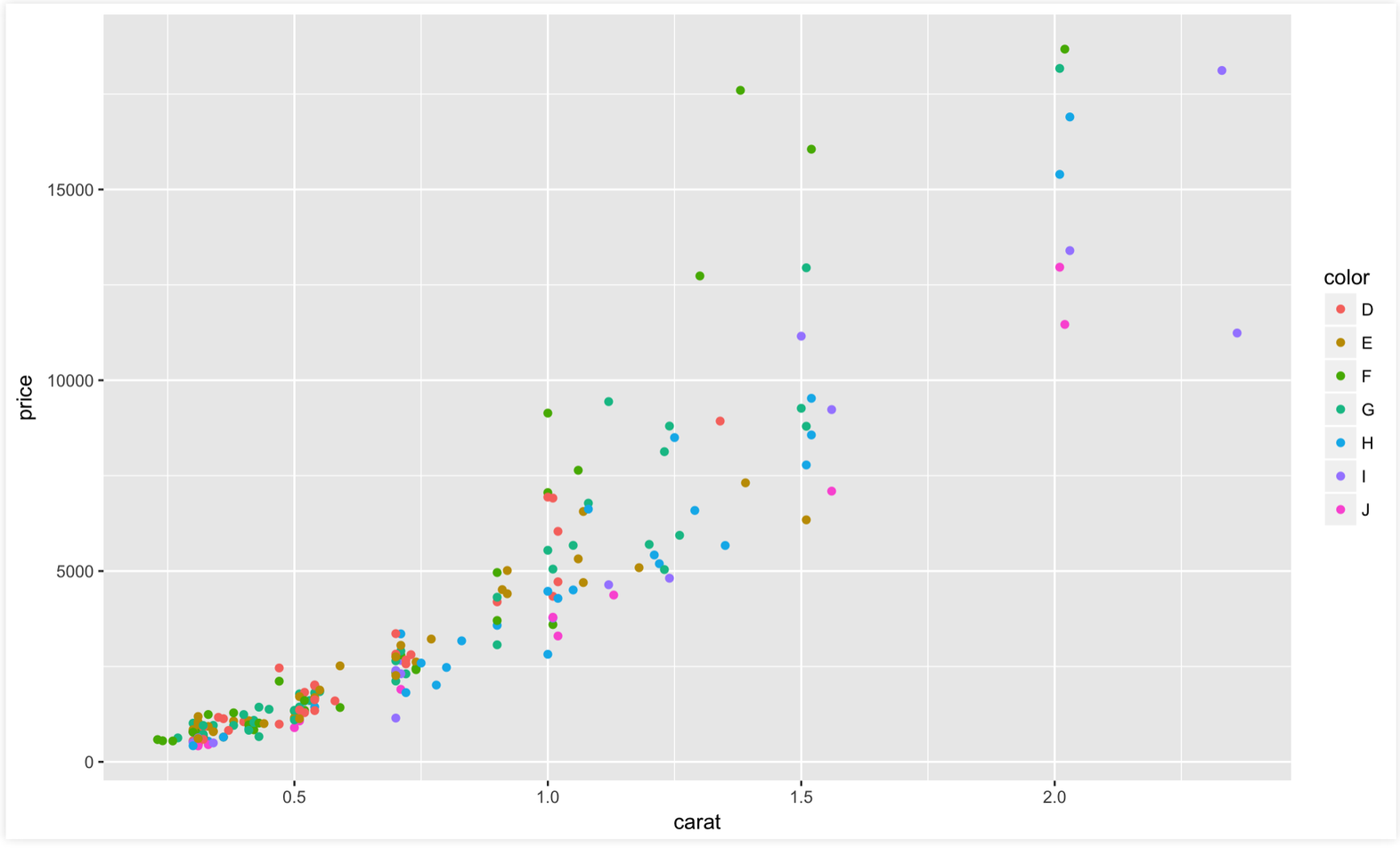
Scatter plots with geom_points

```
p1 <- ggplot(dsmall, aes(x = carat, y = price))
p1 + geom_point()
```



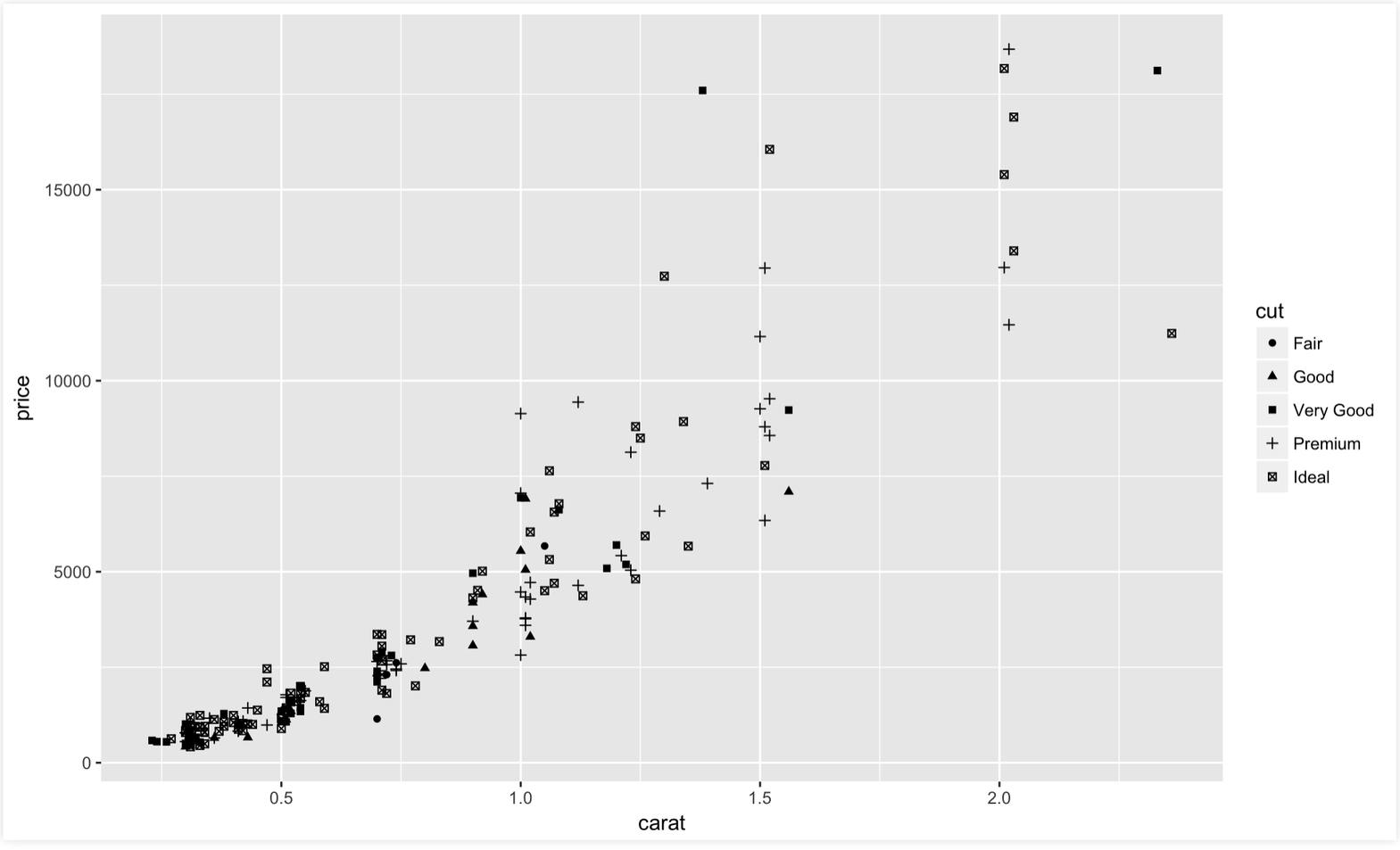
Color points

```
# color by diamonds color
p1 + geom_point(aes(color = color))
```



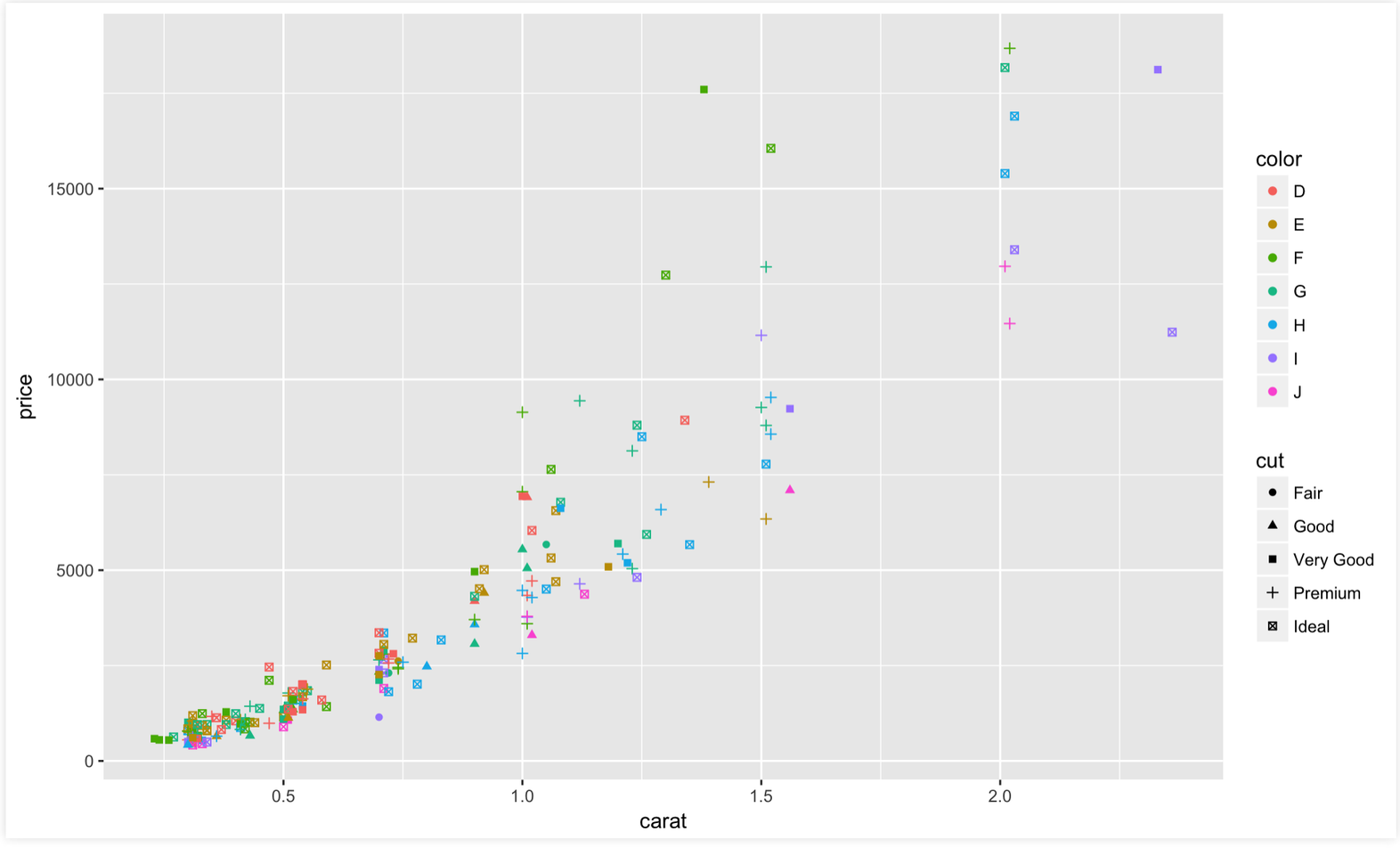
Set the shape of the points

```
# set shape by diamond cut
p1 + geom_point(aes(shape = cut))
```



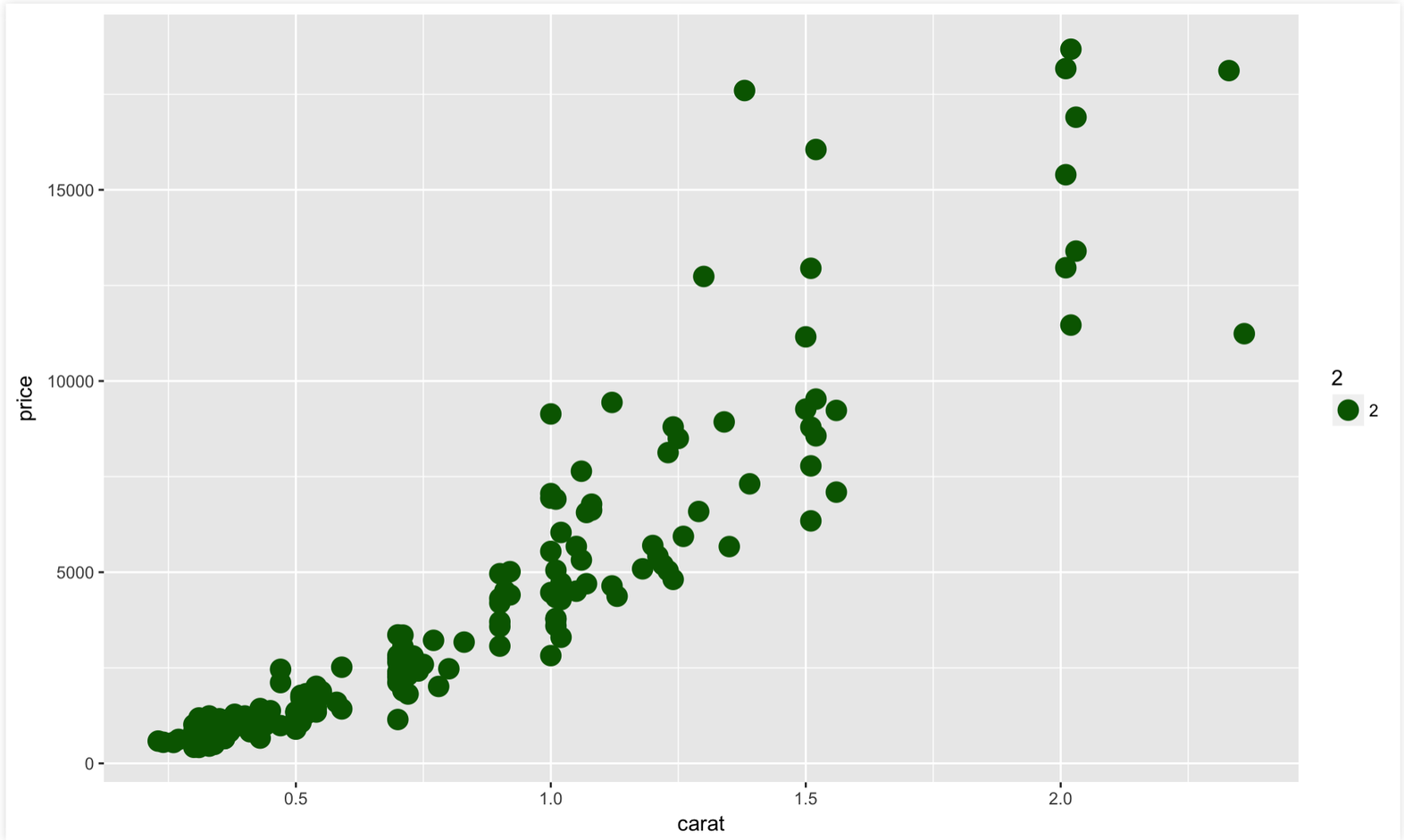
Set color and shape

```
p1 + geom_point(aes(shape = cut, color = color))
```

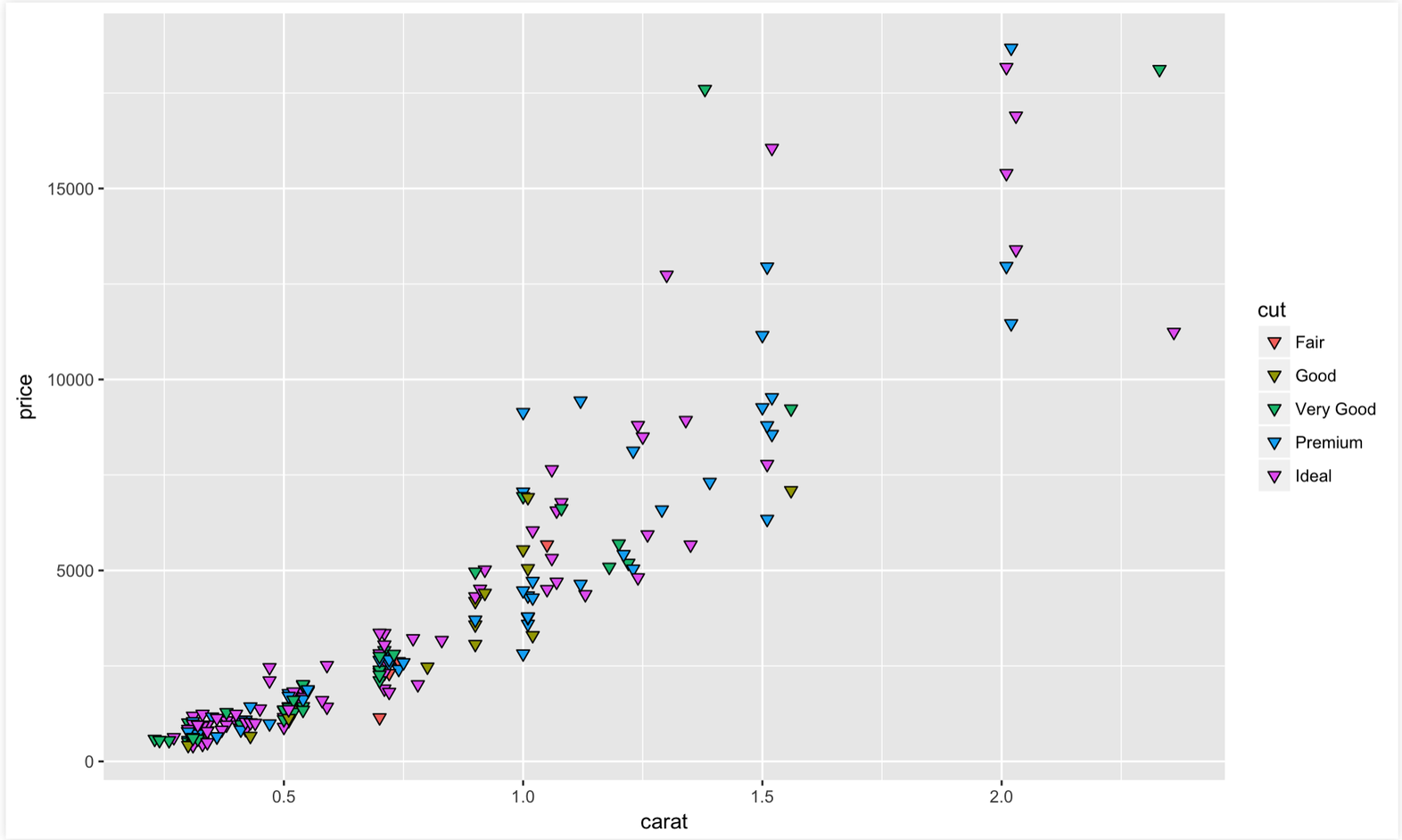


Variable vs fixed aesthetics

```
ggplot(data = dsmall, aes(x = carat, y = price)) +
geom_point(aes(size = 2), color = "darkgreen")
```

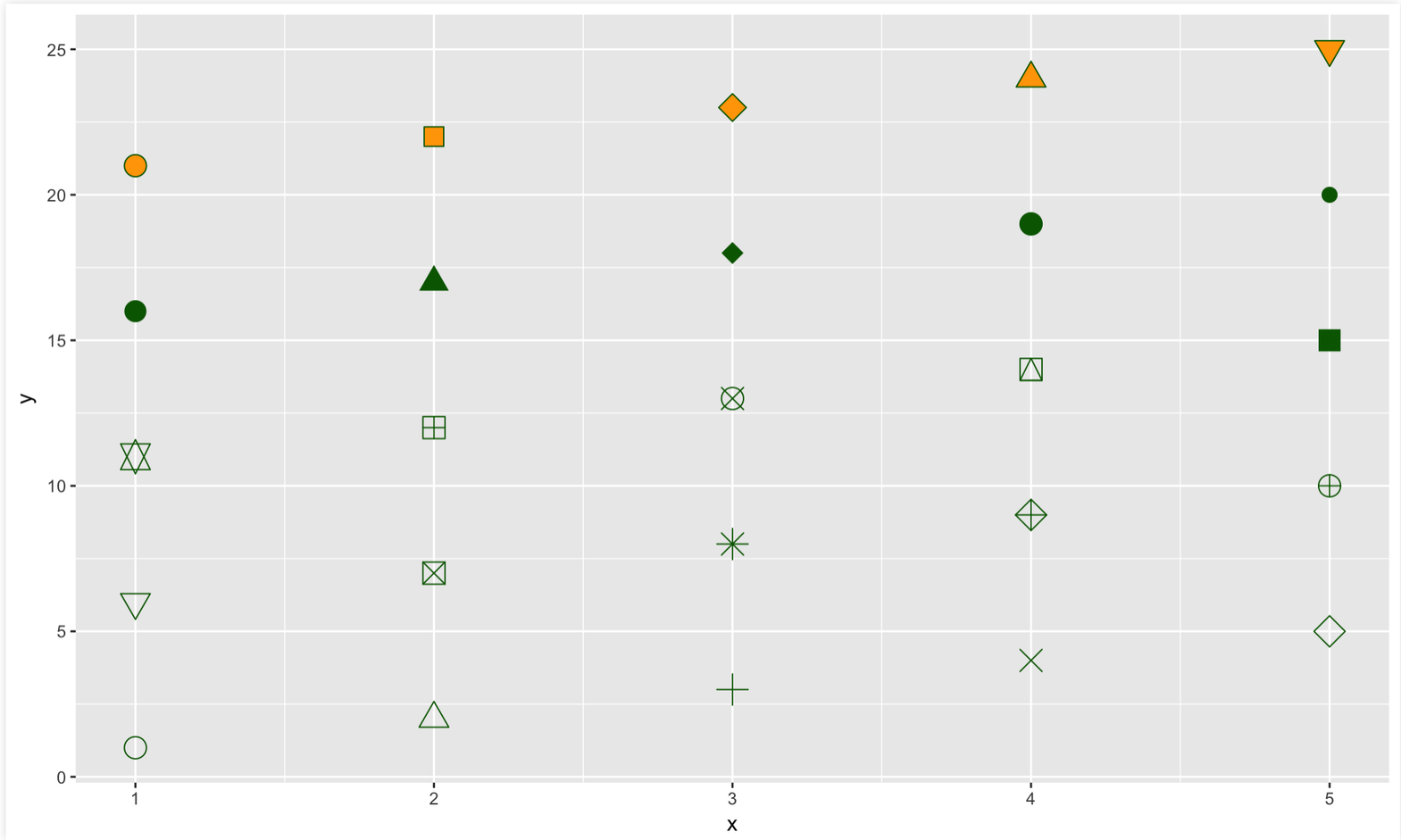


```r
ggplot(data = dsmall, aes(x = carat, y = price)) +
geom_point(aes(fill = cut), size = 2, color = "black", shape = 25)
```



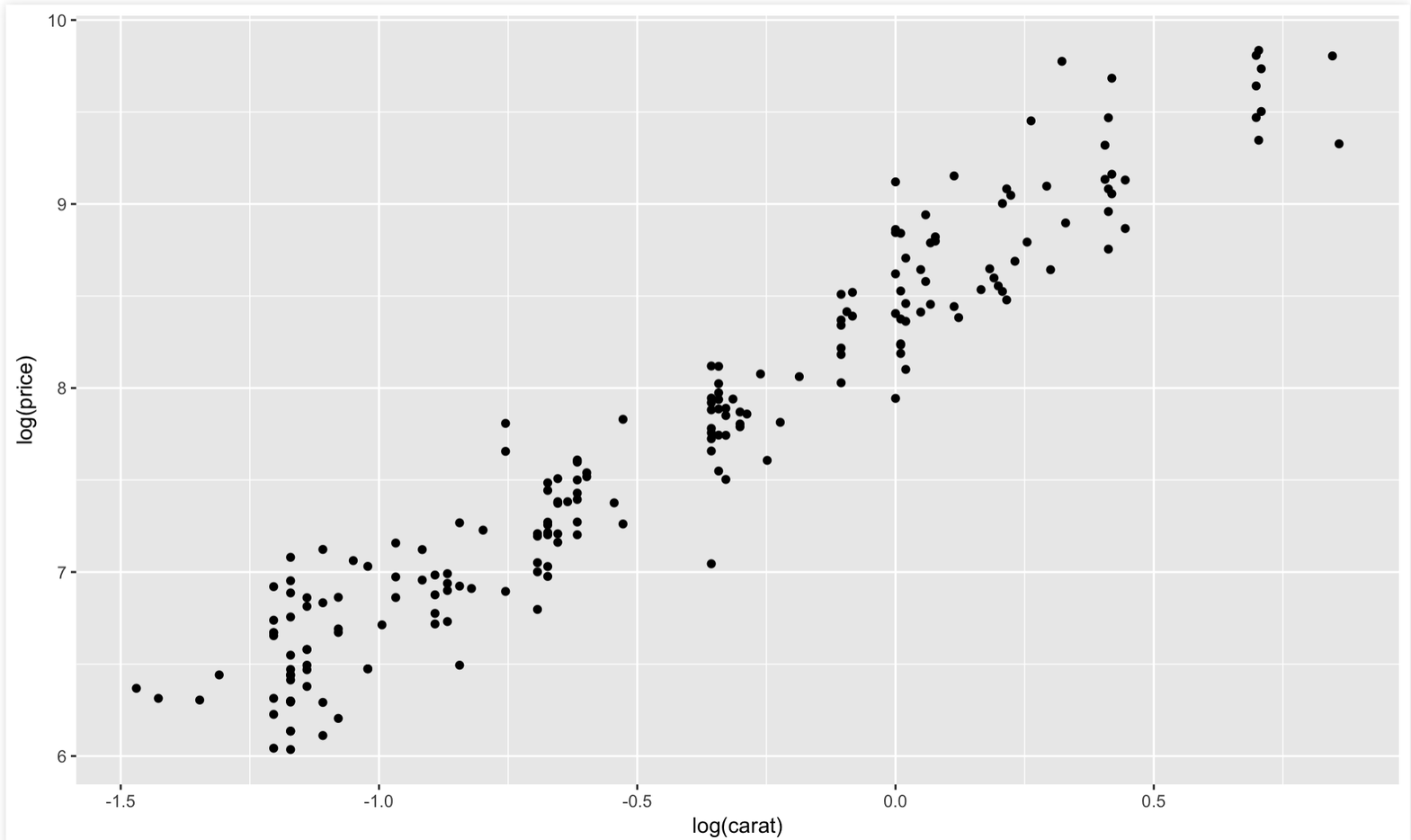
All 25 shape configurations

```
ggplot(data.frame(x = 1:5 , y = 1:25, z = 1:25), aes(x = x, y = y)) +
geom_point(aes(shape = z), size = 5, colour = "darkgreen", fill = "orange") +
scale_shape_identity()
```



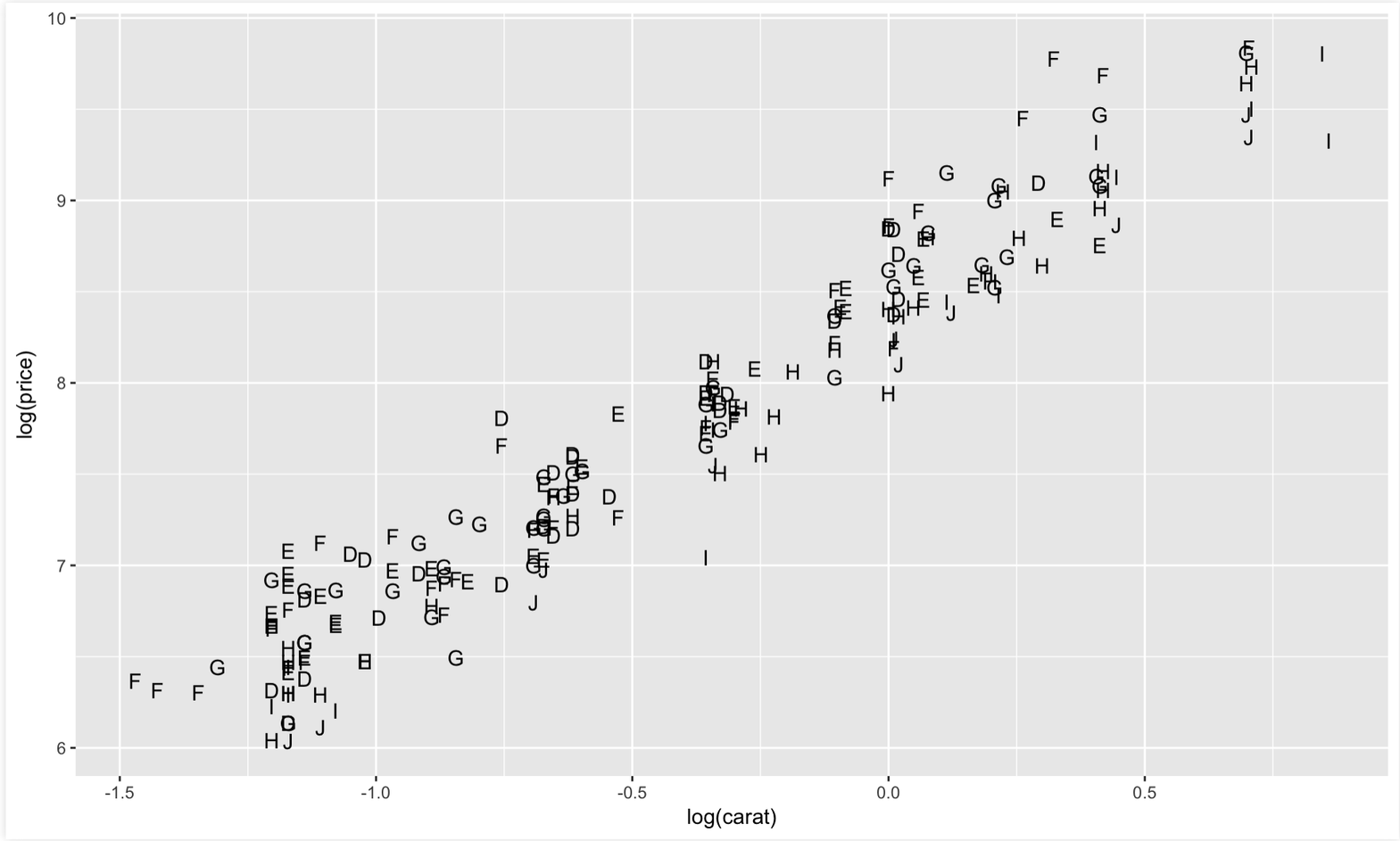
Data transformations

```
ggplot(dsmall, aes(x = log(carat), y = log(price))) + geom_point()
```



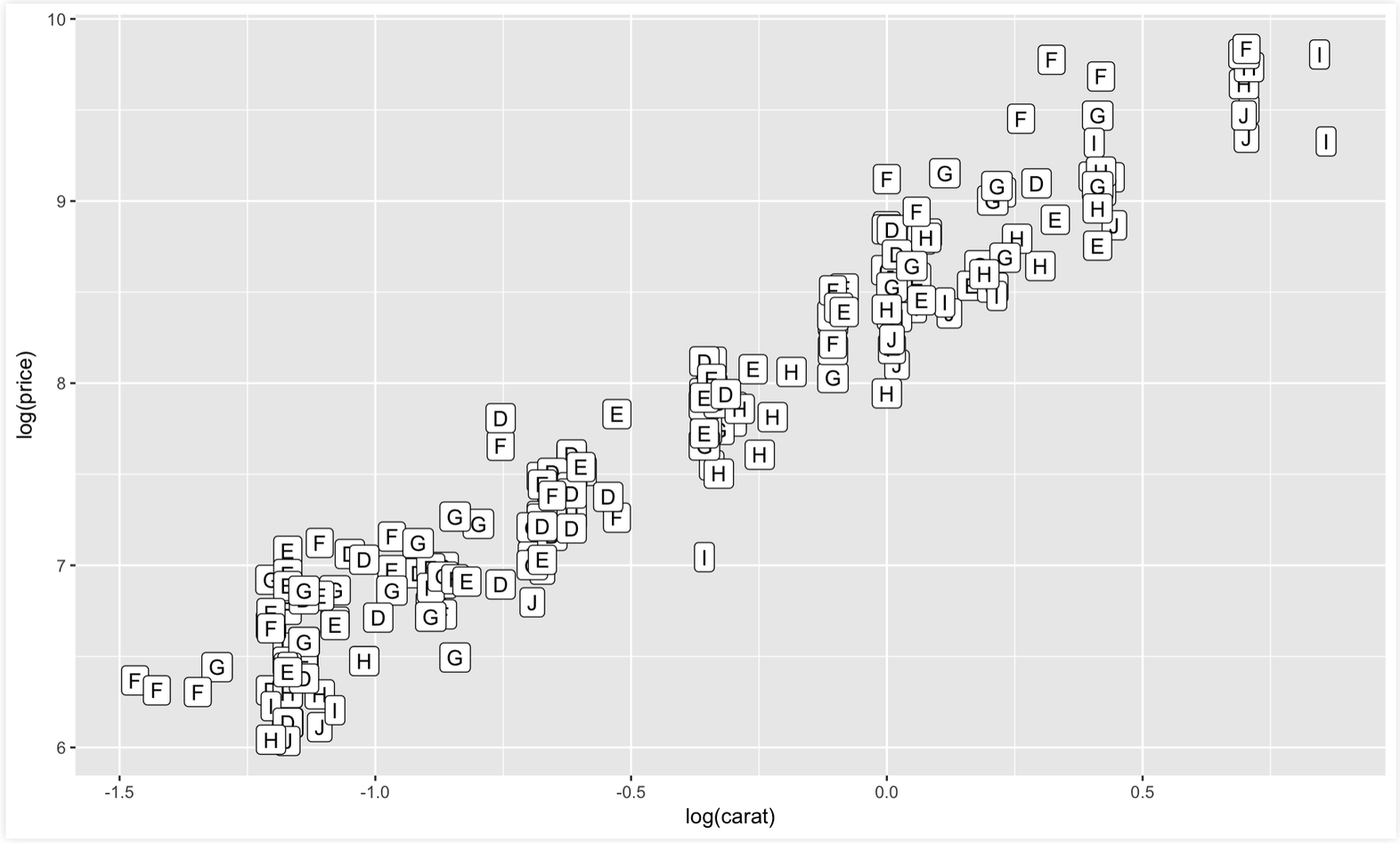
Text labels

```
p2 <- ggplot(dsmall, aes(x = log(carat), y = log(price)))
p2 + geom_text(aes(label = color))
```



Text with rectangle plates

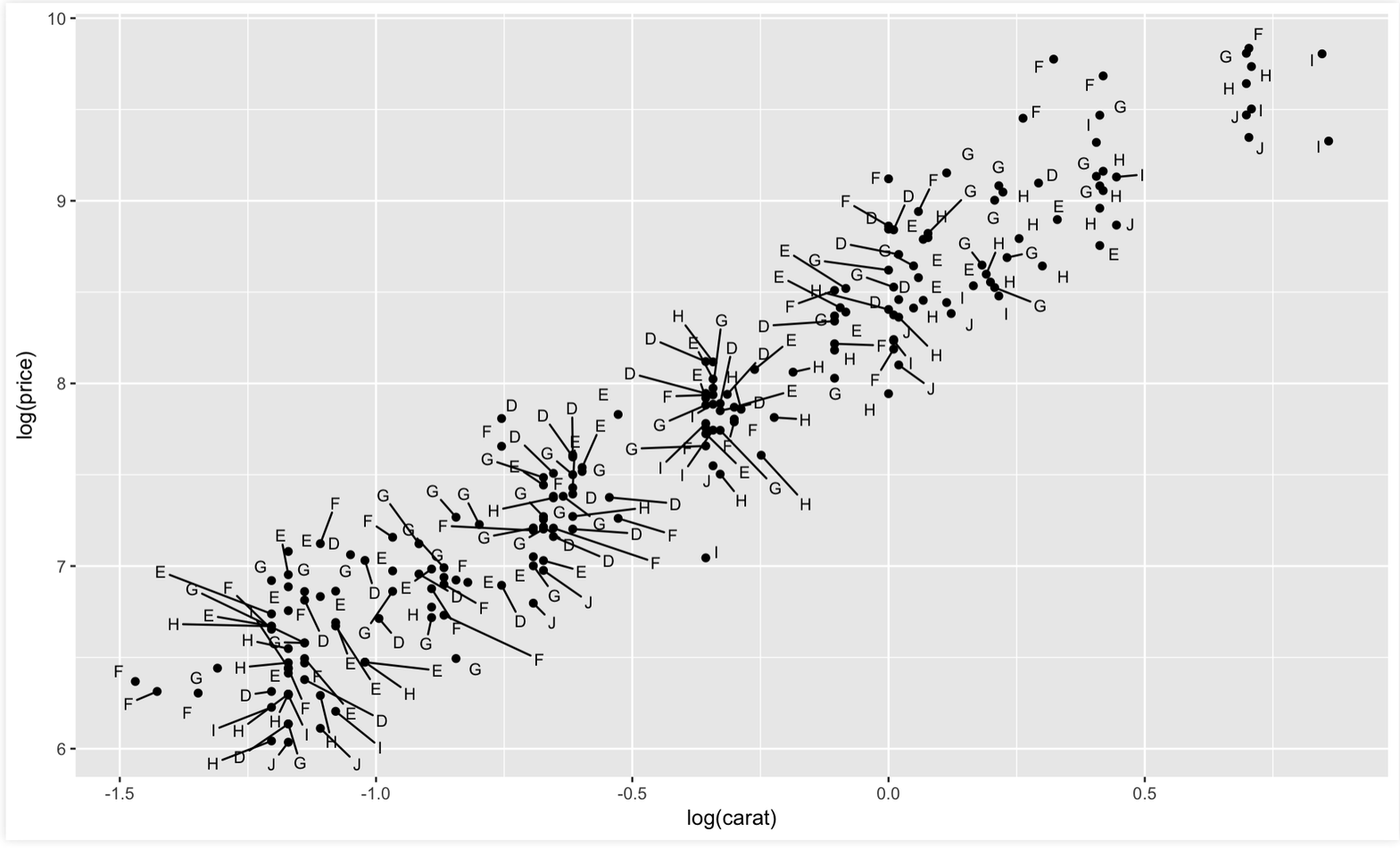
```
p2 + geom_label(aes(label = color))
```



ggrepel package for annotation

`ggrepel` helps annotating **overlapping labels**.

```
library(ggrepel)
p2 + geom_point() + geom_text_repel(aes(label=color), size = 3)
```



Exercise 1

- Go to “Lec4_Exercises.Rmd” on the class website.
- Complete Exercise 1.

Statistical Transformations

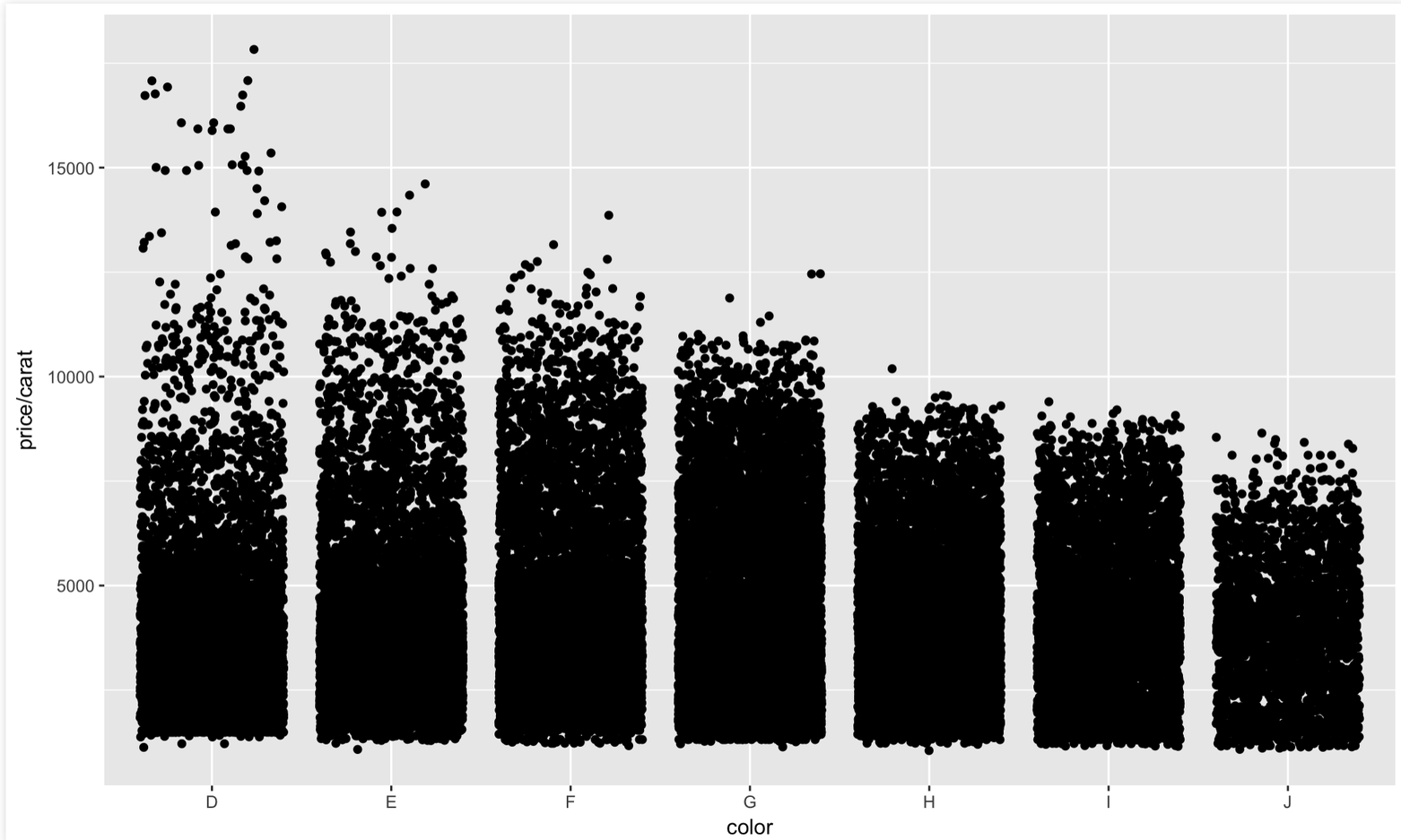
Types of statistical transformations

Plots often require some statistical data transformation or computation before they can be plotted:

- **boxplots:** the the median, lower and upper quartiles,
- **histograms:** group the values into bins,
- **smoothers:** prediction lines / predicted y-values,
- **bar charts:** number of class occurrences.

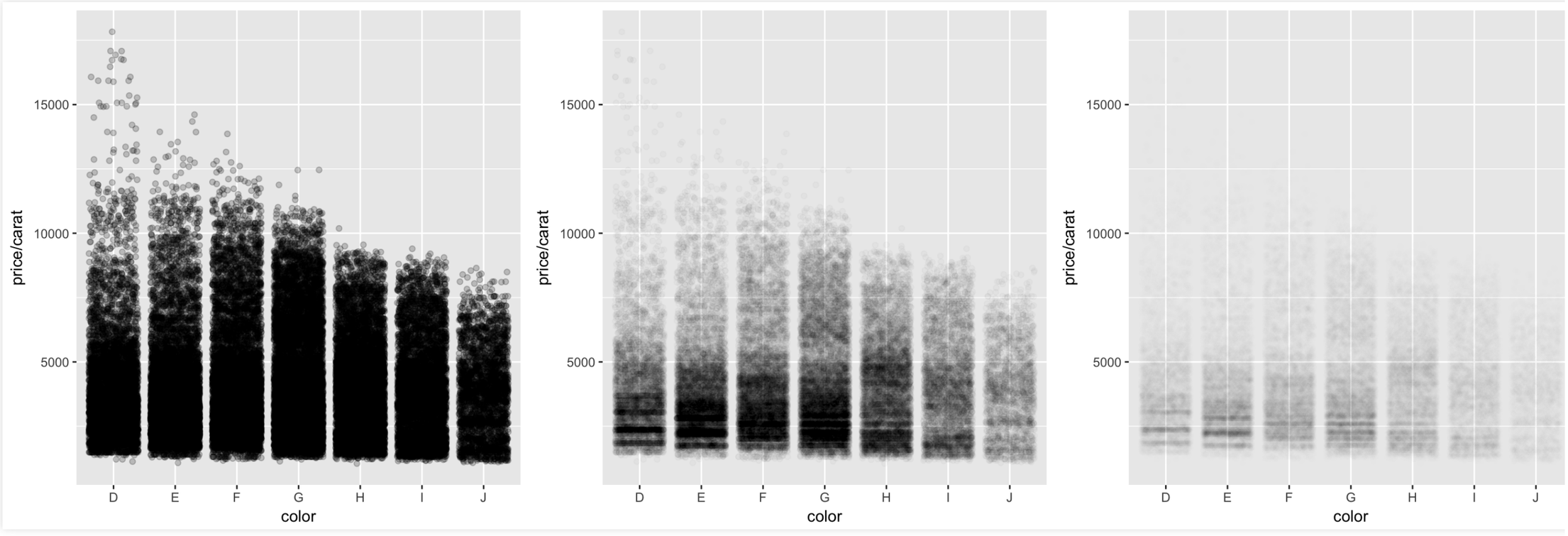
Jittered points

```
ggplot(data = diamonds, aes(x = color, y =price/carat)) +
geom_jitter()
```



Alpha parameter for transparency

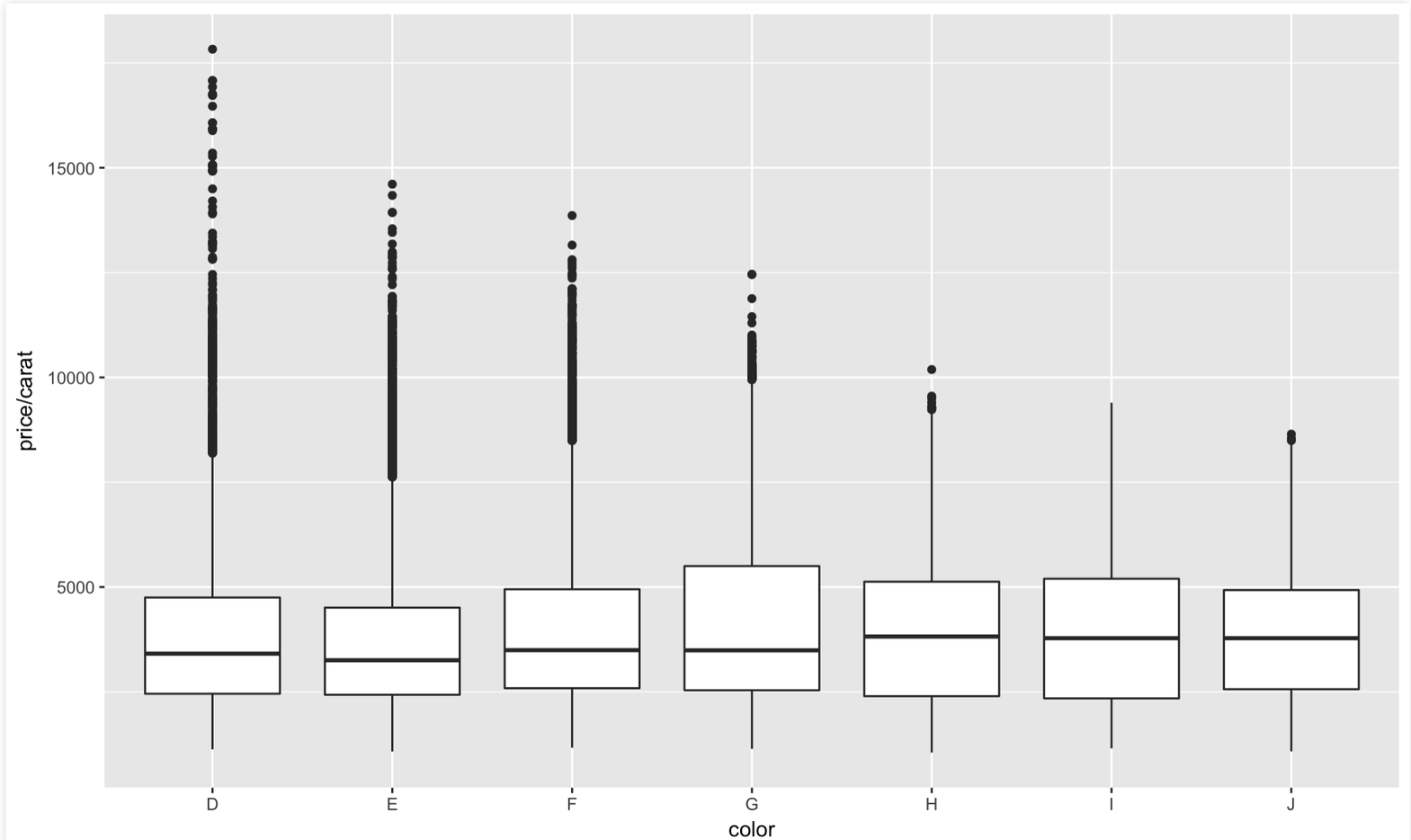
```
j1 <- ggplot(data = diamonds, aes(x = color, y = price/carat)) + geom_jitter(alpha = 1/5)
j2 <- ggplot(data = diamonds, aes(x = color, y = price/carat)) + geom_jitter(alpha = 1/50)
j3 <- ggplot(data = diamonds, aes(x = color, y = price/carat)) + geom_jitter(alpha = 1/200)
# We use grid.arrange from gridExtra to display multiple plots
grid.arrange(j1, j2, j3, ncol = 3)
```



Box plot transformation

Plotting a summary (less data) can be more insightful.

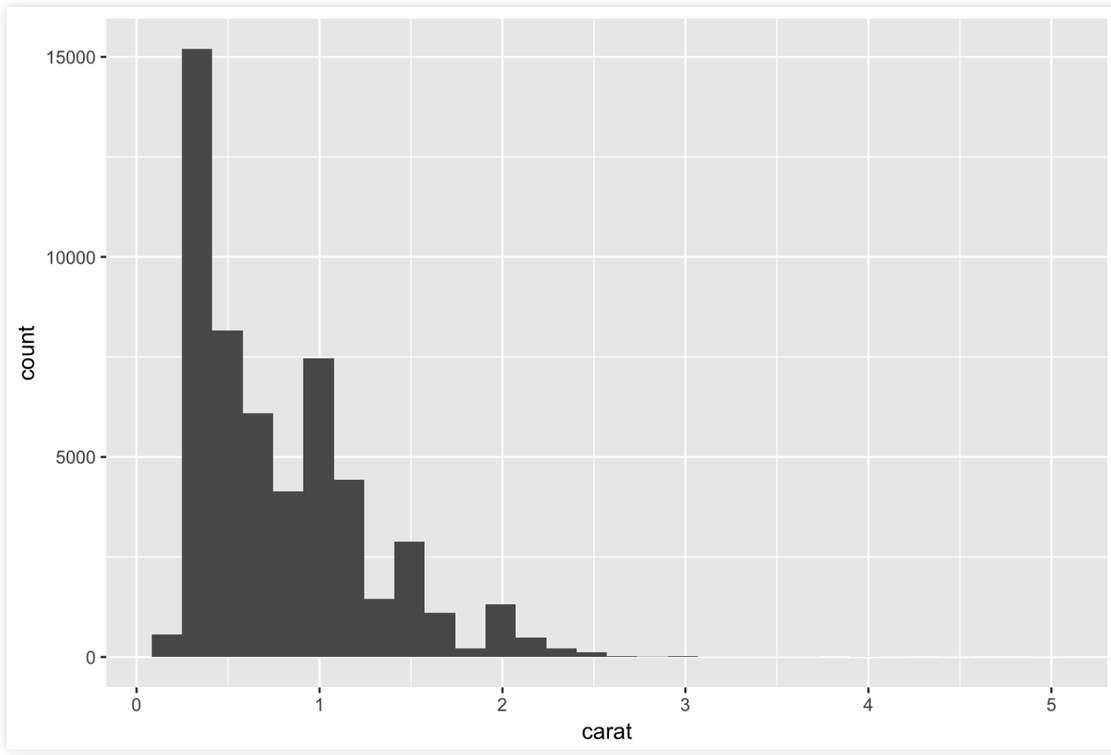
```
ggplot(data = diamonds, aes(x = color, y =price/carat)) +
geom_boxplot()
```

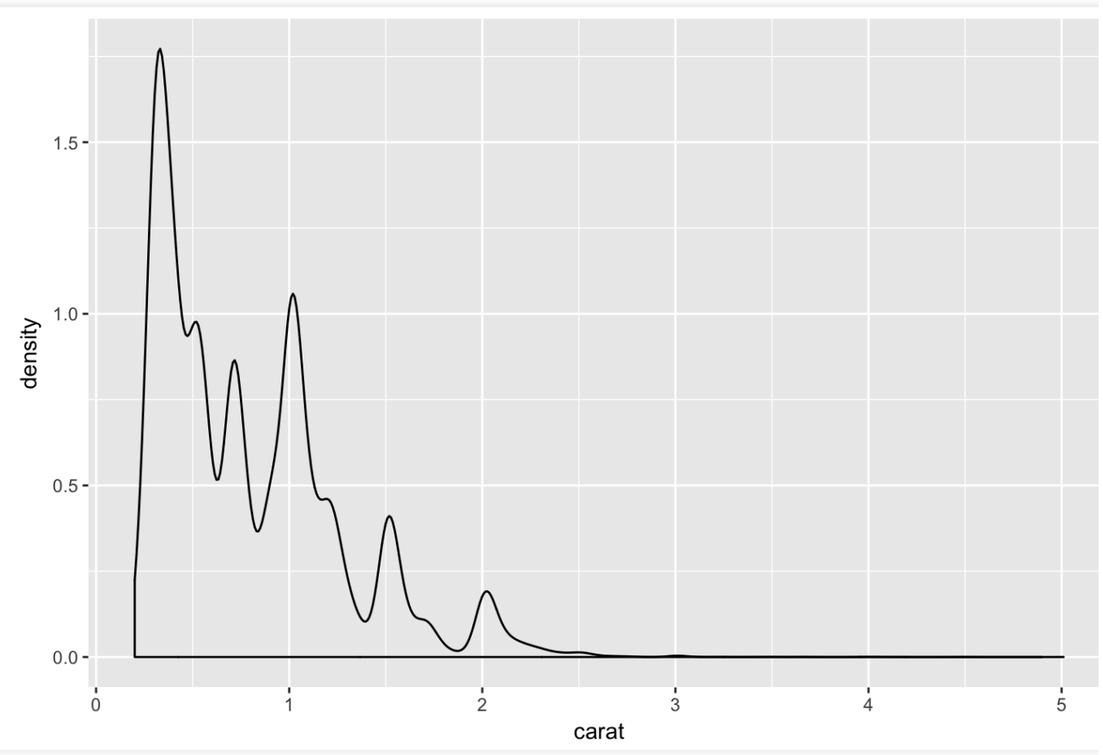


Histogram and density plots

```
# Distribution of the carats (weights) of the diamonds.
h <- ggplot(data = diamonds, aes(x = carat)) + geom_histogram()
d <- ggplot(data = diamonds, aes(x = carat)) + geom_density()
grid.arrange(h, d, ncol = 2)
```

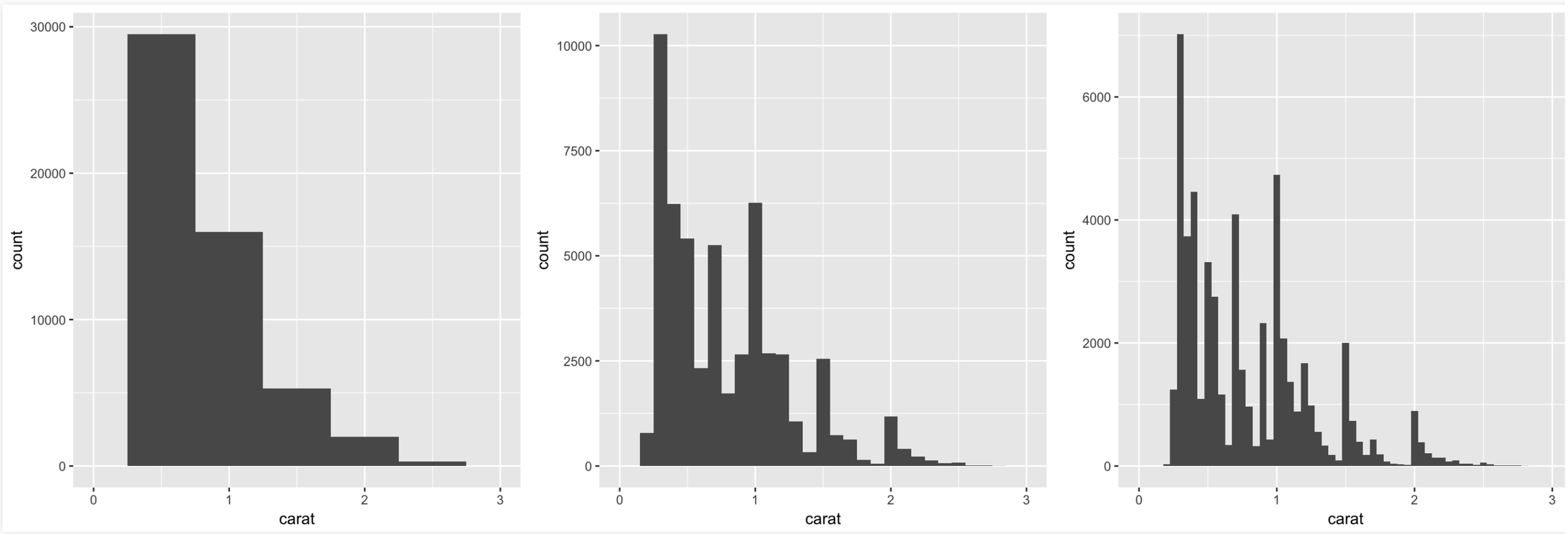
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



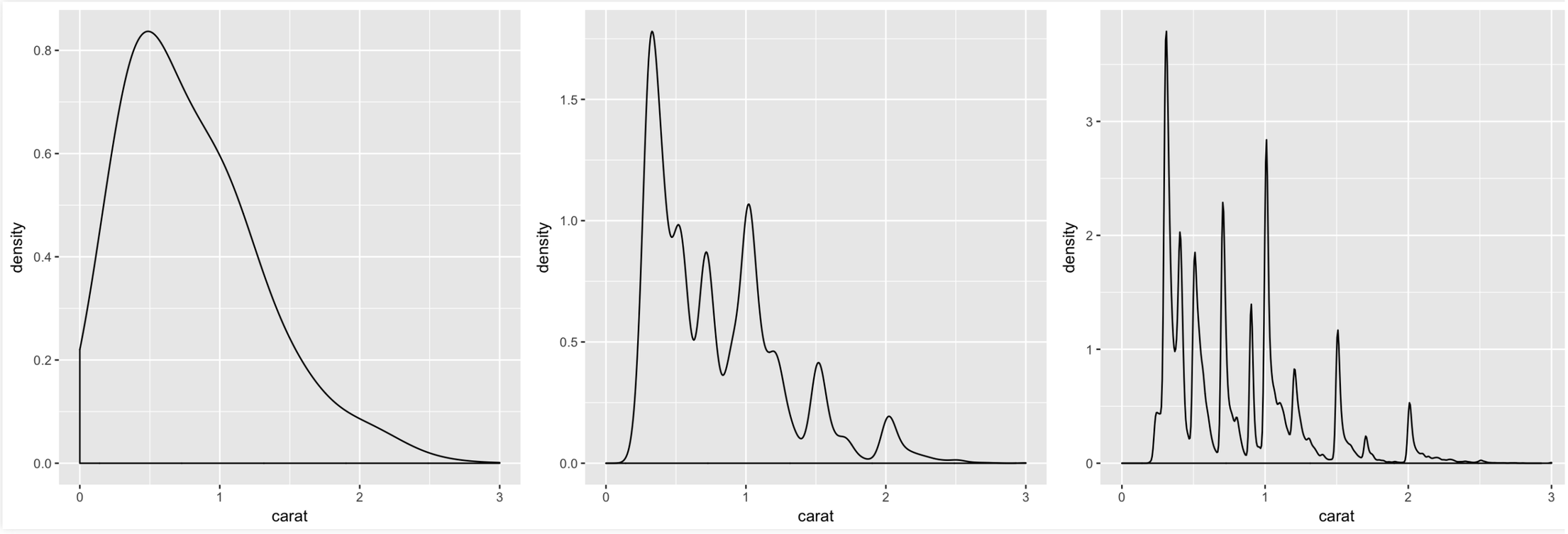


- For the histogram, the smoothness is controlled with **`bins`** and **`binwidth`** arguments. (Break points can also be specified explicitly, using the **`breaks`** argument.)
- For the density plot, the **`bw`** (the smoothing bandwidth) and **`adjust`** argument controls **the degree of smoothness** (high values of adjust produce smoother plots).

```r
p <- ggplot(data = diamonds, aes(x = carat)) + xlim(0, 3)
h1 <- p + geom_histogram(binwidth = 0.5)
h2 <- p + geom_histogram(binwidth = 0.1)
h3 <- p + geom_histogram(binwidth = 0.05)
grid.arrange(h1, h2, h3, ncol = 3)
```

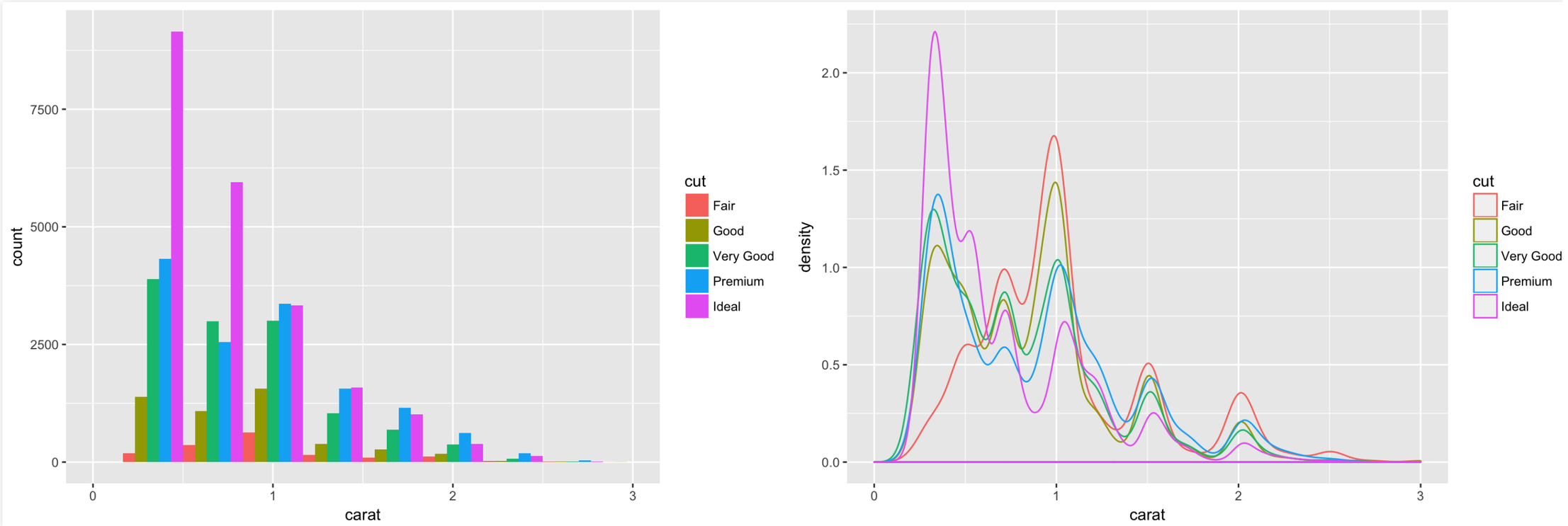


```
d1 <- p + geom_density(adjust = 5)
d2 <- p + geom_density(adjust = 1)
d3 <- p + geom_density(adjust = 1/5)
grid.arrange(d1, d2, d3, ncol = 3)
```



Histograms for separate groups

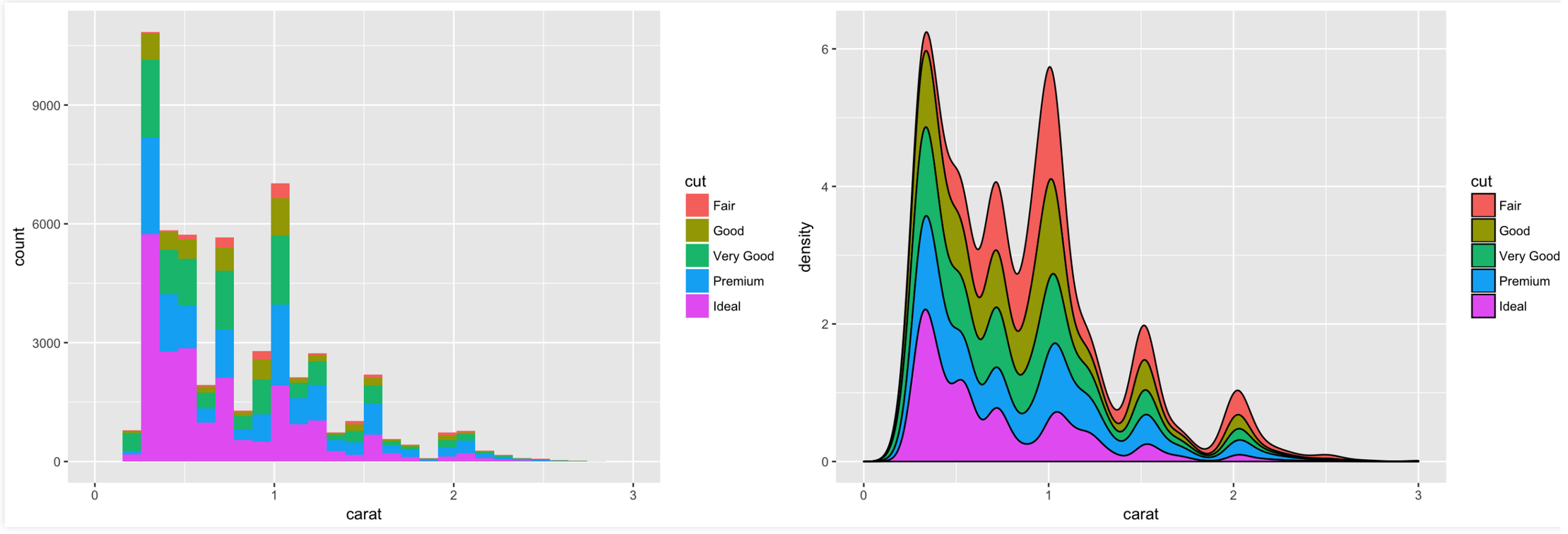
```r
# Here we show grouping by diamonds cut.
h <- p + geom_histogram(aes(fill = cut), position = "dodge", bins = 10)
d <- p + geom_density(aes(color = cut))
grid.arrange(h, d, ncol = 2)
```



Instead of marginal distributions, we can plot distribution of components **stack** on top of each other to see the contribution from each of group.

```
h <- p + geom_histogram(aes(fill = cut), position = "stack")
d <- p + geom_density(aes(fill = cut), position = "stack")
grid.arrange(h, d, ncol = 2)
```

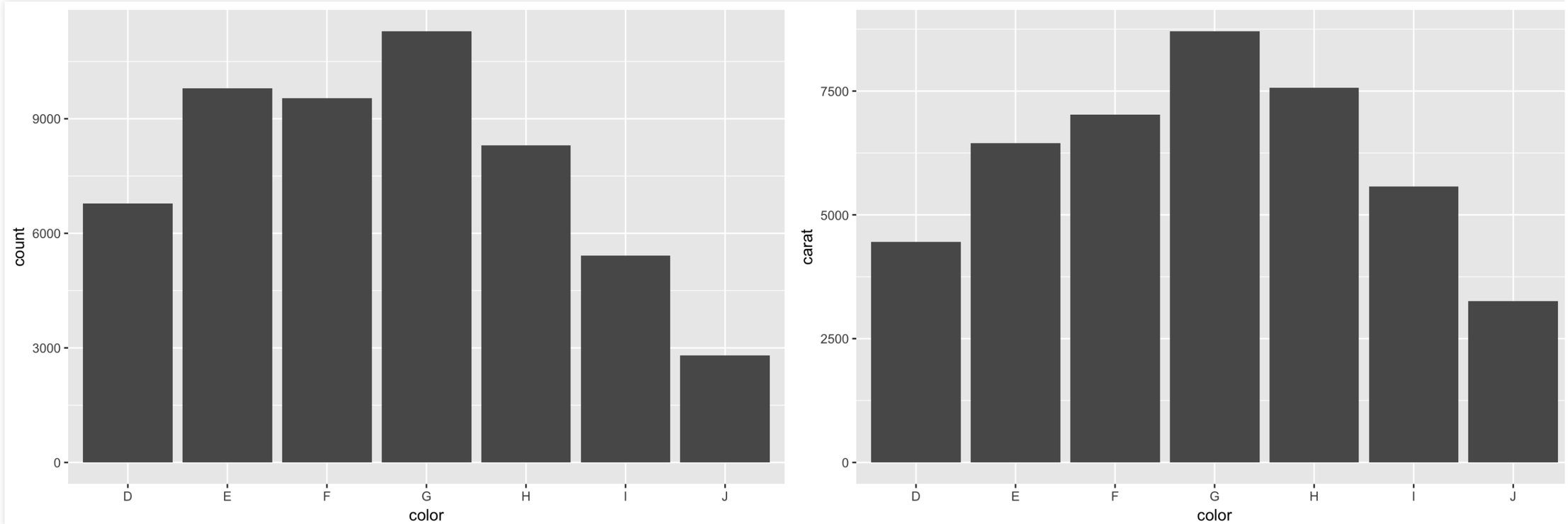
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Bar charts

- A discrete analogue of a histogram is the bar chart, `geom_bar()`.
- Instead of partitioning the values into bins like histograms, the bar geom **counts the number of instances of each discrete class**. The counts are then plotted as columns for each distinct class.
- If you'd like include **unequal weights** for different observations, you can use the `weight` aesthetic.

```
b1 <- ggplot(diamonds, aes(x = color)) + geom_bar()
b2 <- ggplot(diamonds, aes(x = color)) + geom_bar(aes(weight = carat)) + ylab("carat")
grid.arrange(b1, b2, ncol = 2)
```



The left plot shows the number of diamonds in each color group, and the right p
shows the count weighted by carat, which is equivalent to showing the total we
of diamonds in each color group.

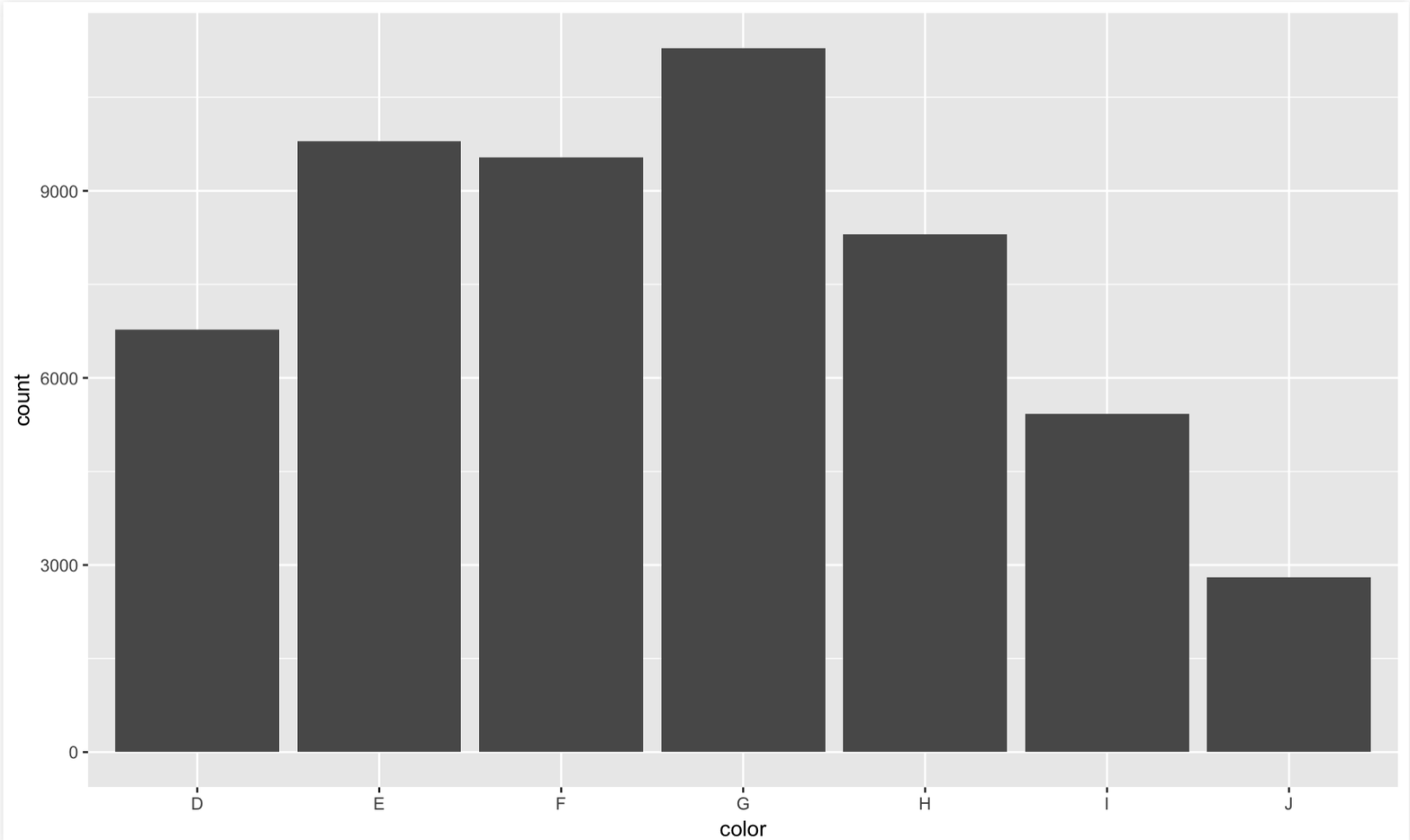
- As you see, in `ggplot2` (unlike base graphics) it is **not necessary tabulate the values**, i.e. compute the counts of each category beforehand. The computation is done automatically for you.
- However, if you have already summarized data, you can still use `geom_bar` but you need to specify an identity transformation, `stat = "identity` rather than the default `stat = "count"`.

```
diamond.counts <- table(diamonds["color"])
df <- data.frame(diamond.counts)
colnames(df) <- c("color", "count")
df
```

```
## color count
## 1 D 6775
## 2 E 9797
## 3 F 9542
## 4 G 11292
## 5 H 8304
## 6 I 5422
## 7 J 2808
```

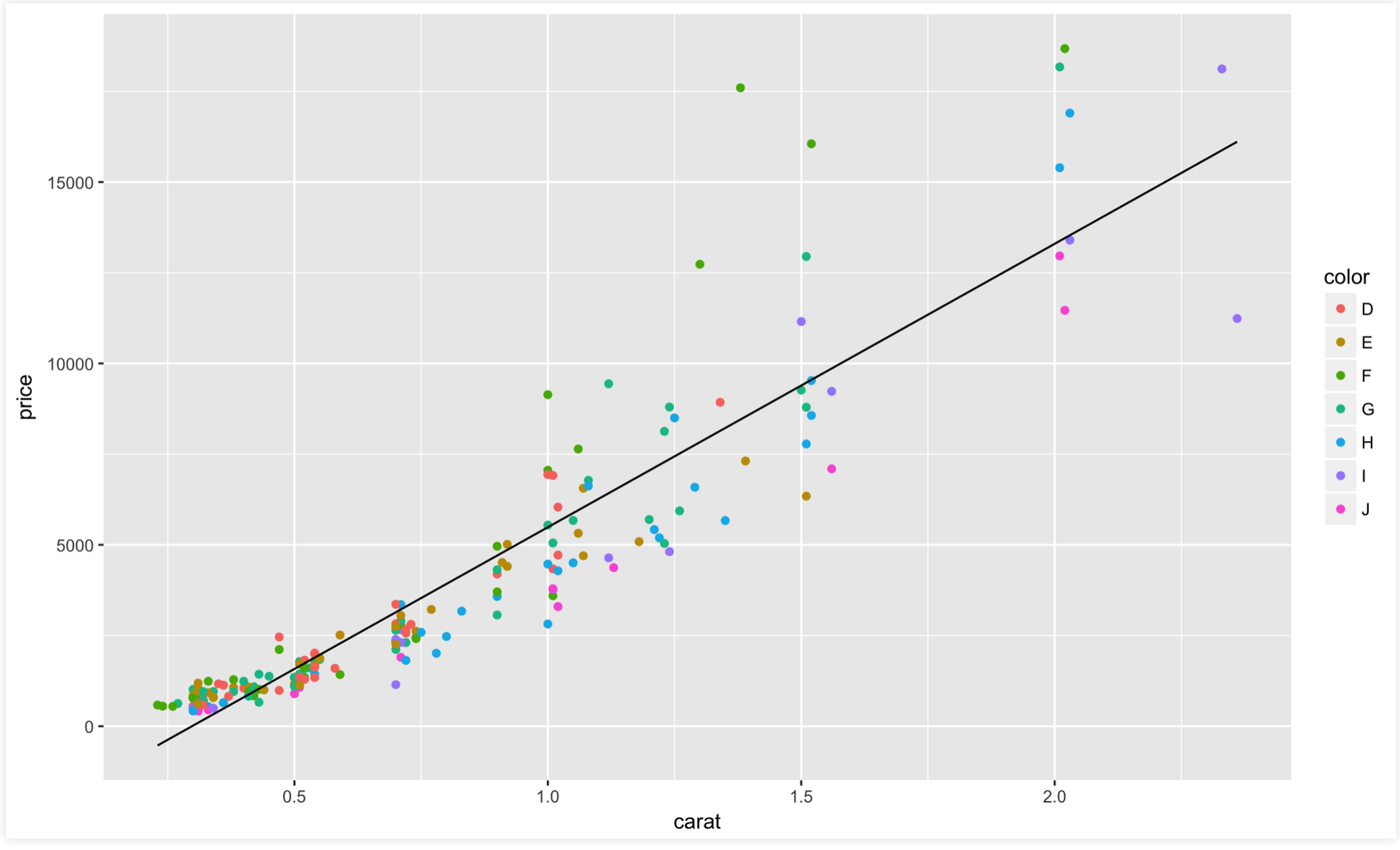
```r
# The default option generates an error:
ggplot(df, aes(x=color, y=count)) + geom_bar()
# Error: stat_count() must not be used with a y aesthetic.
```

```r
# You need to do the following:
ggplot(df, aes(x=color, y=count)) + geom_bar(stat="identity")
```



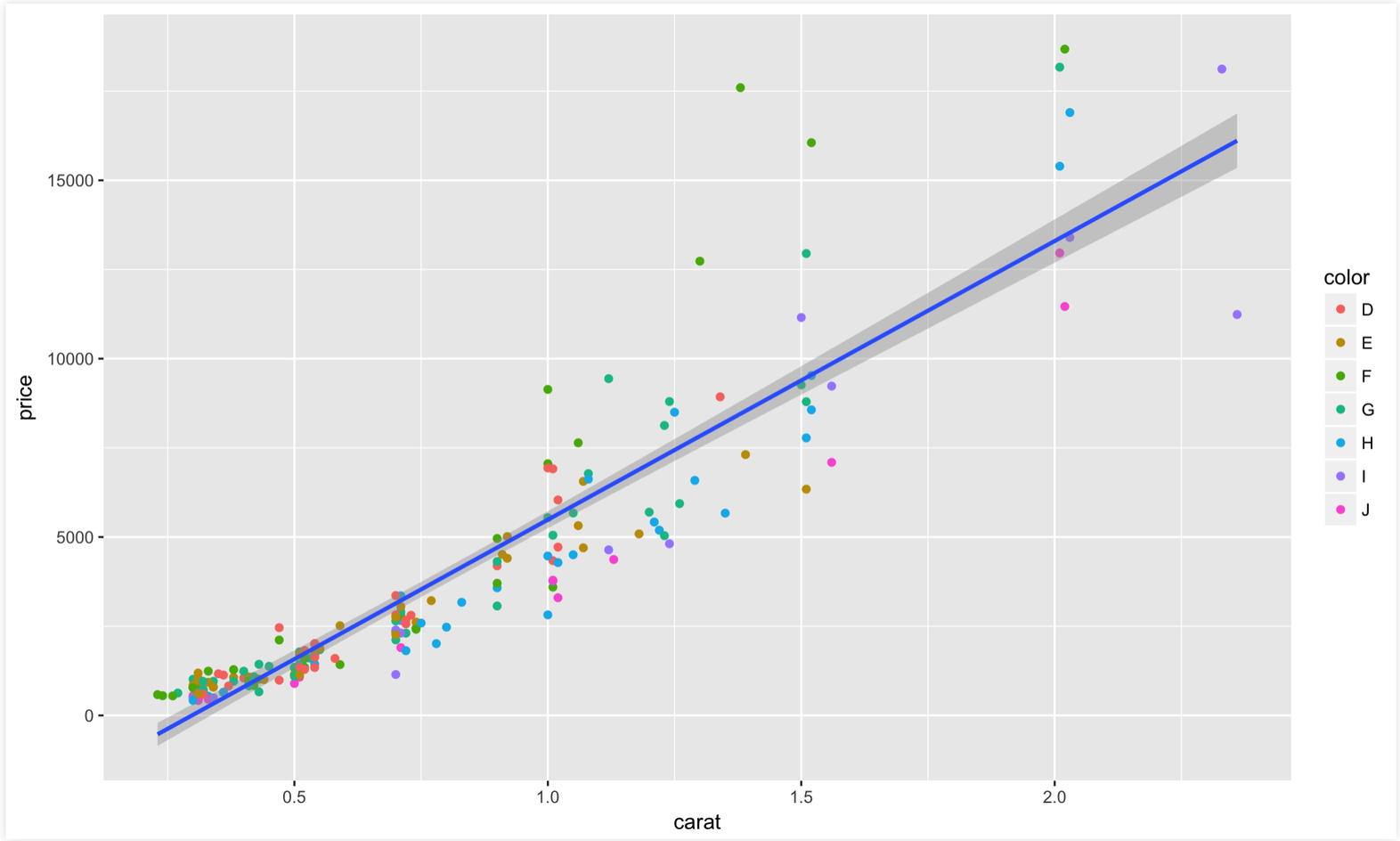
Regression lines

```
# You can fit a linear model with lm(y ~ x, data) and use it for prediction.
dsmall$pred.price <- predict(lm(price ~ carat, data = dsmall))
# And add the regression line in a standard way
p1 <- ggplot(dsmall, aes(x = carat, y = price))
p1 + geom_point(aes(color = color)) + geom_line(aes(y = pred.price))
```



Regression lines with ggplot2

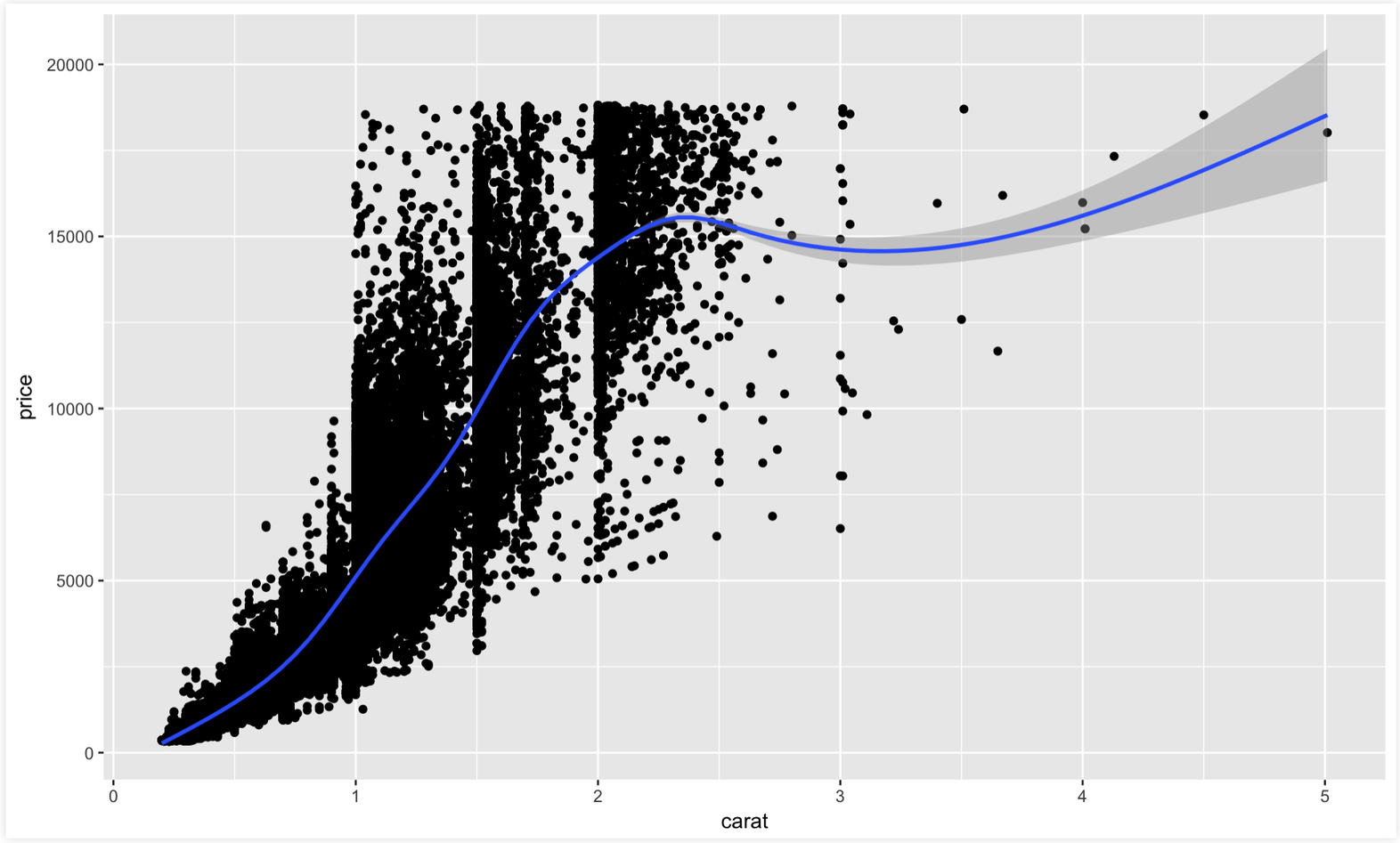
```
# Or you can simply use geom_smooth()!
p1 + geom_point(aes(color = color)) + geom_smooth(method = "lm")
```



Smoothers are trend lines

```
# Smoothers help discern patterns in the data
ggplot(data = diamonds, aes(x = carat, y = price)) +
geom_point() + geom_smooth()
```

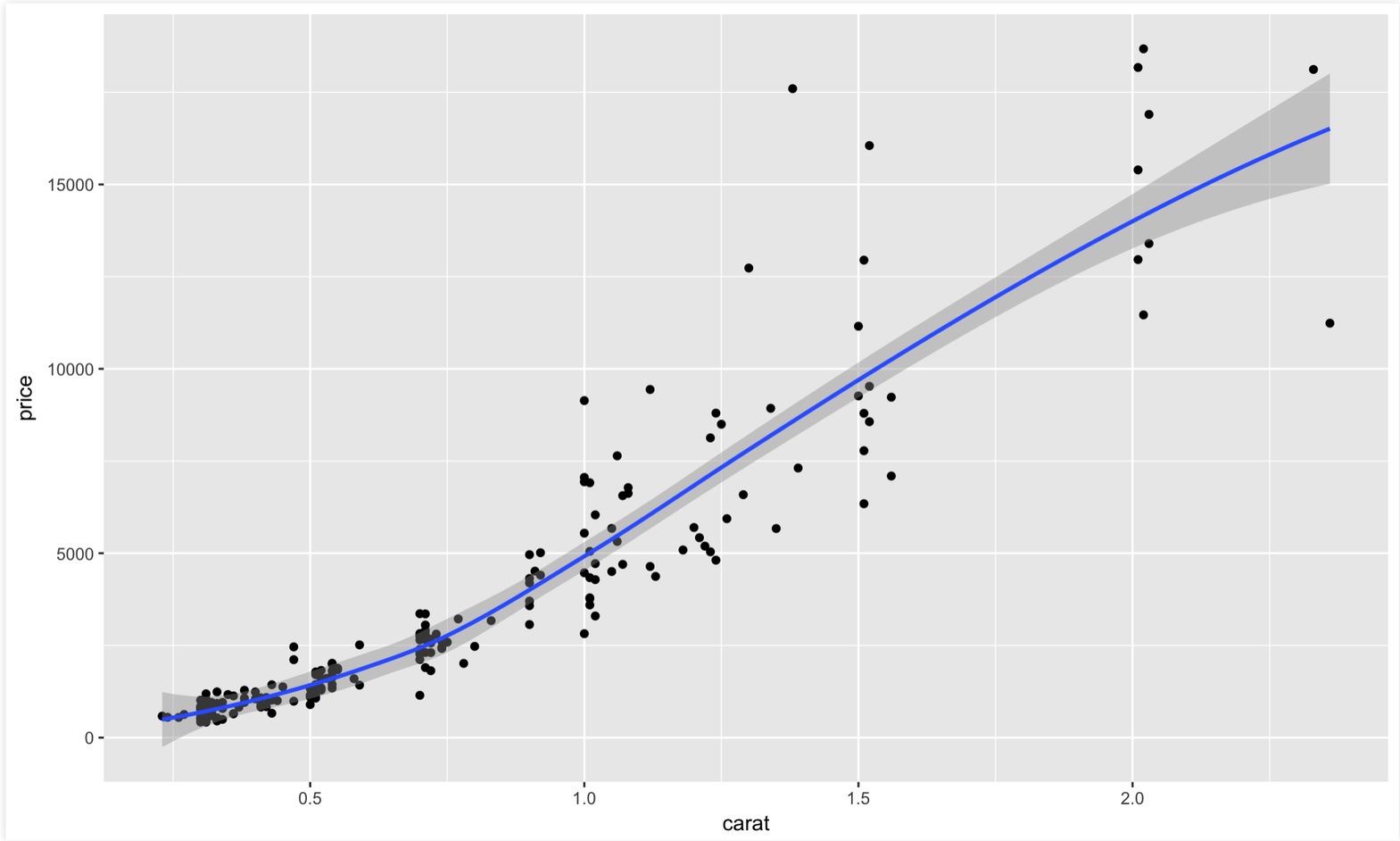
```
## `geom_smooth()` using method = 'gam'
```



For the small subset of the diamonds dataset we have:

```
ggplot(dsmall, aes(x = carat, y = price)) +
geom_point() + geom_smooth()
```

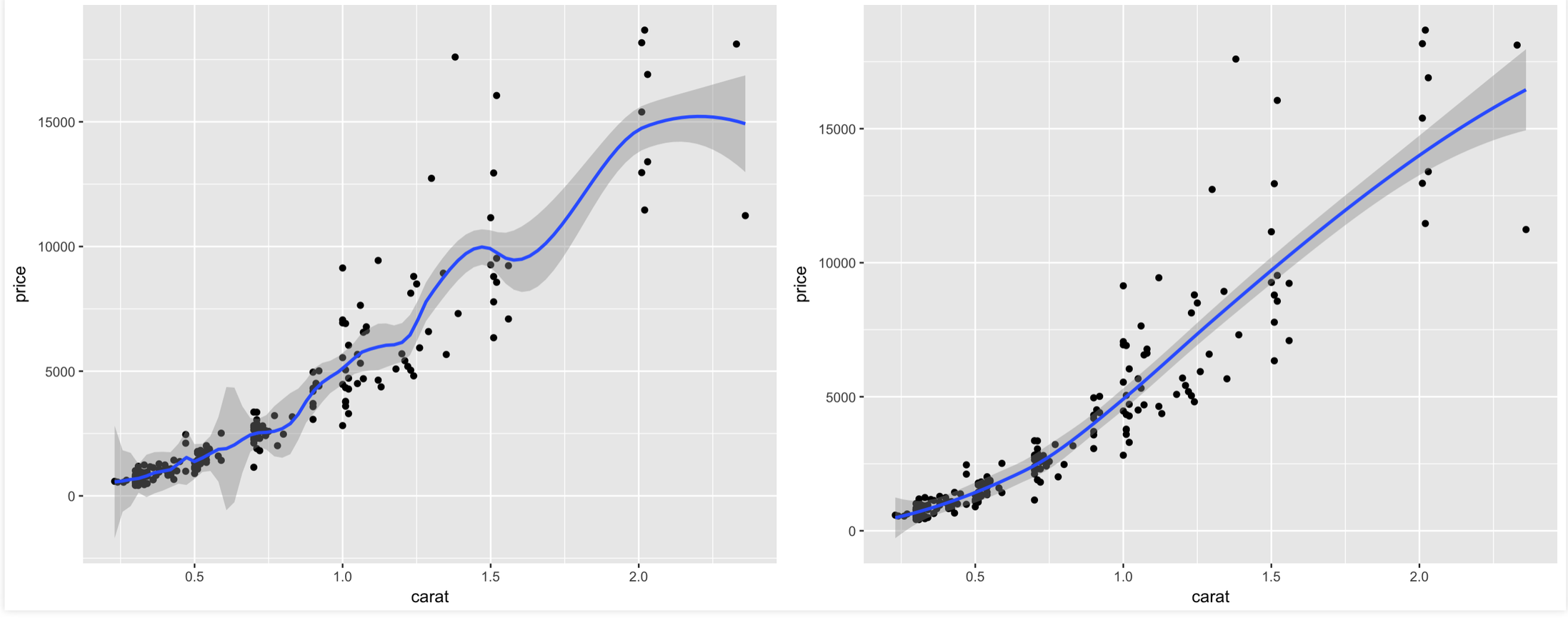
```
## `geom_smooth()` using method = 'loess'
```



‘span’ determines the wigglyness of the curve (smaller span => more wiggly)

```
grid.arrange(p1 + geom_point() + geom_smooth(span = 0.2),
p1 + geom_point() + geom_smooth(span = 0.7), ncol = 2)
```

```
## `geom_smooth()` using method = 'loess'
## `geom_smooth()` using method = 'loess'
```



- By default, when applied to datasets with a few observations (`n < 1000`) `geom_smooth()` uses a `method = "loess"` for fitting a curve.
- This method uses a smooth local regression. More details about the algorithm used can be found in `?loess`.
- Loess does not work well for large datasets (it's $O(n^2)$ in memory), and so an alternative smoothing algorithm is used when n is greater than 1,000.

Exercise 2: The Economist Data

- Go back to “Lec4_Exercises.Rmd”
- Complete the exercise 2

Scales

Aesthetic mapping vs variable scaling

- `aes()` is responsible for assigning an aesthetic to a variable; it doesn't determine how mapping should be done.
- For example, `aes(shape = x)` or `aes(color = z)` do not specify what shapes or what colors should be used. To choose colors/shapes/sizes etc. you need to **modify the corresponding scale**.
- `ggplot2` includes scales for:
  - position
  - color and fill
  - size
  - shape
  - line type

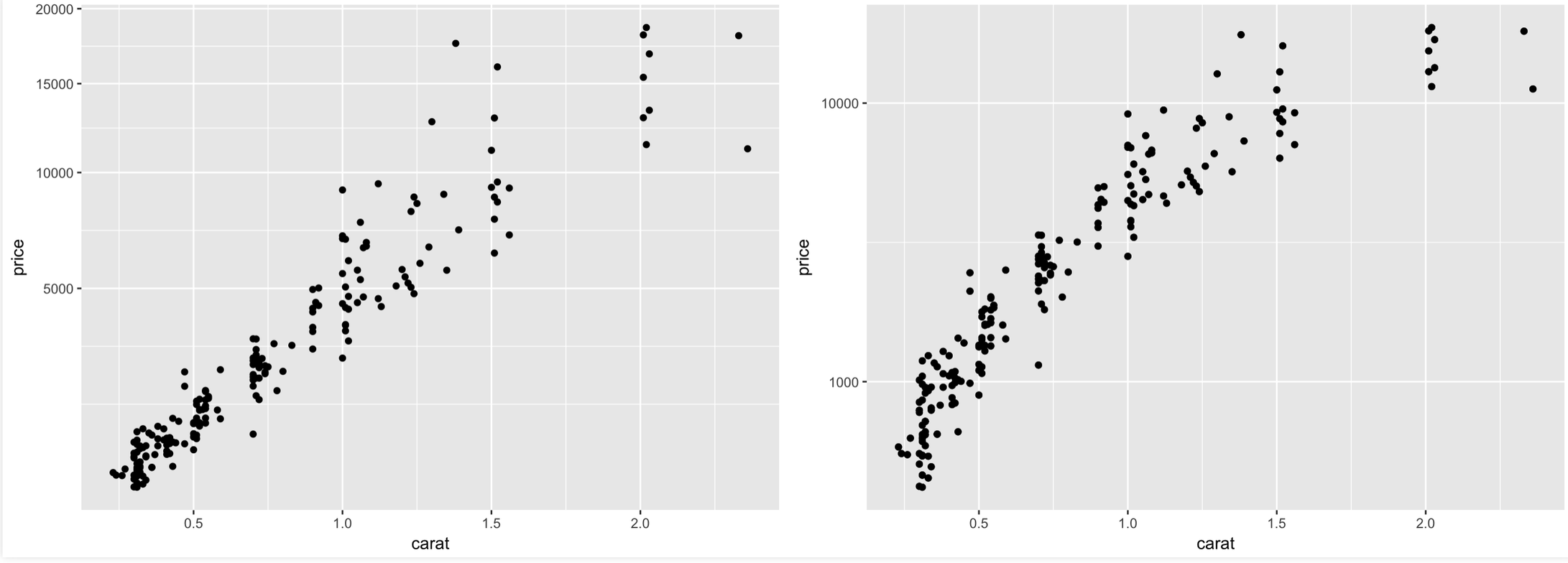
Scales can be modified with functions of the form: `scale_<aesthetic>_<type>()`, e.g. `scale_color_discrete()`.

Try typing `scale_<tab>()` to see a list of scale modification functions.

- **Common Scale Arguments:**
- **name**: the first argument gives the axis or legend title
- **limits**: the minimum and maximum of the scale
- **breaks**: the points along the scale where labels should appear
- **labels**: the labels that appear at each break

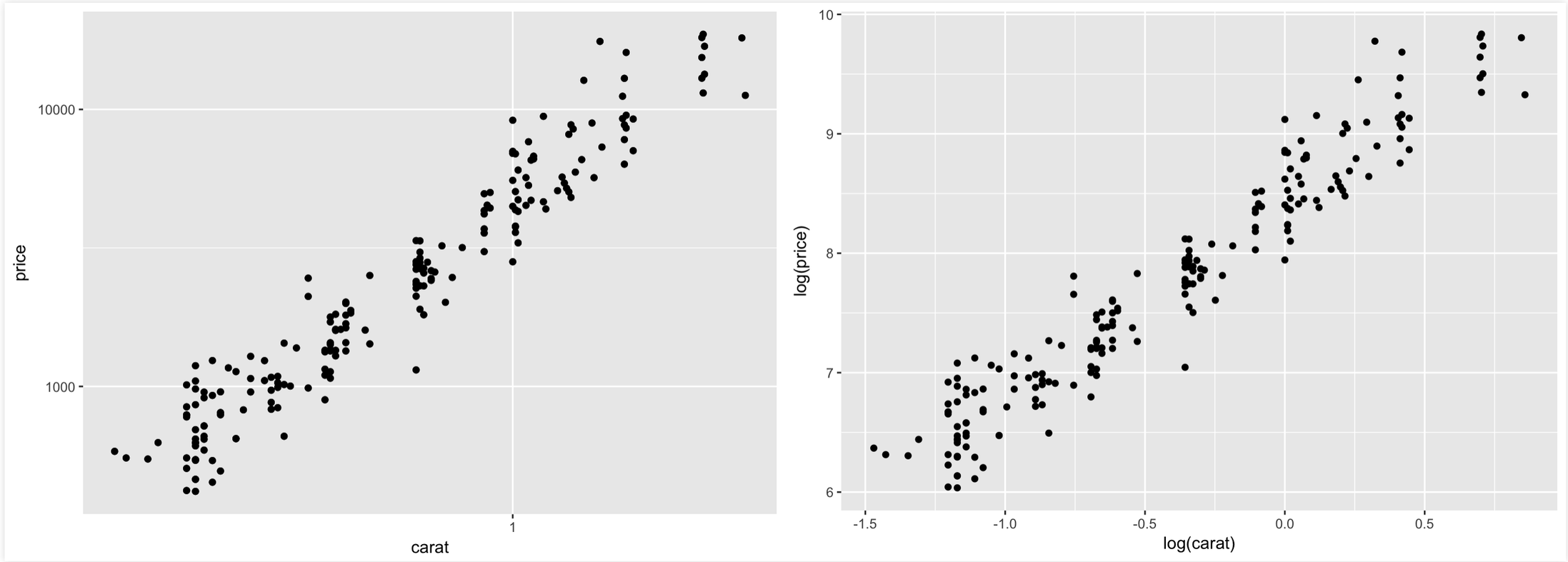
Scale for axes

```
# Square root y-axis transformation
p1 <- ggplot(dsmall, aes(x = carat, y = price)) + geom_point()
psqrt <- p1 + scale_y_sqrt()
# Log base 10 y-axis transformation
plog10 <- p1 + geom_point() + scale_y_log10()
grid.arrange(psqrt, plog10, ncol = 2)
```



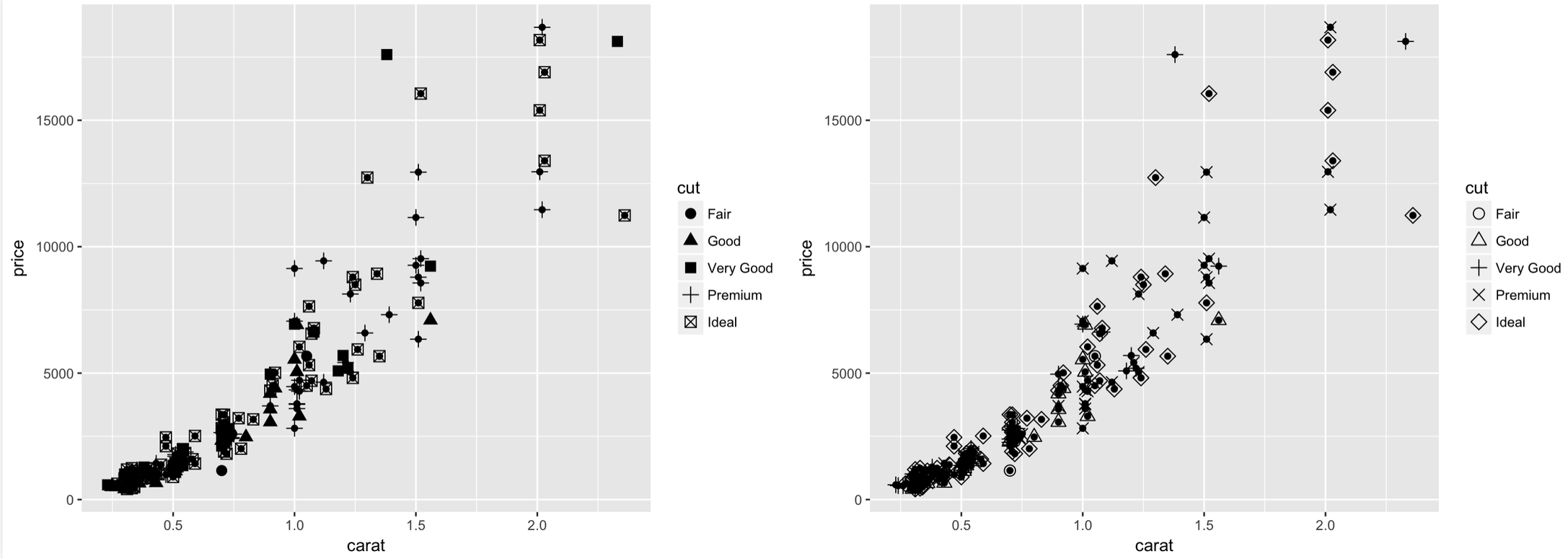
Log base 10 transformation of x and y axes. Note the differences.

```
ploglog1 <- p1 + geom_point() + scale_y_log10() + scale_x_log10()
ploglog2 <- ggplot(dsmall, aes(x = log(carat), y = log(price))) + geom_point()
grid.arrange(ploglog1, ploglog2, ncol = 2)
```



Scale for shapes

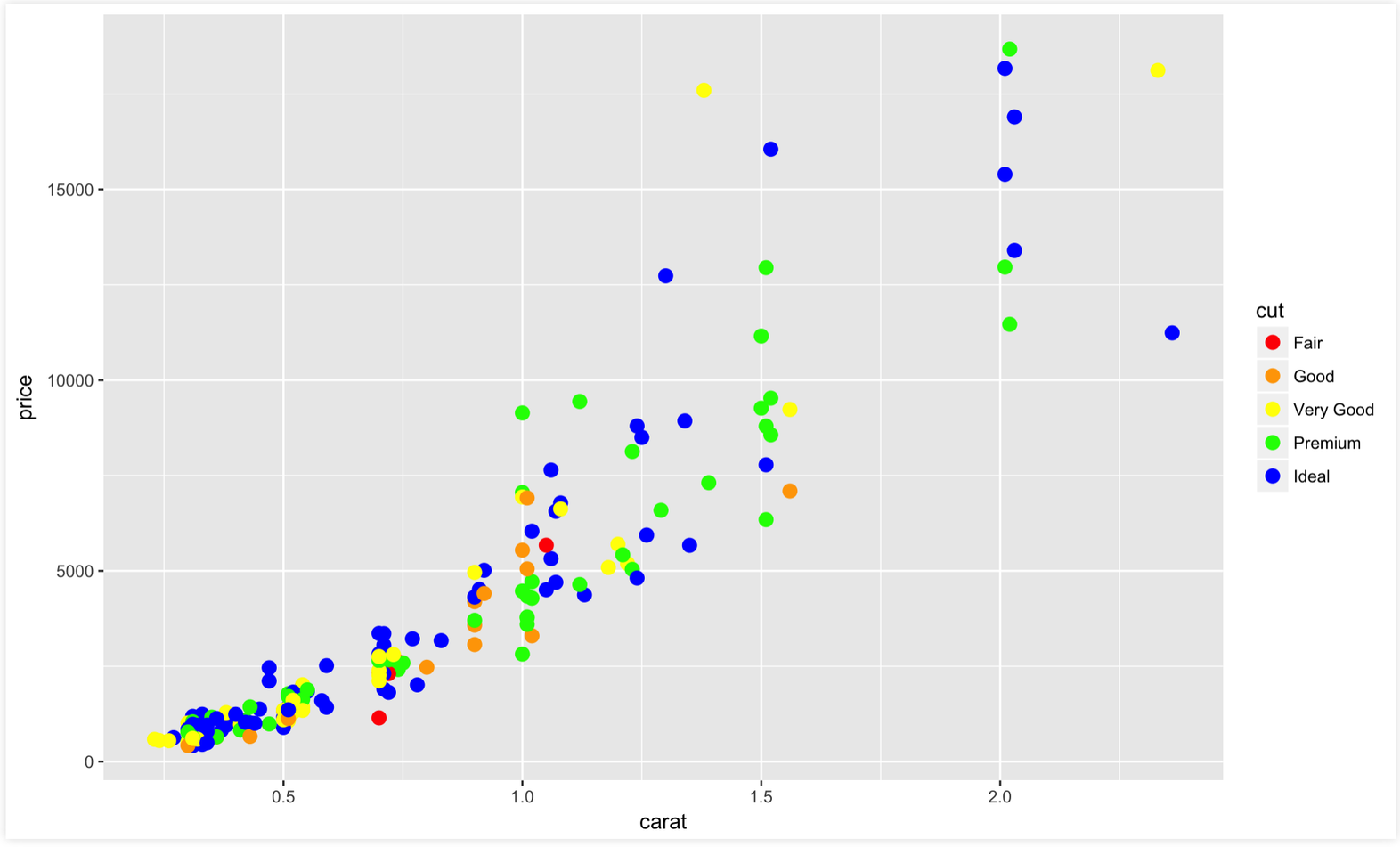
```
p11 <- p1 + geom_point(aes(shape = cut), size = 3)
p12 <- p1 + geom_point(aes(shape = cut), size = 3) + scale_shape_manual(values = c(1:5))
grid.arrange(p11, p12, ncol = 2)
```



Scale for colors

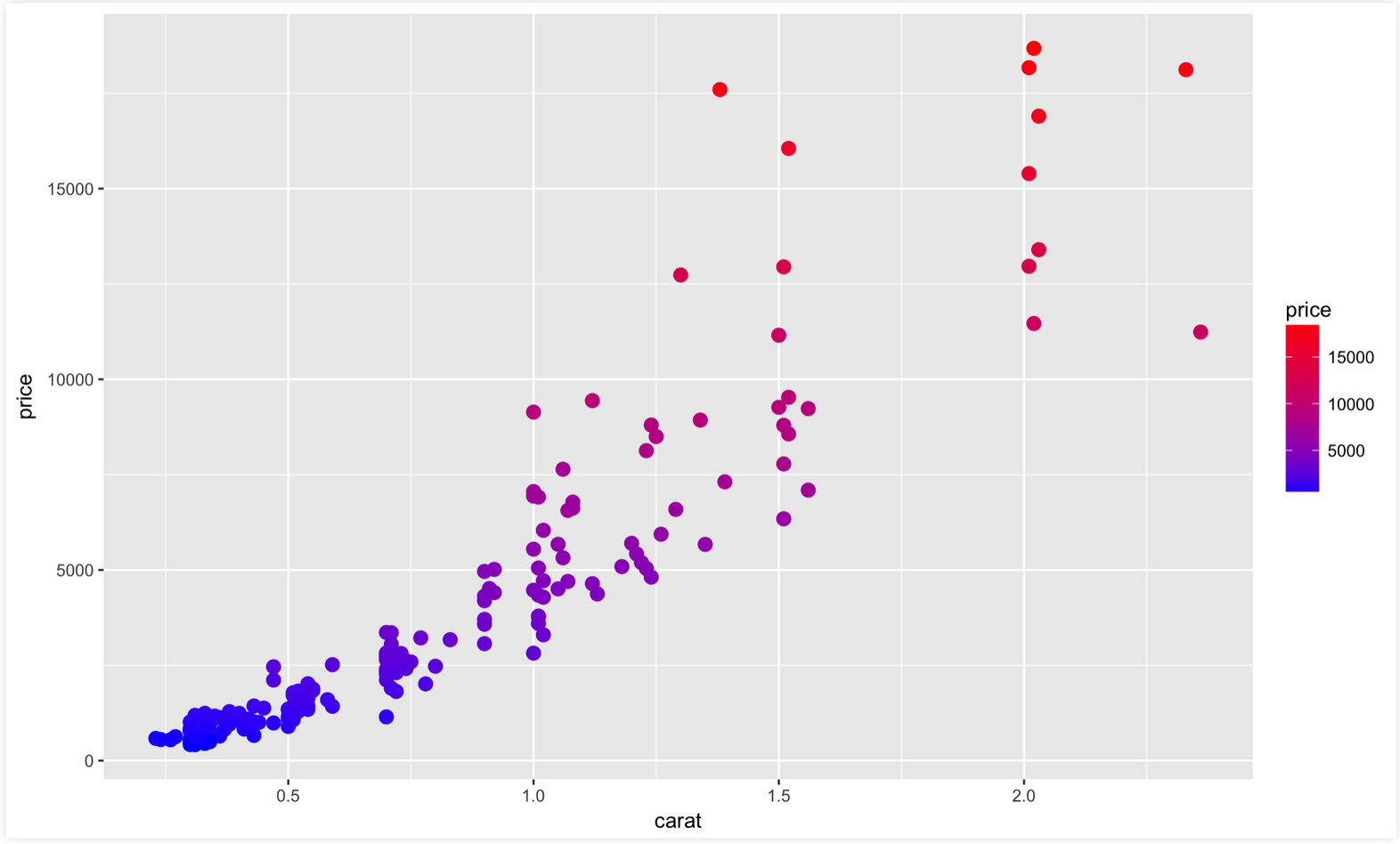
To choose specific colors for **discrete** variables we use `scale_color_manual`:

```
p1 + geom_point(aes(color = cut), size = 3) +
scale_color_manual(values = c("red", "orange", "yellow", "green", "blue"))
```



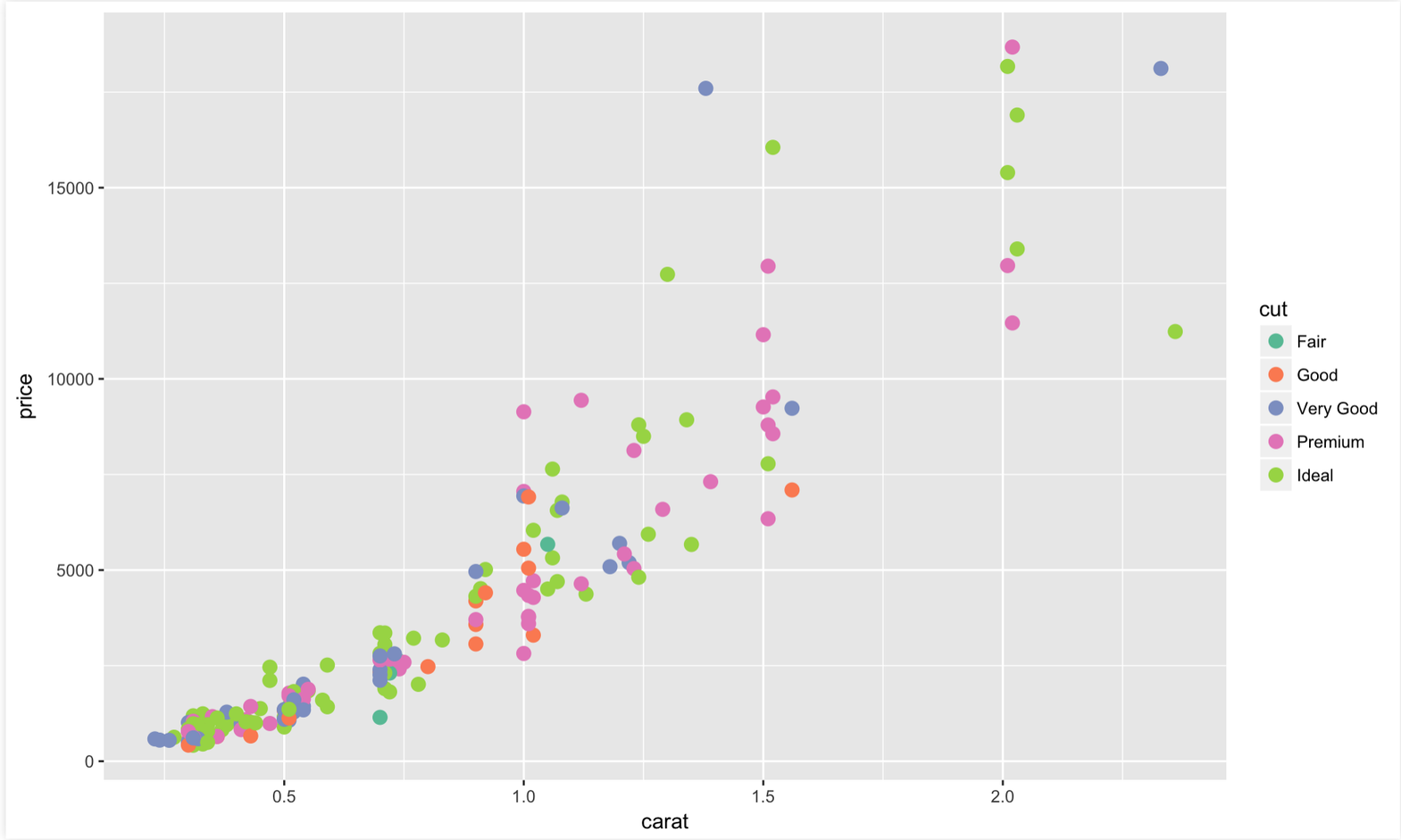
For **continuous** variables we use `scale_color_gradient`, and specify the e of the color spectrum.

```
p1 + geom_point(aes(color = price), size = 3) +
scale_color_gradient(low = "blue", high = "red")
```



`scale_color_brewer` lets you choose **nice color palettes for discrete varia**

```
p1 + geom_point(aes(color = cut), size = 3) +
scale_color_brewer(palette = "Set2")
```

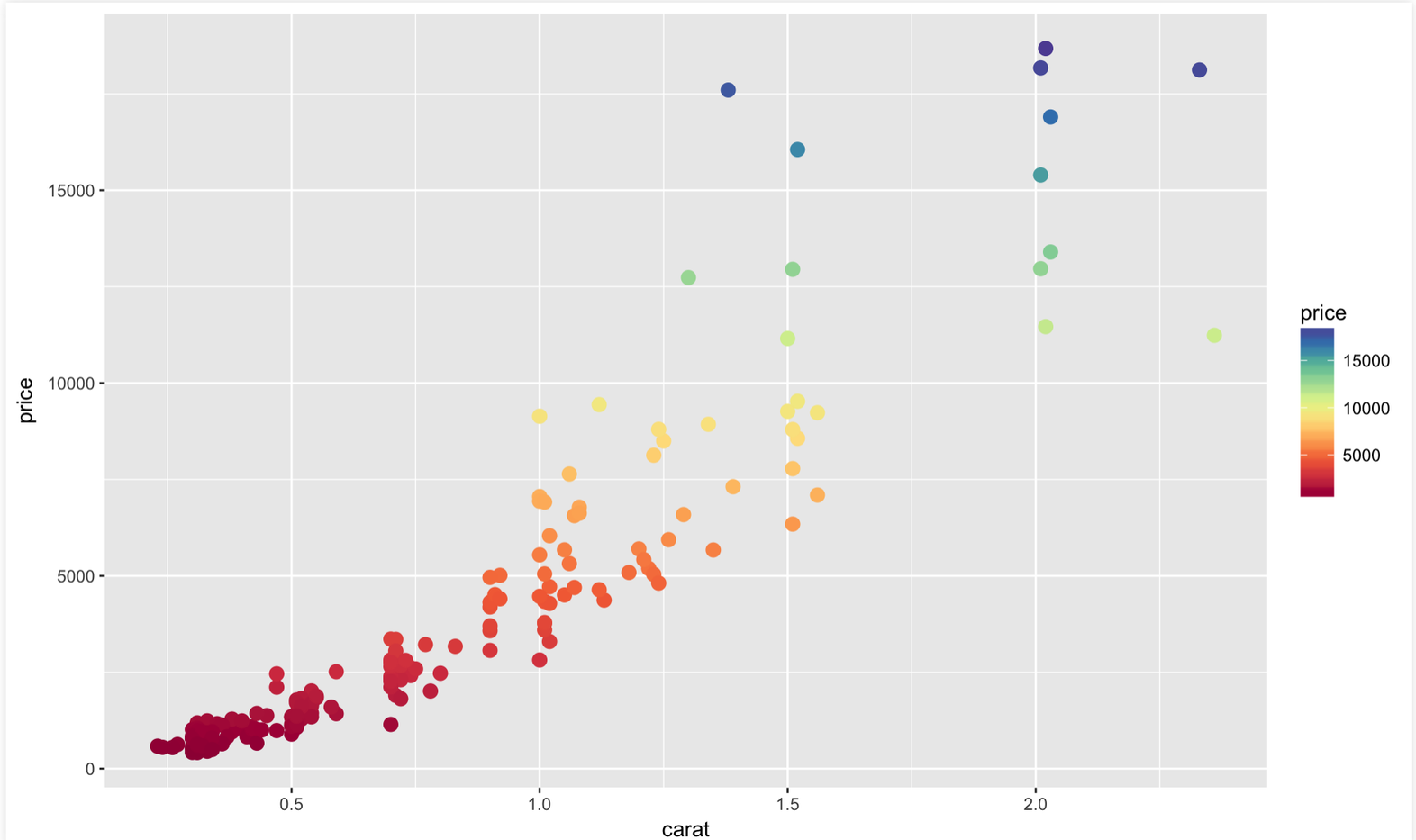


Unfortunately, `scale_color_brewer` doesn't work for continuous variables

```
# scale_color_brewer() does not work with continuous variables
# and will result in an error
p1 + geom_point(aes(shape = price), size = 3) +
scale_color_brewer(palette = "Spectral")
# Error: A continuous variable can not be mapped to shape
```

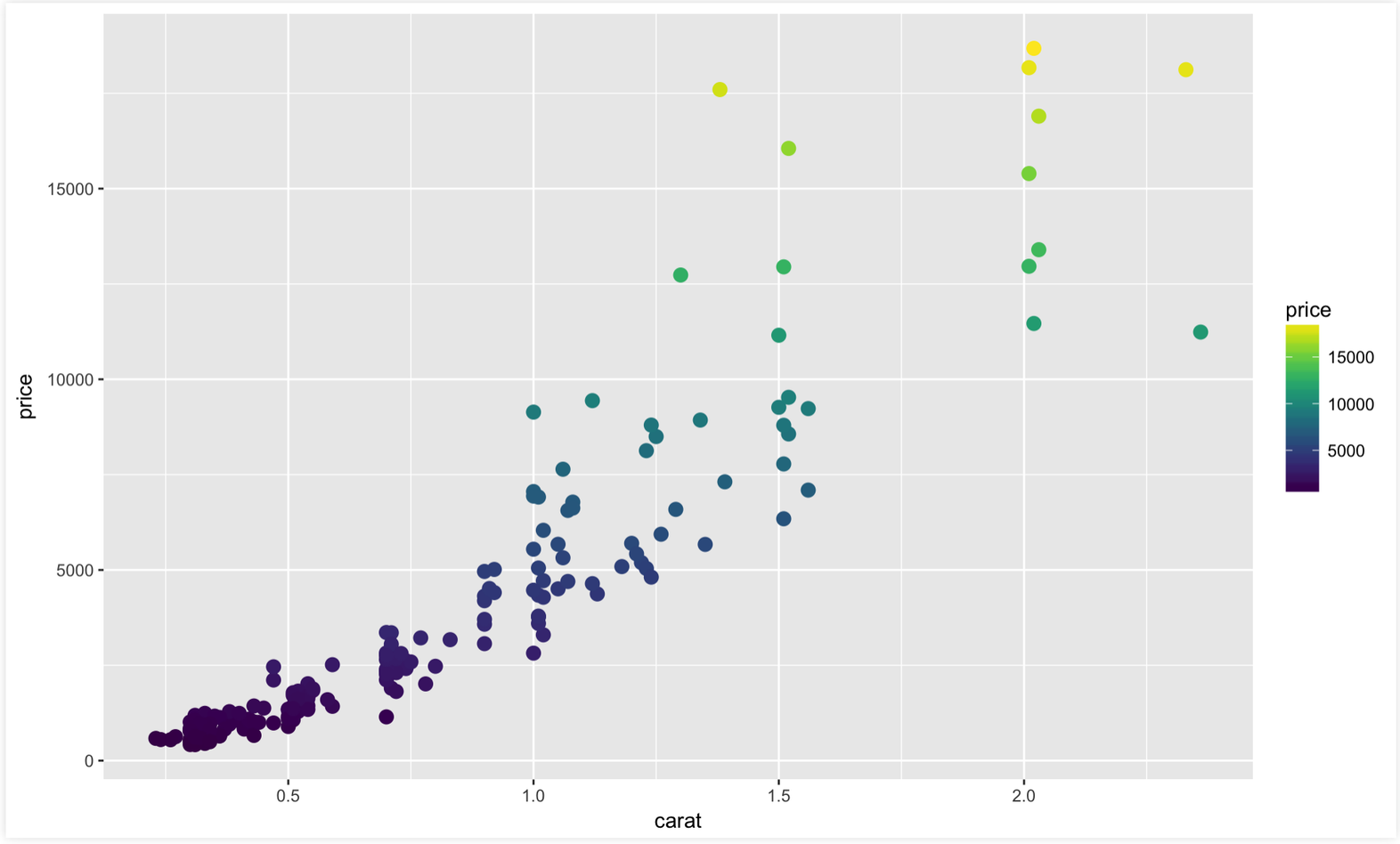
We can get around this issue using the `RColorBrewer` package and `scale_color_gradientn` function, which **interpolates colors** from the brew palettes.

```r
# install.packages("RColorBrewer")
library(RColorBrewer)
p1 + geom_point(aes(color = price), size = 3) +
scale_color_gradientn(colours = brewer.pal(name = "Spectral", n = 10))
```

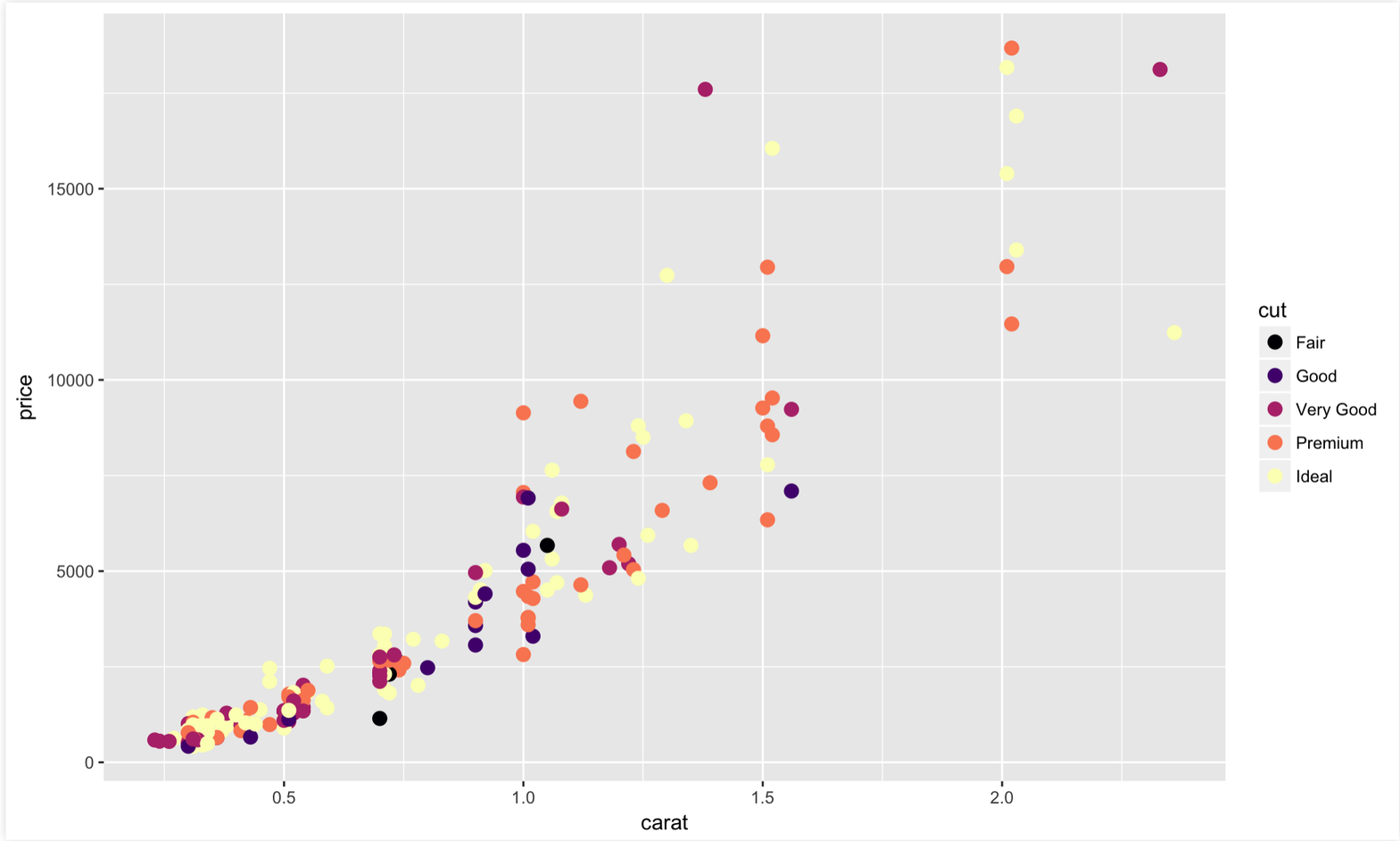


Another popular color scheme package, `viridis`, supports both discrete and continuous variables:

```
# install.packages("viridis")
library(viridis)
p1 + geom_point(aes(color = price), size = 3) + scale_color_viridis()
```



```
p1 + geom_point(aes(color = cut), size = 3) +
scale_color_viridis(discrete = TRUE, option = "magma")
```



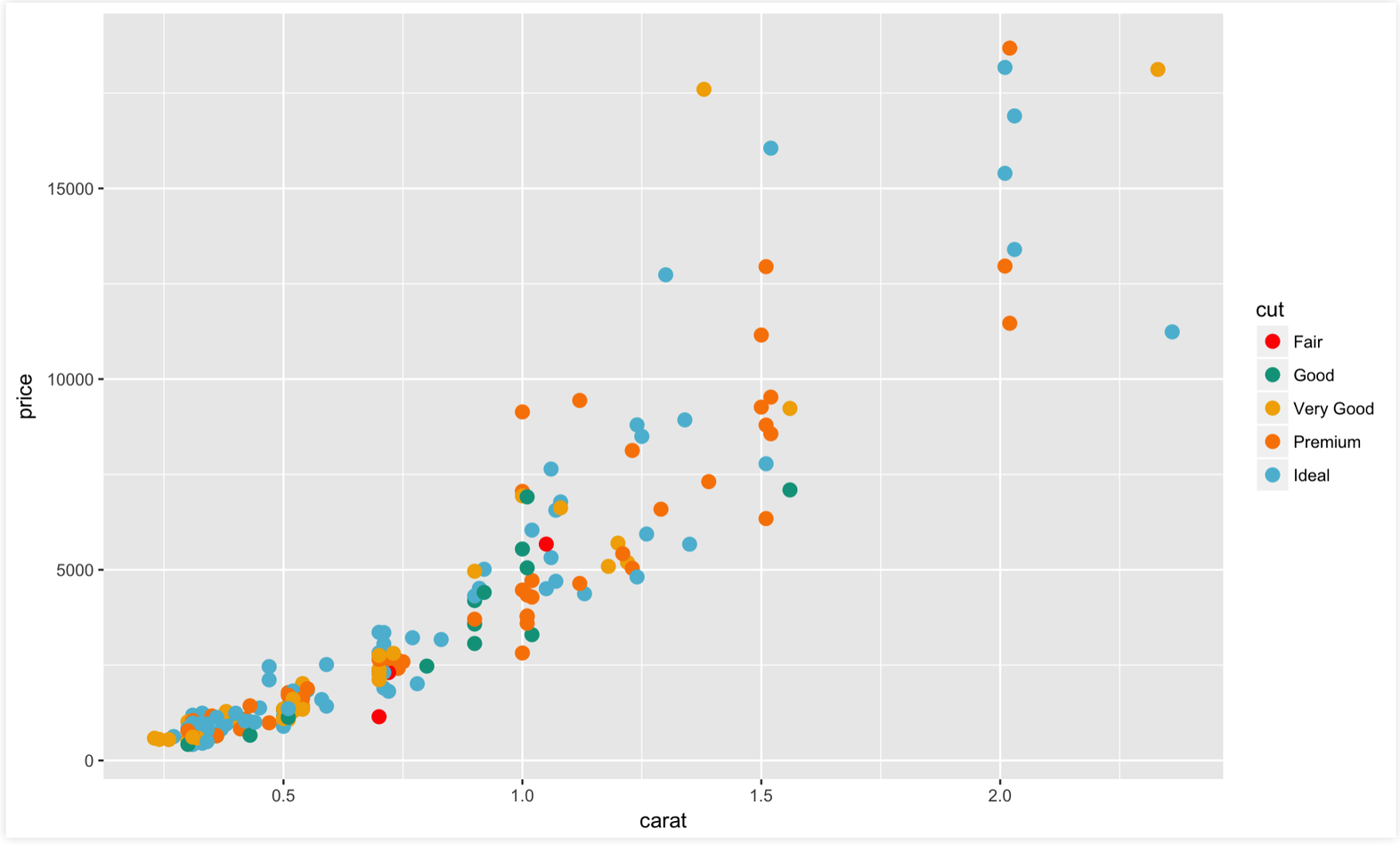
… there are also other unconventional schemes such as, one based on Wes Anderson movies :

```
#install.packages("wesanderson")
library(wesanderson)
names(wes_palettes)
```

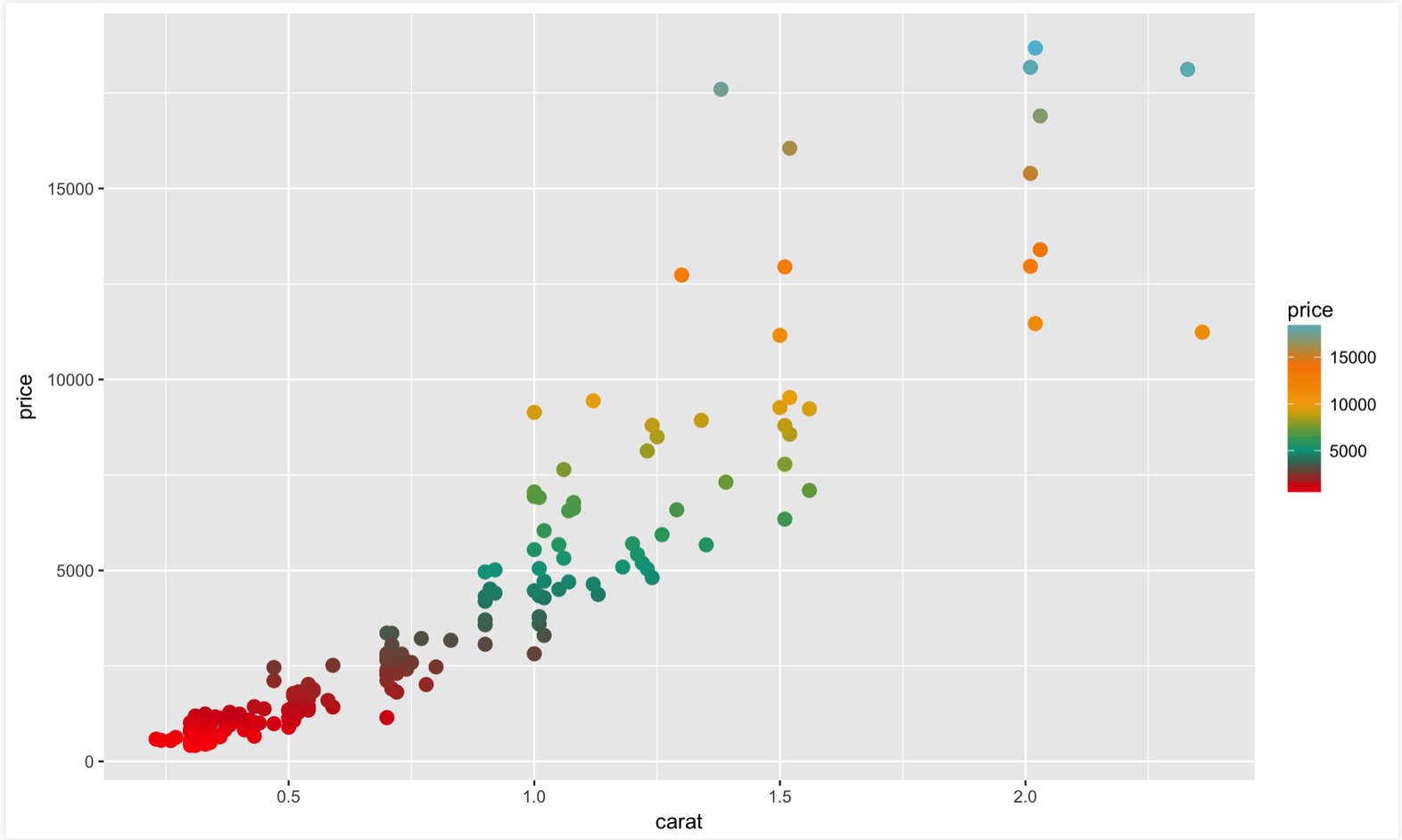
```
## [1] "GrandBudapest" "Moonrise1" "Royal1" "Moonrise2"
## [5] "Cavalcanti" "Royal2" "GrandBudapest2" "Moonrise3"
## [9] "Chevalier" "Zissou" "FantasticFox" "Darjeeling"
## [13] "Rushmore" "BottleRocket" "Darjeeling2"
```

Wes Anderson color palette:

```
# For discrete variables
p1 + geom_point(aes(color = cut), size = 3) +
scale_color_manual(values = wes_palette("Darjeeling", n = 5))
```

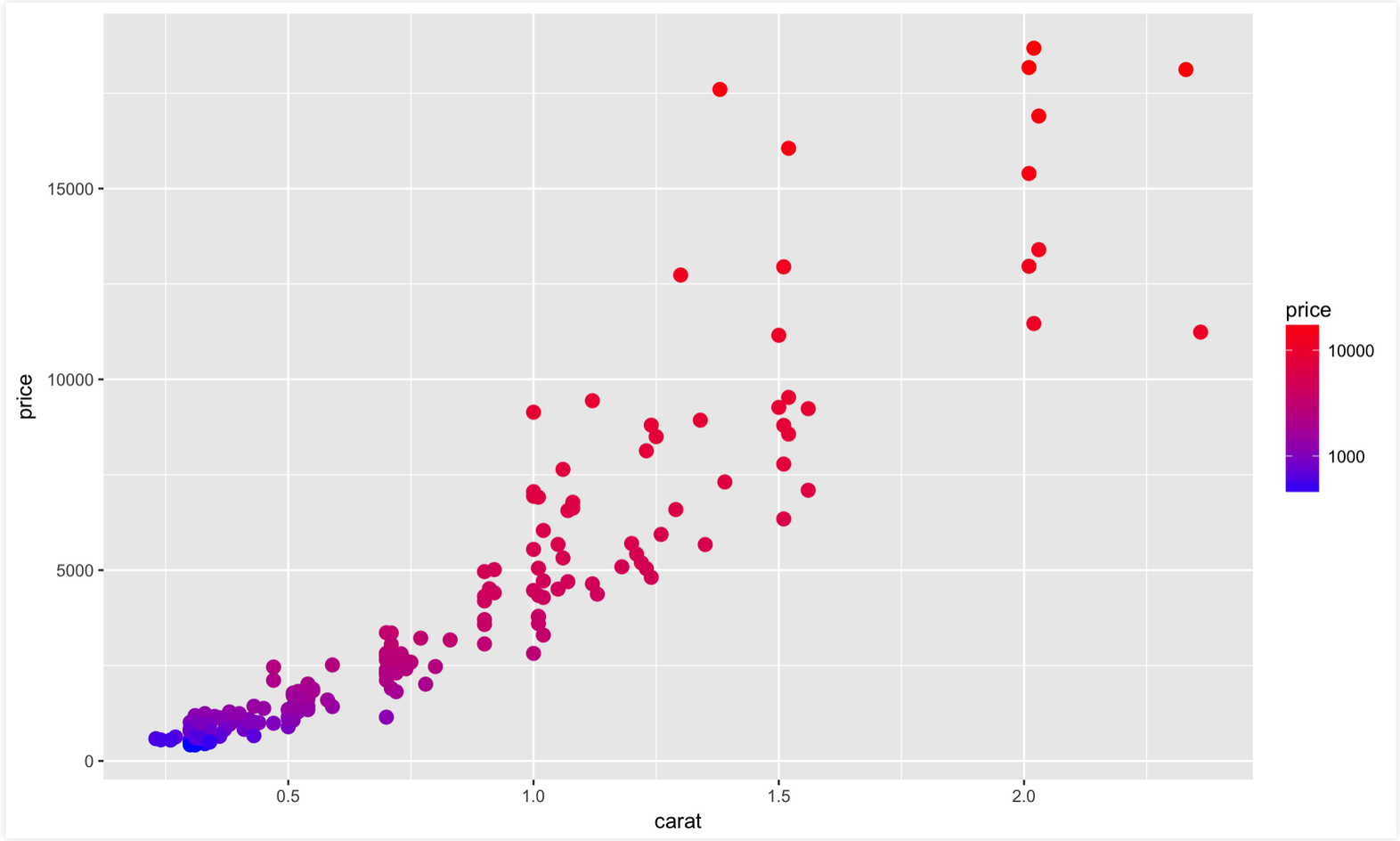


```r
# For continuous variables:
p1 + geom_point(aes(color = price), size = 3) +
scale_color_gradientn(colours = wes_palette("Darjeeling", 100, type = "continuous"))
```



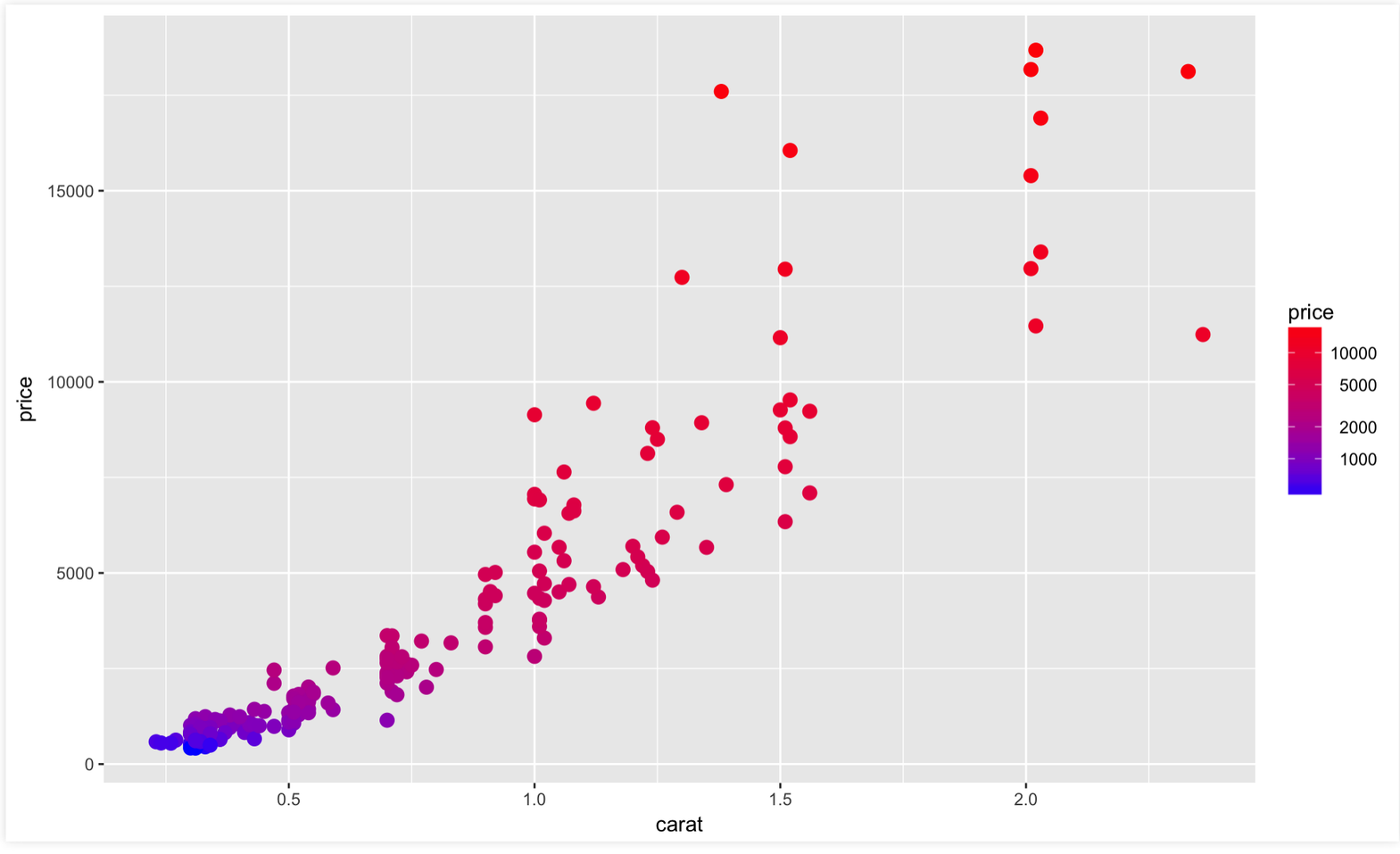
You can also **scale the values of the variable corresponding to color.**

```
p1 + geom_point(aes(color = price), size = 3) +
scale_color_gradient(low = "blue", high = "red", trans = "log10")
```



Or and add your own breaks

```
p1 + geom_point(aes(color = price), size = 3) +
scale_color_gradient(low = "blue", high = "red", trans = "log10",
breaks = c(1000, 2000, 5000, 10000),
labels = c(" 1000", " 2000", " 5000", "10000"))
```



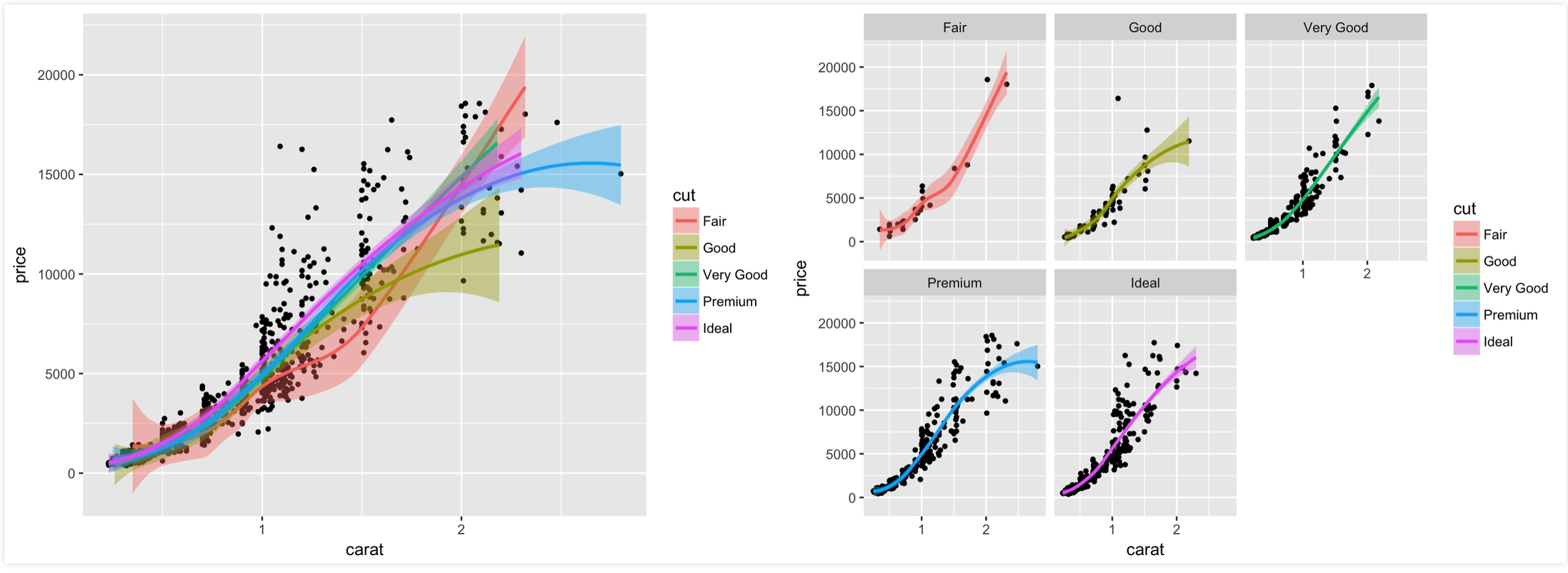
Exercise 3

- Go to back “Lec4_Exercises.Rmd”
- Complete Exercise 3

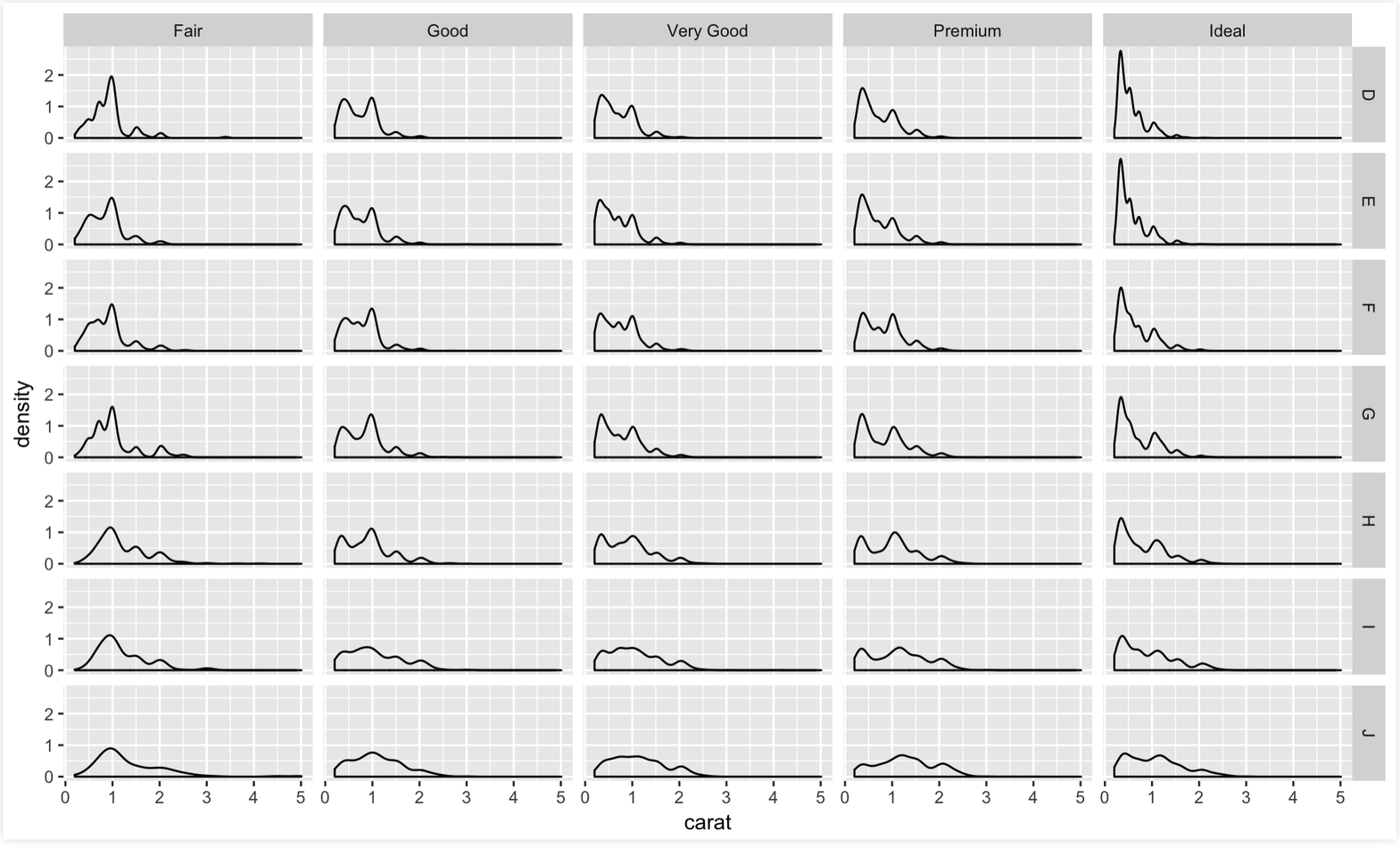
Faceting

Facettng allows you to split up your data by one or more variables and plot the subsets of data together.

```
dsmall <- diamonds[sample(nrow(diamonds), 1000), ]
p0 <- ggplot(data = dsmall, aes(x = carat, y = price)) +geom_point(size = 1) +
geom_smooth(aes(colour = cut, fill = cut))
p1 <- p0 + facet_wrap(~ cut)
grid.arrange(p0, p1, ncol = 2)
```



```
ggplot(diamonds, aes(x = carat)) +
geom_density() +
facet_grid(color ~ cut)
```



Exercise 4,5

- Go to back “Lec4_Exercises.Rmd”
- Complete Exercise 4,5