# Lesson 06 - Creating graphics

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*Last Updated 01-06-2019*

This lesson is a brief excerpt from the [Applied Statistics Notebook].

## Introduction

Visualizing your data is hands down the most important thing you can learn to do. Seeing is critical to understanding. There are two audiences in mind when creating data visualizations:

1. For your eyes only (FYEO). These are quick and dirty plots, without annotation. Meant to be looked at once or twice.
2. To share with others. These need to completely stand on their own. Axes labels, titles, colors as needed, possibly captions.

You will see, and slowly learn, how to add these annotations and how to clean up your graphics to make them sharable. Functions inside the `ggplot2` package automatically does a lot of this work for you. Remember this package has to be loaded prior to being able to access the functions within.

### Student Learning Outcomes

After completing this lesson students will be able to

- create basic data visualizations

### Preparation

Prior to this lesson students should

- Download the [[06_plots_notes.Rmd]] R markdown file and save into your Math130 folder.
- Install the `ggplot2` package.

### The syntax of `ggplot`

The reason we use the functions in `ggplot2` is for consistency in the structure of it's arguments. Here is a bare bones generic plotting function:

```
ggplot(data, aes(x=x, y=y, col=col, fill=fill, group=group)) +  geom_THING()
```

#### Required arguments

- `data`: What data set is this plot using? This is ALWAYS the first argument.
- `aes()`: This is the *aestetics* of the plot. What's varible is on the x, what is on the y? Do you want to color by another variable, perhaps fill some box by the value of another variable, or group by a variable.
- `geom_THING()`: Every plot has to have a geometry. What is the shape of the thing you want to plot? Do you want to plot points - use `geom_points()`. Want to connect those points with a line? Use `geom_lines()`. We will see many varieties in this lab.

### The Diamonds Data

We will use a subset of the `diamonds` dataset that comes with the `ggplot2` package. This dataset contains the prices and other attributes of almost 54,000 diamonds. Review `?diamonds` to learn about the variables we will be using.

```
library(ggplot2)
data("diamonds")
set.seed(1410) # Make the sample reproducible
dsmall <- diamonds[sample(nrow(diamonds), 1000), ]
```

---

## Univariate (One Variable)

### Categorical variables

Both Nominal and Ordinal data types can be visualized using the same methods: tables, barcharts and pie charts.

#### Tables

Tables are the most common way to get summary statistics of a categorical variable. The `table()` function produces a frequency table, where each entry represents the number of records in the data set holding the corresponding labeled value.

```
table(dsmall$cut)
```

```
##
##      Fair      Good Very Good   Premium     Ideal
##        27        83       226       277       387
```

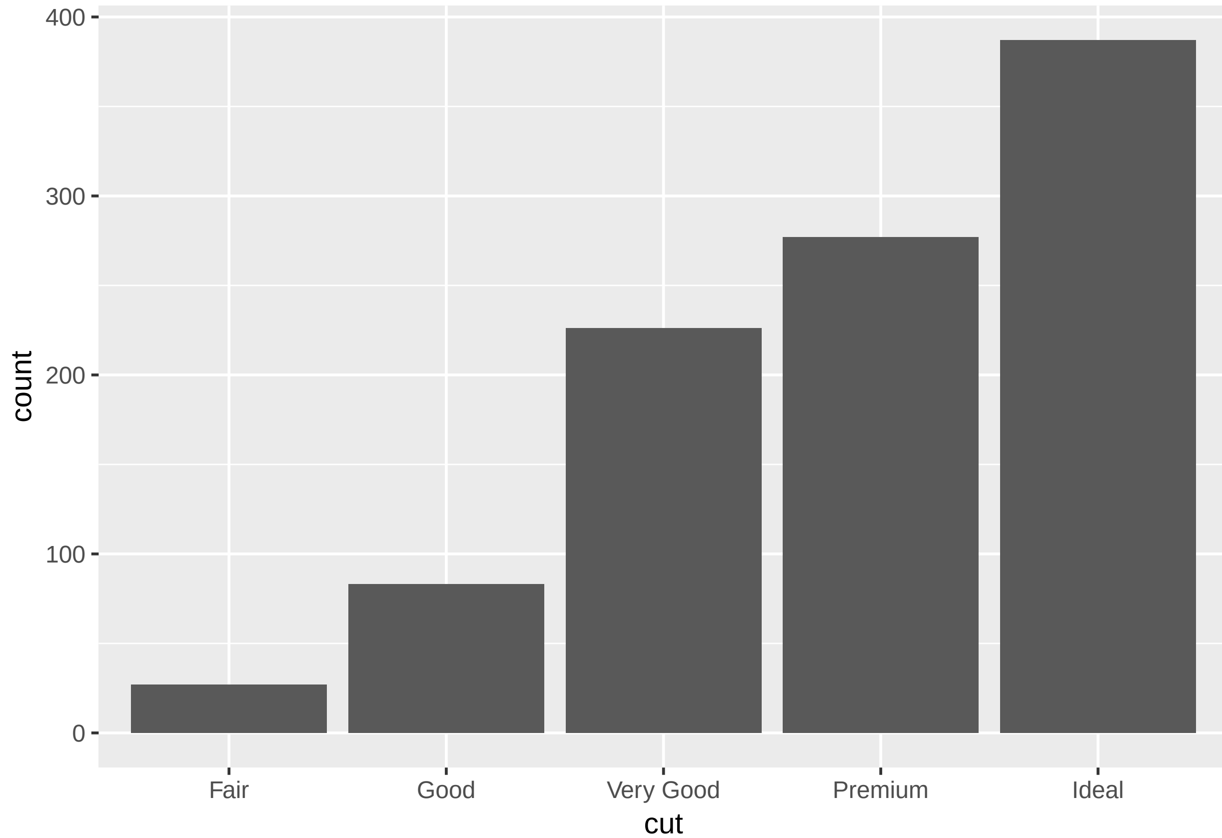
There are 27 Fair quality diamonds, 83 good quality and 387 Ideal quality diamonds in this sample.

#### Barcharts / Barplots

A Barchart or barplot takes these frequencies, and draws bars along the X-axis where the height of the bars is determined by the frequencies seen in the table.

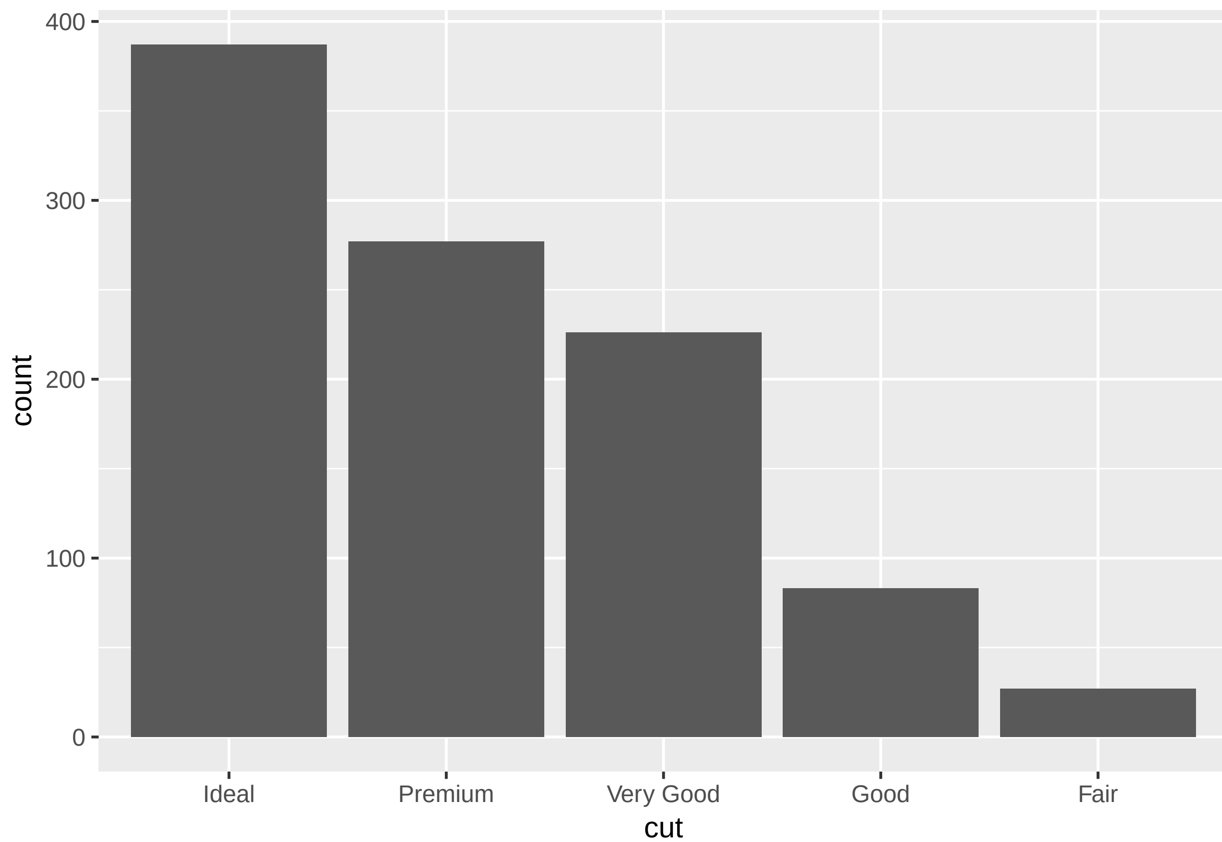
The geometry needed to draw a barchart in ggplot is `geom_bar()`.

```
ggplot(dsmall, aes(x=cut)) + geom_bar()
```




We can reorder these levels on the fly. Here i'm using `forcats` but that's only one option.

```
ggplot(dsmall, aes(x=forcats::fct_infreq(cut))) + geom_bar() + xlab("cut")
```




## Continuous variable

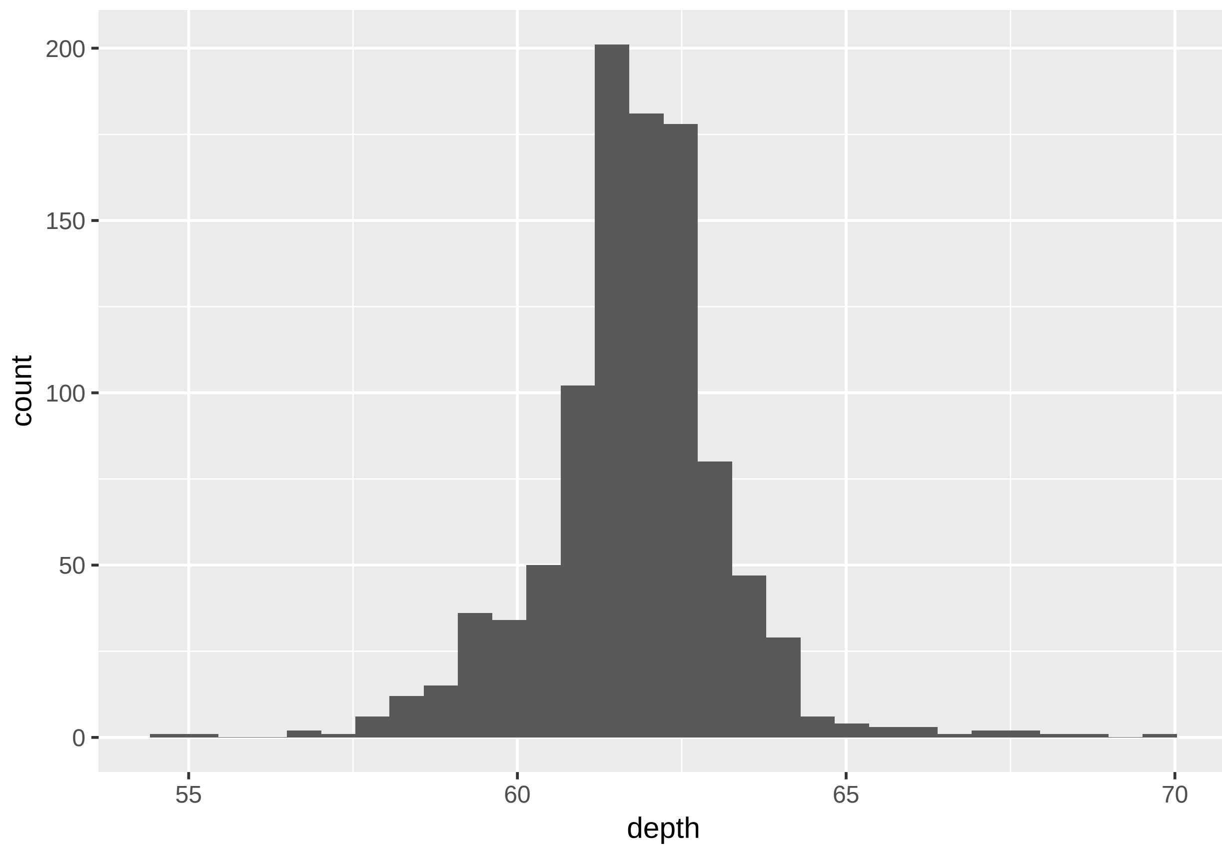
The price, carat, and depth of the diamonds are all continuous variables.

### Histograms

Rather than showing the value of each observation, we prefer to think of the value as belonging to a *bin*. The height of the bars in a histogram display the frequency of values that fall into those of those bins.

Since the x-axis is continuous the bars touch. This is unlike the barchart that has a categorical x-axis, and vertical bars that are separated.

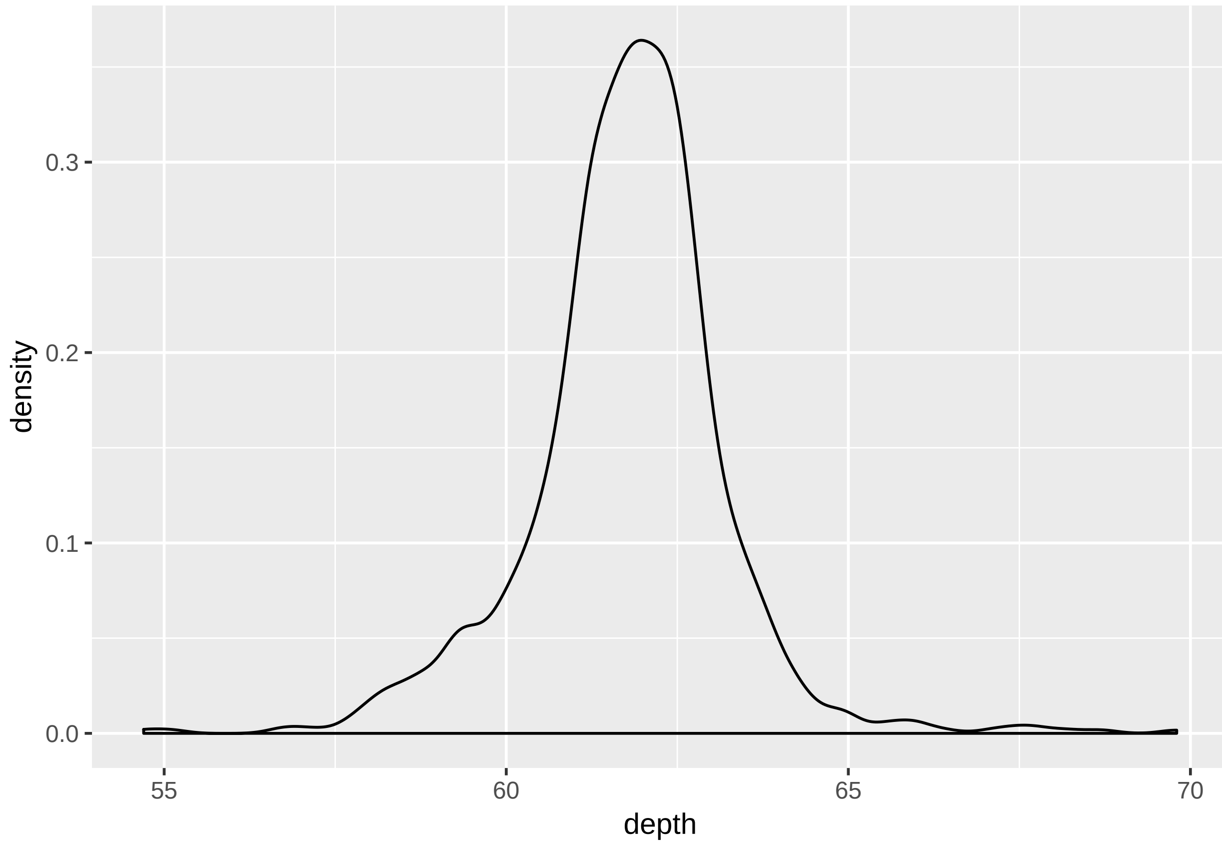
```
ggplot(dsmall, aes(x=depth)) + geom_histogram()
```




**Density plots**

To get a better idea of the true shape of the distribution we can “smooth” out the bins and create what’s called a `density` plot or curve. Notice that the shape of this distribution curve is much more… “wigglier” than the histogram may have implied.

```
ggplot(dsmall, aes(x=depth)) + geom_density()
```

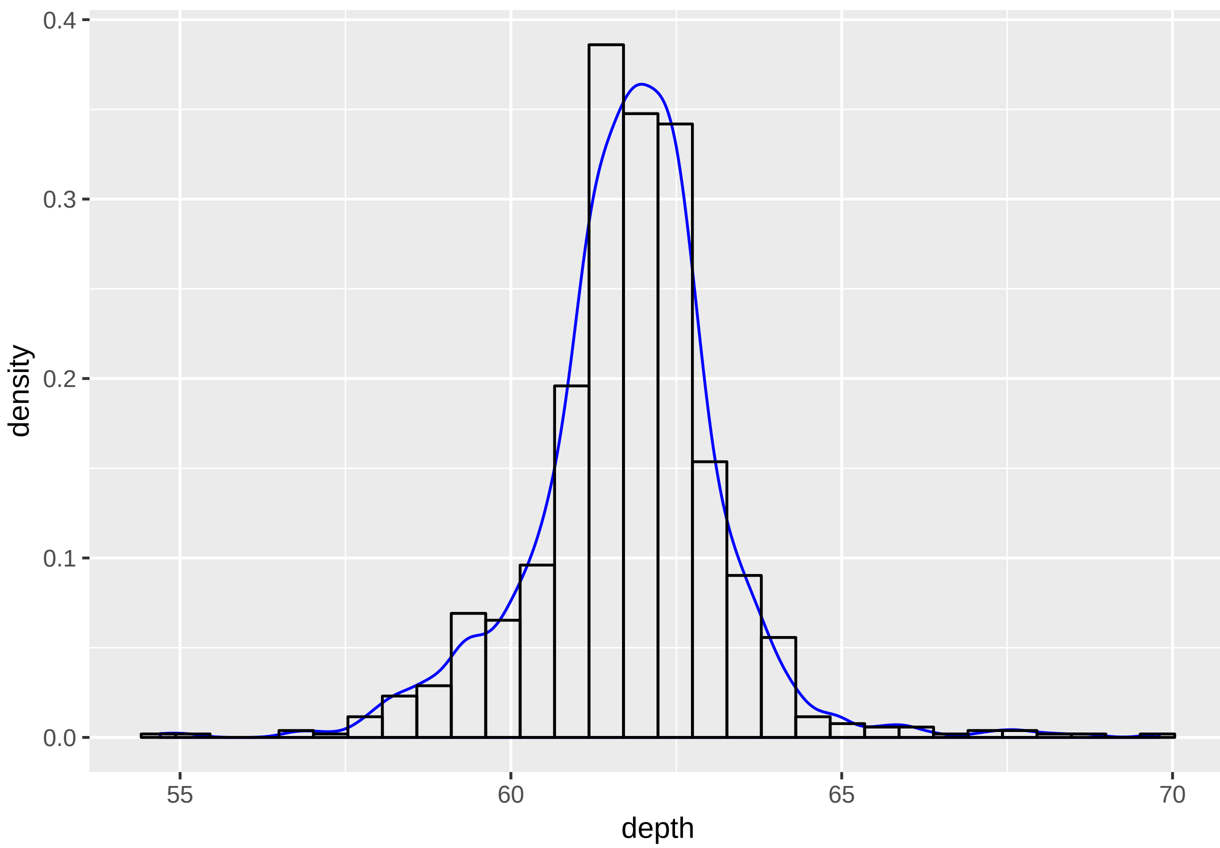



**Histograms + density**

Often is is more helpful to have the density (or kernal density) plot *on top of* a histogram plot.

- The syntax starts the same, we'll add a new geom, `geom_density` and color the line blue.
- Then we add the histogram geom using `geom_histogram` but must specify that the y axis should be on the density, not frequency, scale.
  - Note that this has to go inside the aestetic statement `aes()`.
- I'm also going to get rid of the fill by using `NA` so the colored bars don't plot over the density line.

```
ggplot(dsmall, aes(x=depth)) + geom_density(col="blue") +
  geom_histogram(aes(y=..density..), colour="black", fill=NA)
```

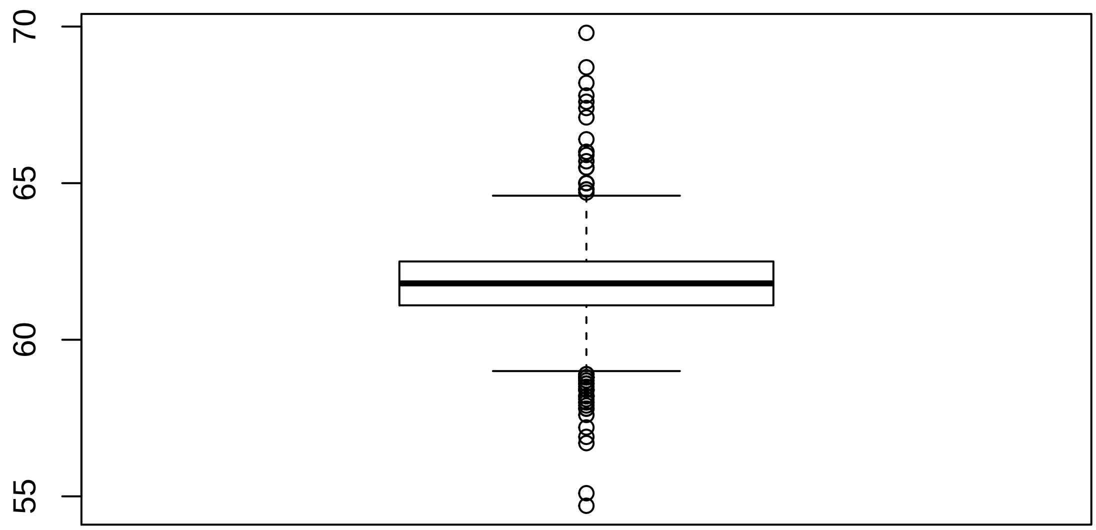



**Boxplots**

Another very common way to visualize the distribution of a continuous variable is using a boxplot. Boxplots are useful for quickly identifying where the bulk of your data lie. R specifically draws a "modified" boxplot where values that are considered outliers are plotted as dots.

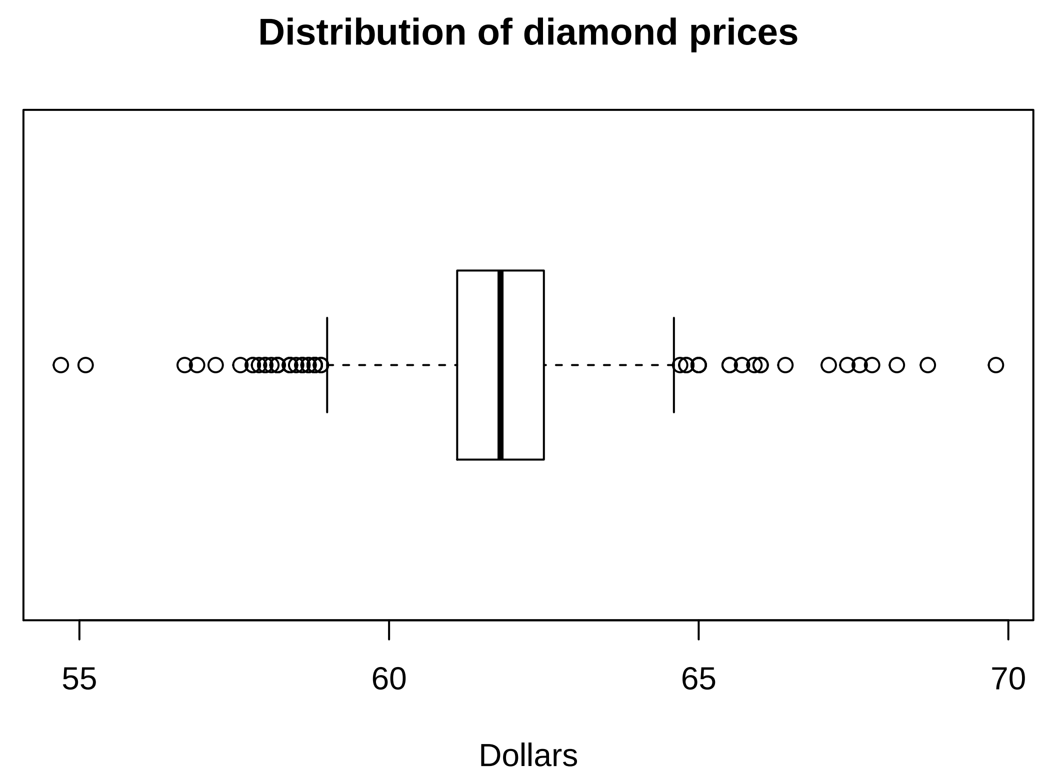
**base**

```
boxplot(dsmall$depth)
```




Notice that the only axis labeled is the y=axis. Like a dotplot the x axis, or "width", of the boxplot is meaningless here. We can make the axis more readable by flipping the plot on it's side.

```
boxplot(dsmall$depth, horizontal = TRUE, main="Distribution of diamond prices", xlab="Dollars")
```




Horizontal is a bit easier to read in my opinion.

What about ggplot? ggplot doesn't really like to do univariate boxplots. You'll see those later when we create one boxplot per group.

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# Bivariate (Two Variables)

## Categorical v. Categorical

### Two-way Tables

Cross-tabs, cross-tabulations and two-way tables (all the same thing, different names) can be created by using the `table()` function.

### Frequency table

The frequency table is constructed using the `table()` function.

```
table(dsmall$cut, dsmall$color)
```

```
##
##              D  E  F  G  H  I  J
##   Fair       4  5  4  3 10  1  0
##   Good      13  6 19 16 10 13  6
```

```
##   Very Good 30 60 37 50 26 18  5
##   Premium   39 42 40 55 46 40 15
##   Ideal     63 69 52 77 65 40 21
```

There are 4 Fair diamonds with color D, and 21 Ideal quality diamonds with color J.

### Cell proportions

Wrapping `prop.table()` around a table gives you the **cell** proportions.

```
table(dsmall$cut, dsmall$color) %>% prop.table()
```

```
##
##                 D     E     F     G     H     I     J
##   Fair      0.004 0.005 0.004 0.003 0.010 0.001 0.000
##   Good      0.013 0.006 0.019 0.016 0.010 0.013 0.006
##   Very Good 0.030 0.060 0.037 0.050 0.026 0.018 0.005
##   Premium   0.039 0.042 0.040 0.055 0.046 0.040 0.015
##   Ideal     0.063 0.069 0.052 0.077 0.065 0.040 0.021
```

0.4% of all diamonds are D color and Fair cut, 2.1% are J color and Ideal cut.

### Row proportions

To get the **row** proportions, you specify `margin=1`. The percentages now add up to 1 across the rows.

```
table(dsmall$cut, dsmall$color) %>% prop.table(margin=1) %>% round(3)
```

```
##
##                 D     E     F     G     H     I     J
##   Fair      0.148 0.185 0.148 0.111 0.370 0.037 0.000
##   Good      0.157 0.072 0.229 0.193 0.120 0.157 0.072
##   Very Good 0.133 0.265 0.164 0.221 0.115 0.080 0.022
##   Premium   0.141 0.152 0.144 0.199 0.166 0.144 0.054
##   Ideal     0.163 0.178 0.134 0.199 0.168 0.103 0.054
```

14.8% of all Fair quality diamonds are color D. 5.4% of all Ideal quality diamonds have color J.

### Column proportions

To get the **column** proportions, you specify `margin=2`. The percentages now add up to 1 down the columns.

```
table(dsmall$cut, dsmall$color) %>% prop.table(margin=2) %>% round(3)
```

```
##
##                 D     E     F     G     H     I     J
##   Fair      0.027 0.027 0.026 0.015 0.064 0.009 0.000
##   Good      0.087 0.033 0.125 0.080 0.064 0.116 0.128
##   Very Good 0.201 0.330 0.243 0.249 0.166 0.161 0.106
##   Premium   0.262 0.231 0.263 0.274 0.293 0.357 0.319
##   Ideal     0.423 0.379 0.342 0.383 0.414 0.357 0.447
```

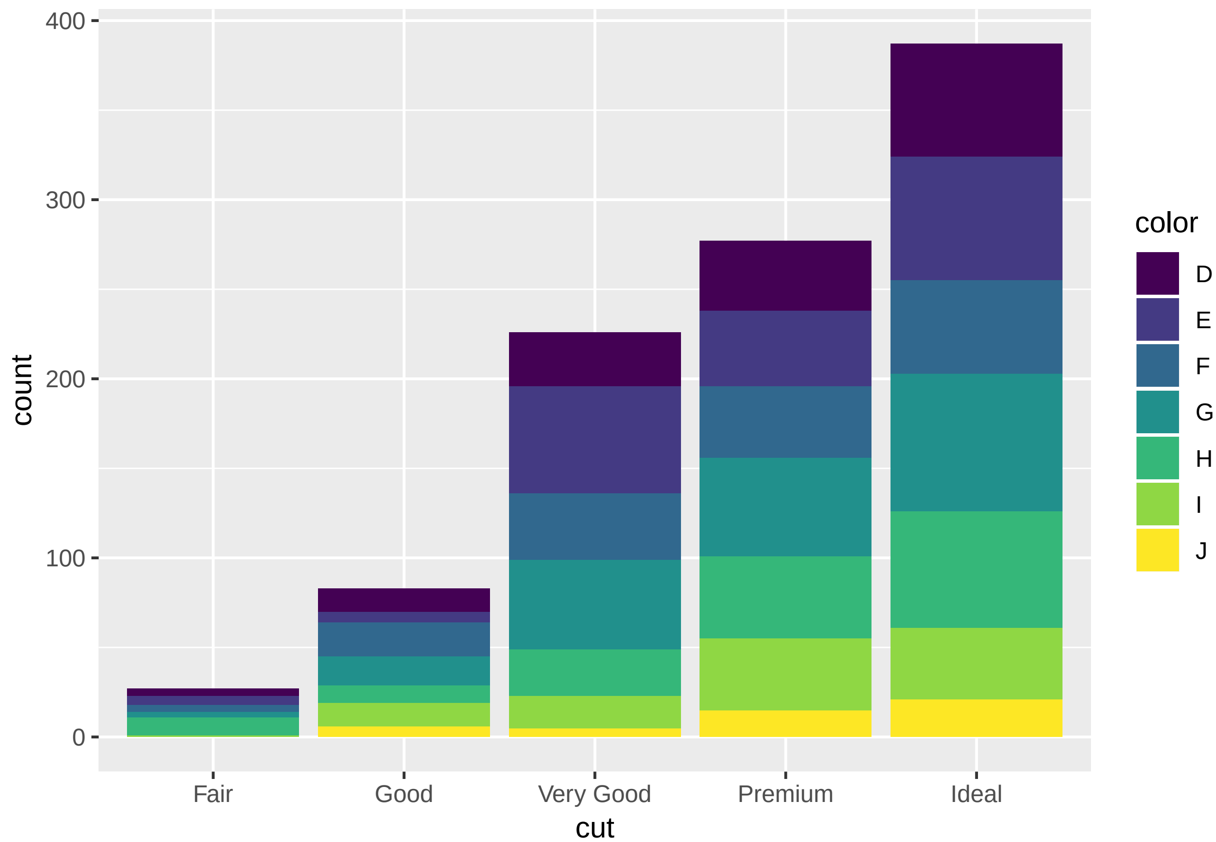
2.7% of all D color diamonds are of Fair quality. 44.7% of all J color diamonds are of Ideal quality.

### Grouped bar charts

To compare proprtions of one categorical variable within the same level of another, is to use grouped barcharts.

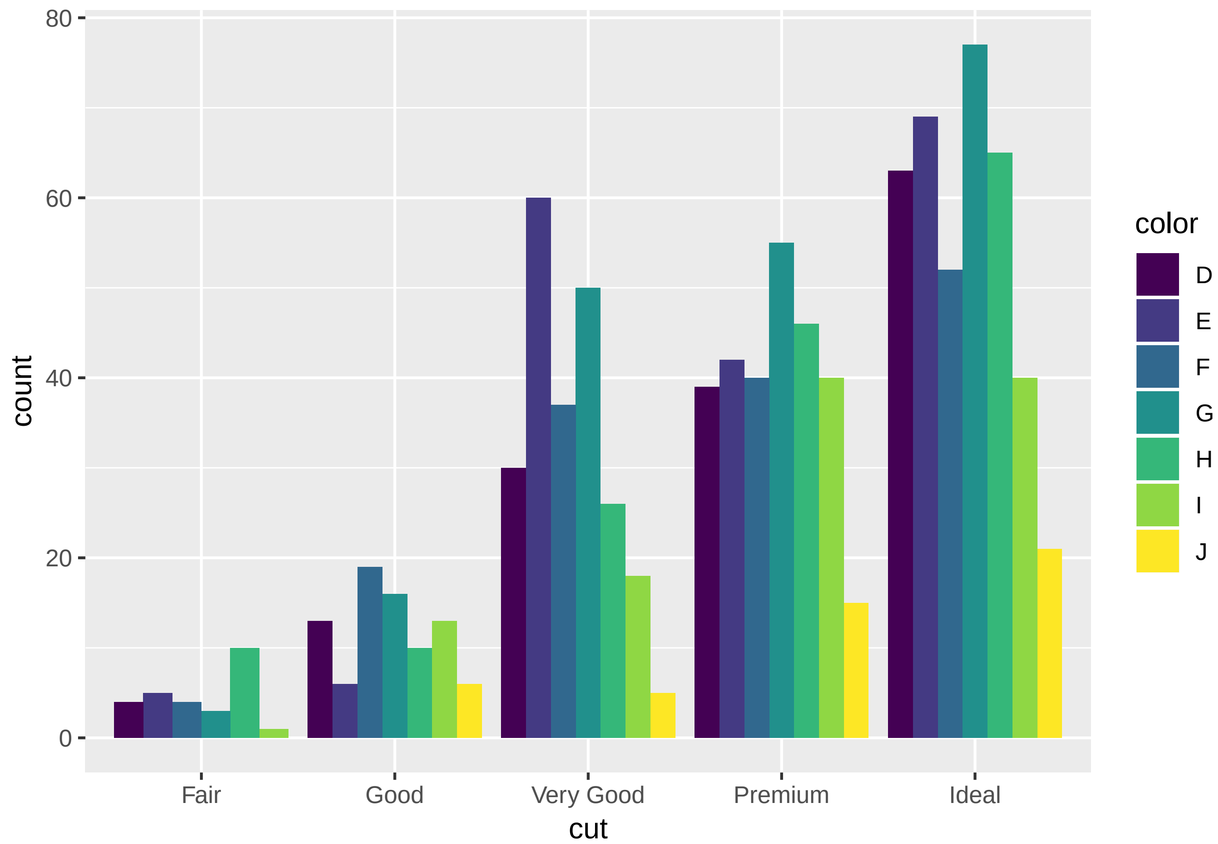
Plot the cut on the x axis, but then `fill` using the second categorical variable. This has the effect of visualizing the **row** percents from the table above. The percent of color, within each type of cut.

```
ggplot(dsmall, aes(x=cut, fill=color)) + geom_bar()
```



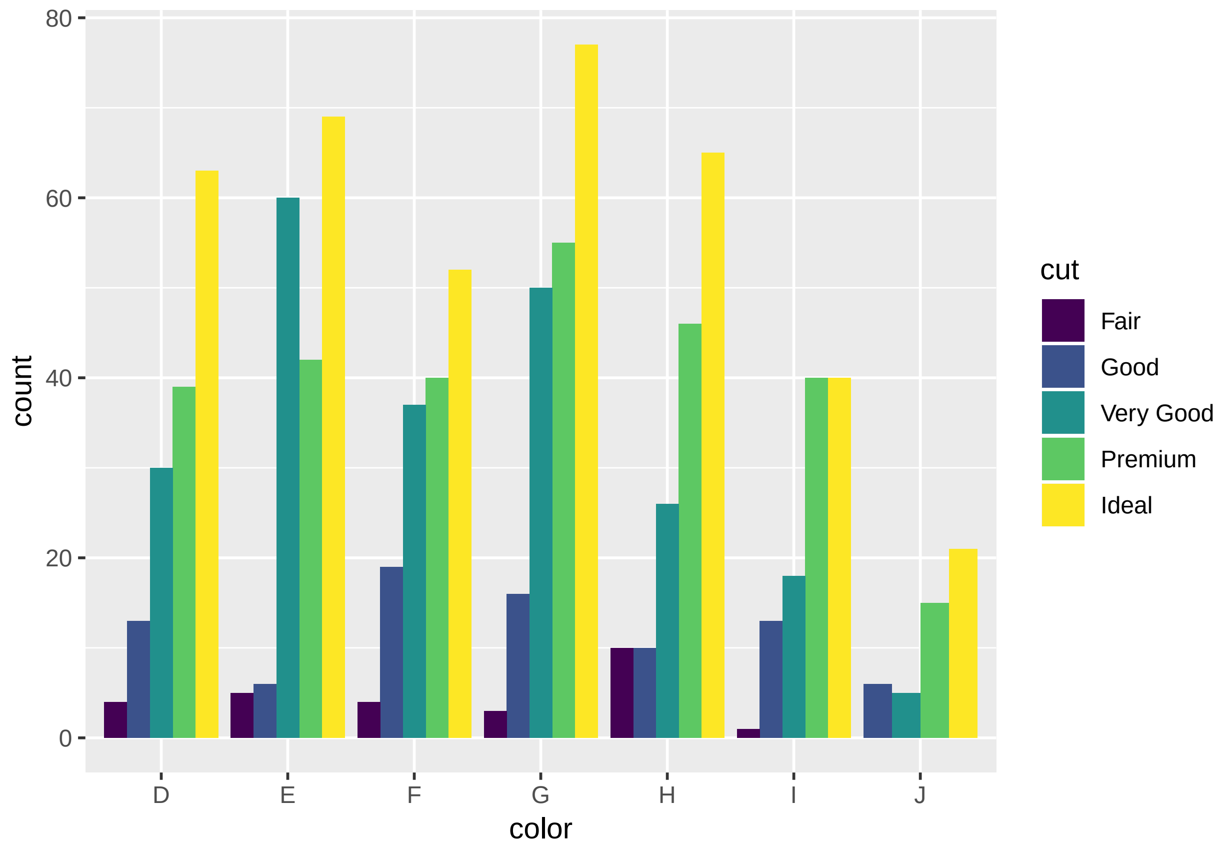

The default is a stacked barchart. So add the argument `position=dodge` inside the `geom_bar` layer to put the bars side by side.

```
ggplot(dsmall, aes(x=cut, fill=color)) + geom_bar(position = "dodge")
```




And look, an automatic legend. What if I wanted to better compare cut within color group? This is the **column** percentages. Just switch which variable is the x axis and which one is used to fill the colors!

```
ggplot(dsmall, aes(x=color, fill=cut)) + geom_bar(position = "dodge")
```




And this easy change is why we love `ggplot2`.

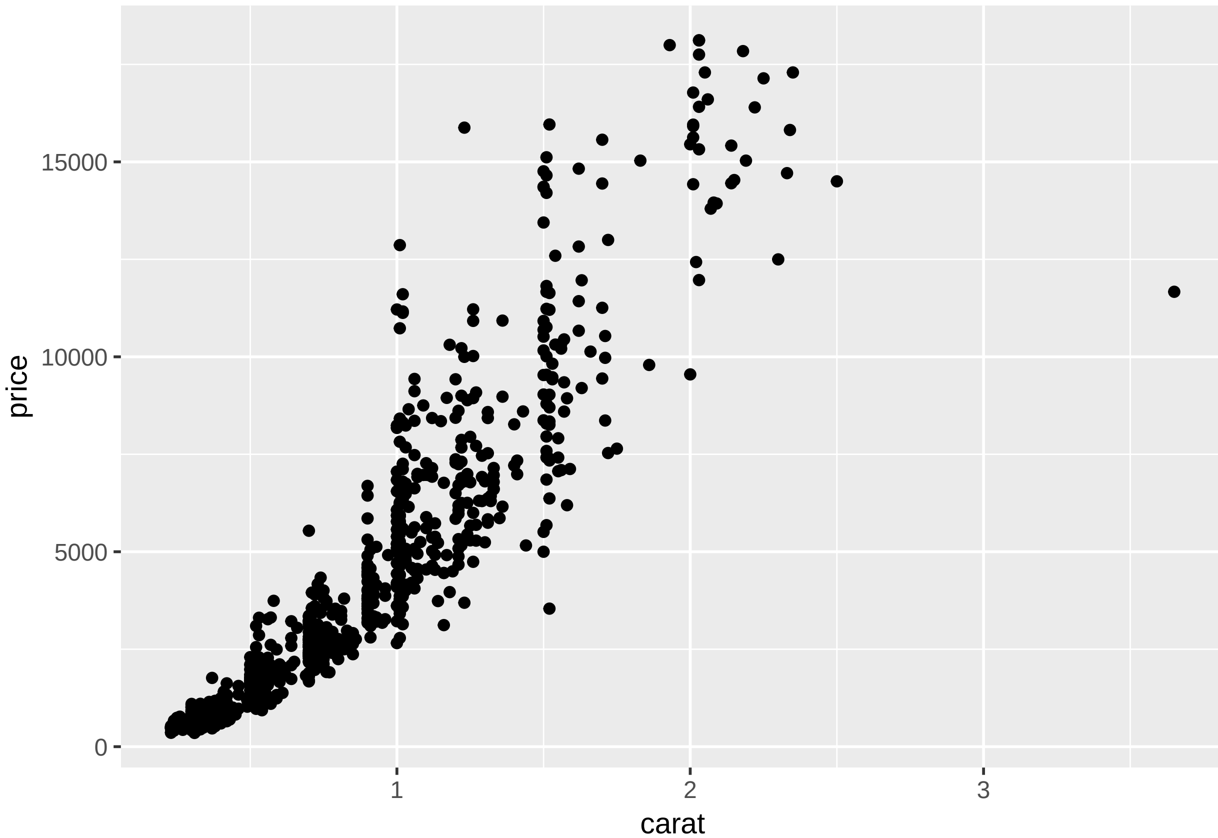
## Continuous v. Continuous

### Scatterplot

The most common method of visualizing the relationship between two continuous variables is by using a scatterplot.

With ggplot we specify both the x and y variables, and add a point.

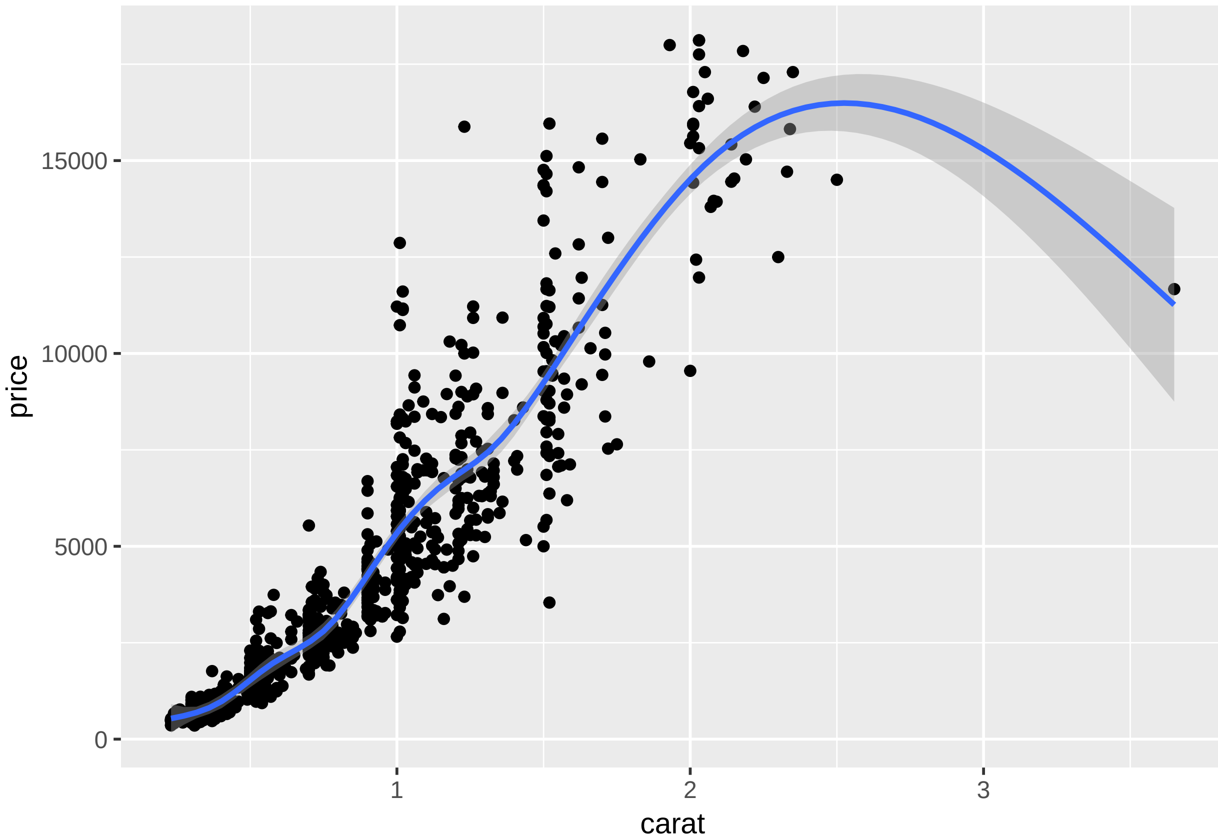
```
ggplot(dsmall, aes(x=carat, y=price)) + geom_point()
```




**Adding lines to the scatterplots**

Two most common trend lines added to a scatterplots are the “best fit” straight line and the “lowess” smoother line. This is done by adding a `geom_smooth()` layer.

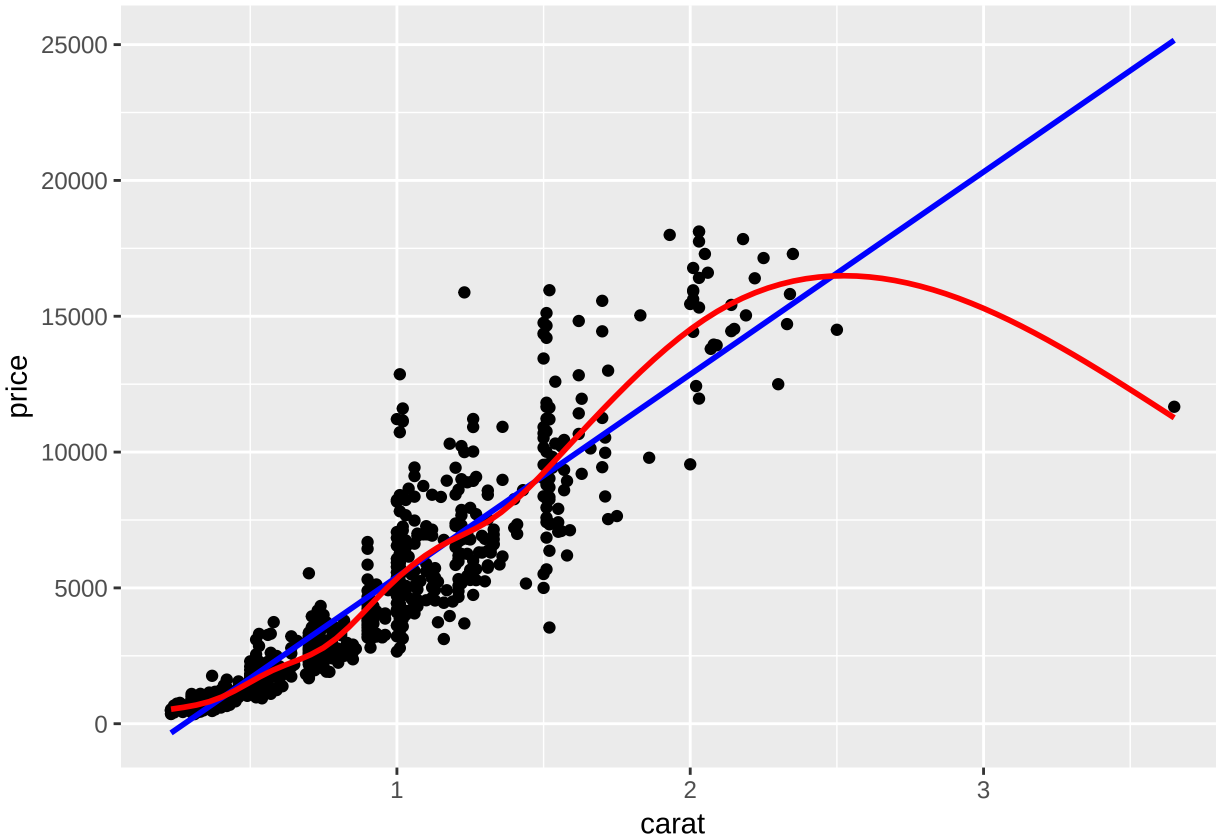
```
ggplot(dsmall, aes(x=carat, y=price)) + geom_point() + geom_smooth()
```




Here the point-wise confidence interval for this lowess line is shown in grey. If you want to turn the confidence interval off, use `se=FALSE`. Also notice that the smoothing geom uses a different function or window than the `lowess` function used in base graphics.

Here it is again using the `ggplot` plotting function and adding another `geom_smooth()` layer for the `lm` (linear model) line in blue, and the lowess line (by not specifying a method) in red.

```
ggplot(dsmall, aes(x=carat, y=price)) + geom_point() +
  geom_smooth(se=FALSE, method="lm", color="blue") +
  geom_smooth(se=FALSE, color="red")
```



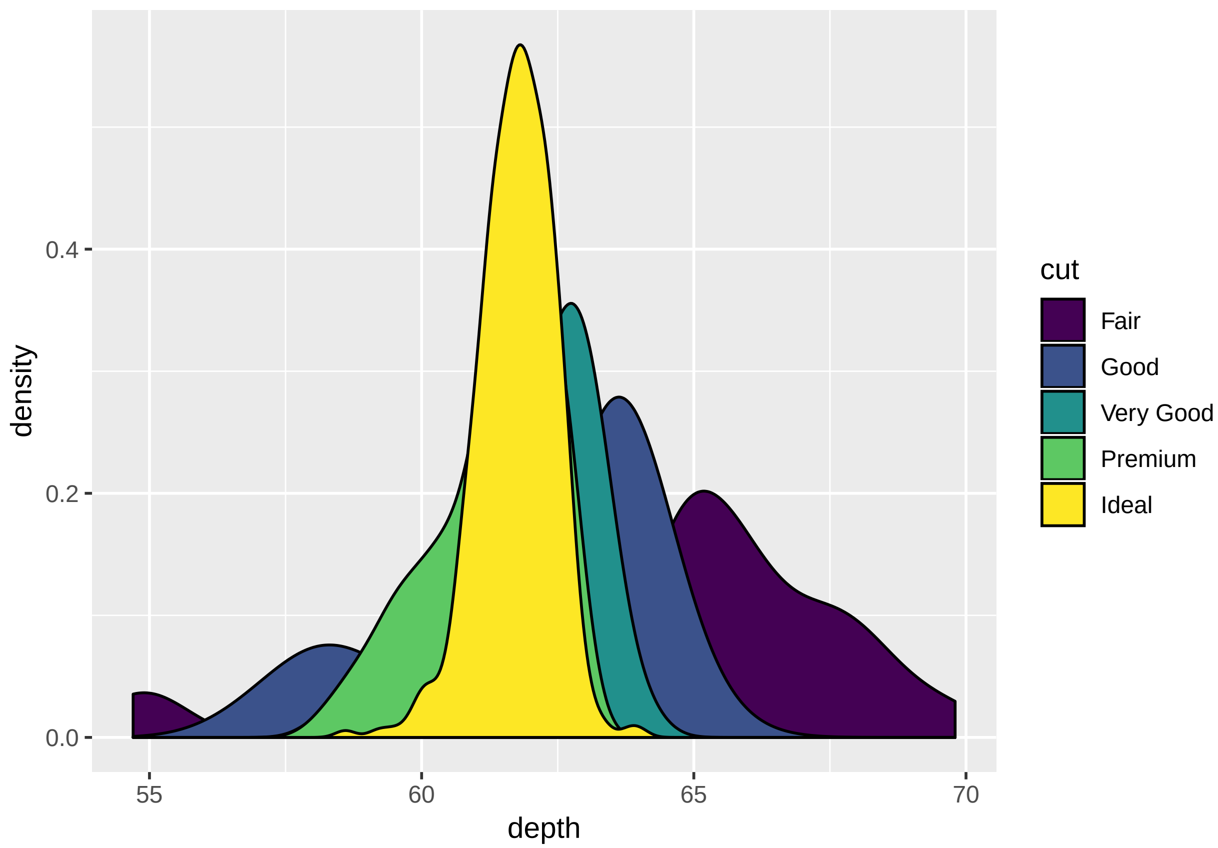

## Continuous v. Categorical

Create an appropriate plot for a continuous variable, and plot it for each level of the categorical variable by shading the plots or coloring the lines depending on the group.

### Overlaid density plots

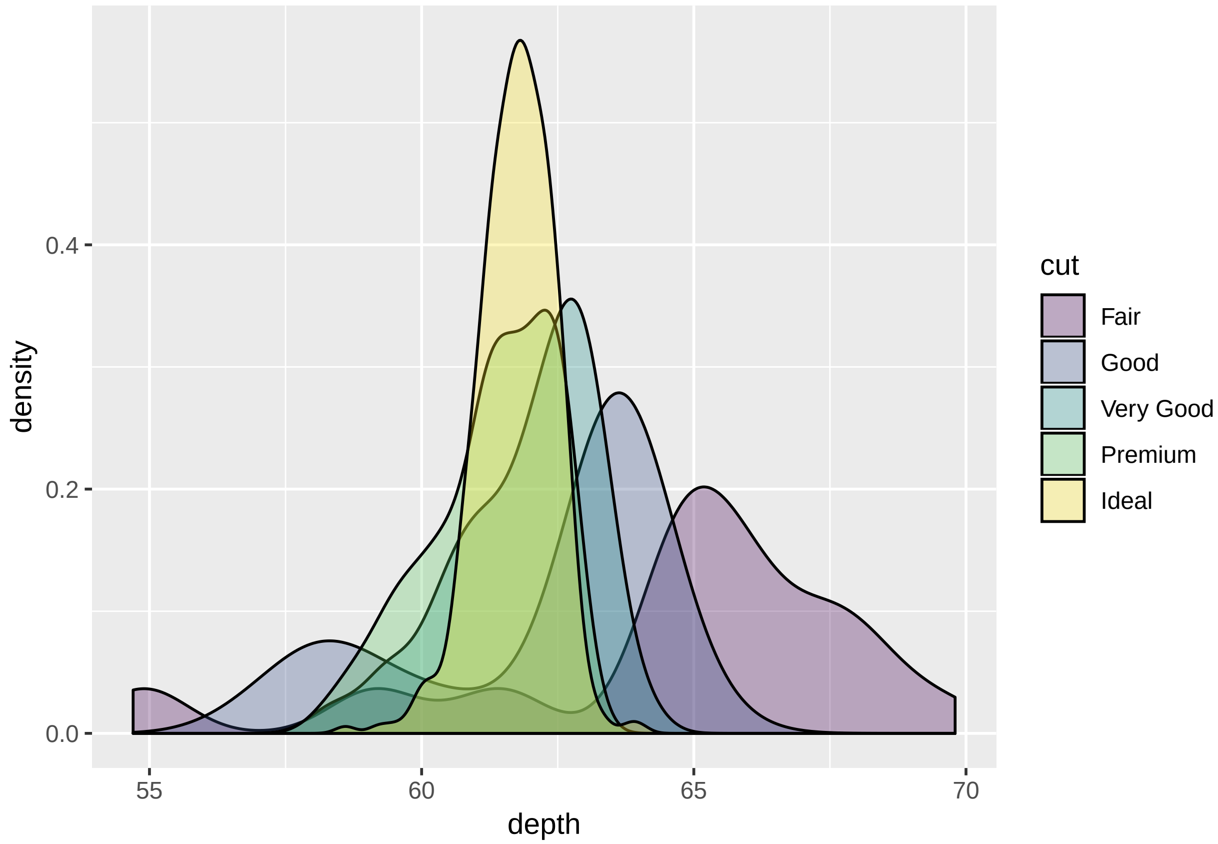
You could `fill` the density curves depending on the group, but then it's hard to see overlap.

```
ggplot(dsmall, aes(x=depth, fill=cut)) + geom_density()
```




We can adjust the transparency of the density curve by applying a value to `alpha` inside the density layer. Alpha is a measure of transparency, from 0=clear to 1=opaque.

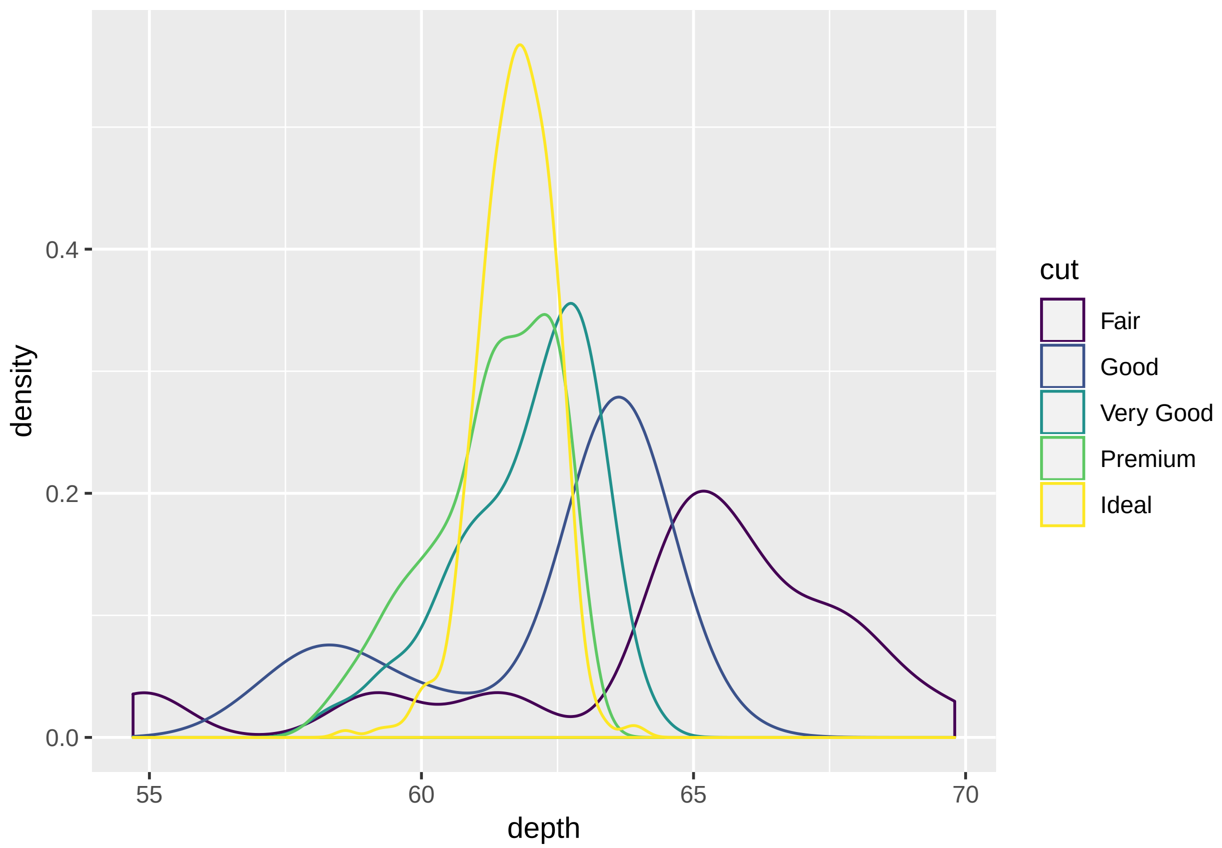
```
ggplot(dsmall, aes(x=depth, fill=cut)) + geom_density(alpha=.3)
```




Now we can see that there are some fair cut diamonds with deptsh around 60. This peak was hidden from us before.

You could also just color the lines and leave the fill alone.

```
ggplot(dsmall, aes(x=depth, color=cut)) + geom_density()
```

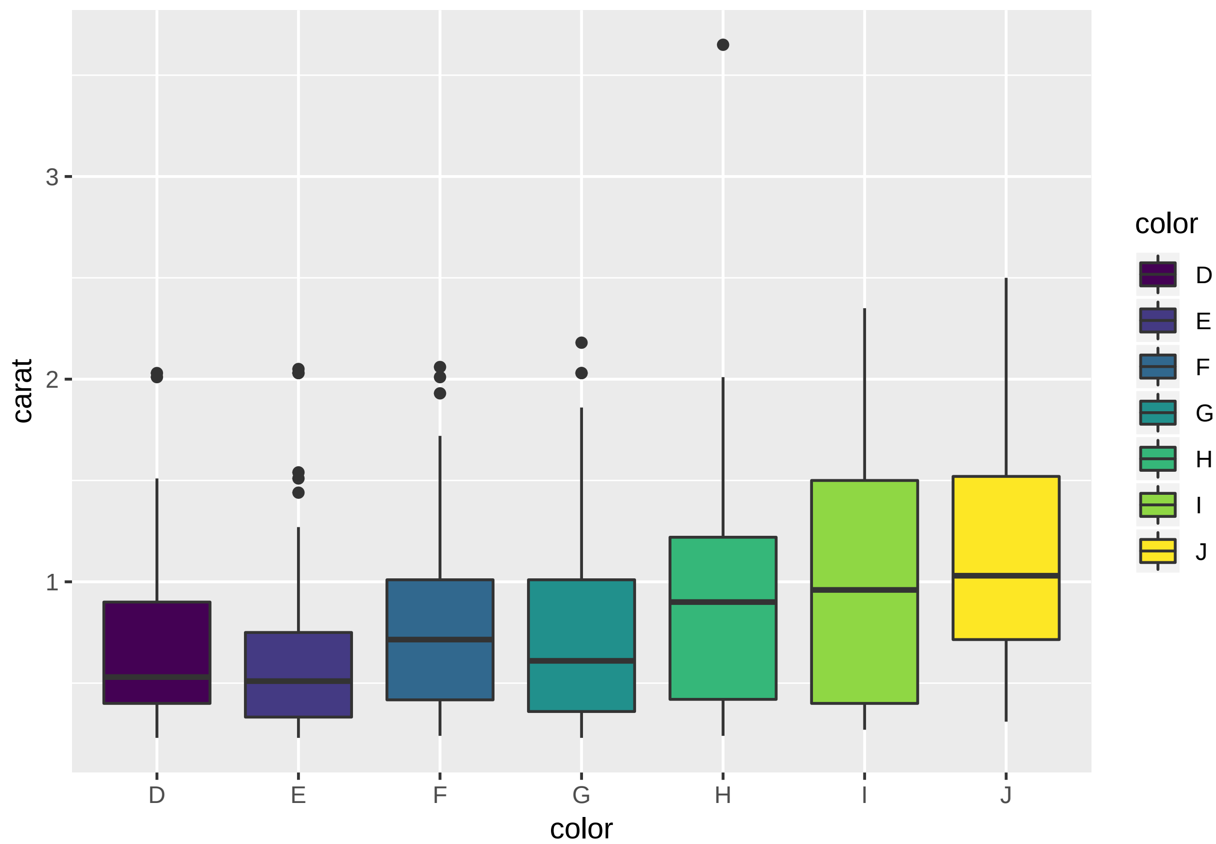



We won't talk about changing colors in this lab, but the yellow is prety hard to read.

### Grouped boxplots

A simple addition, just define your x and y accordingly. Specifying your `fill` to be the same variable as your `x`, gives you an automatic legend.

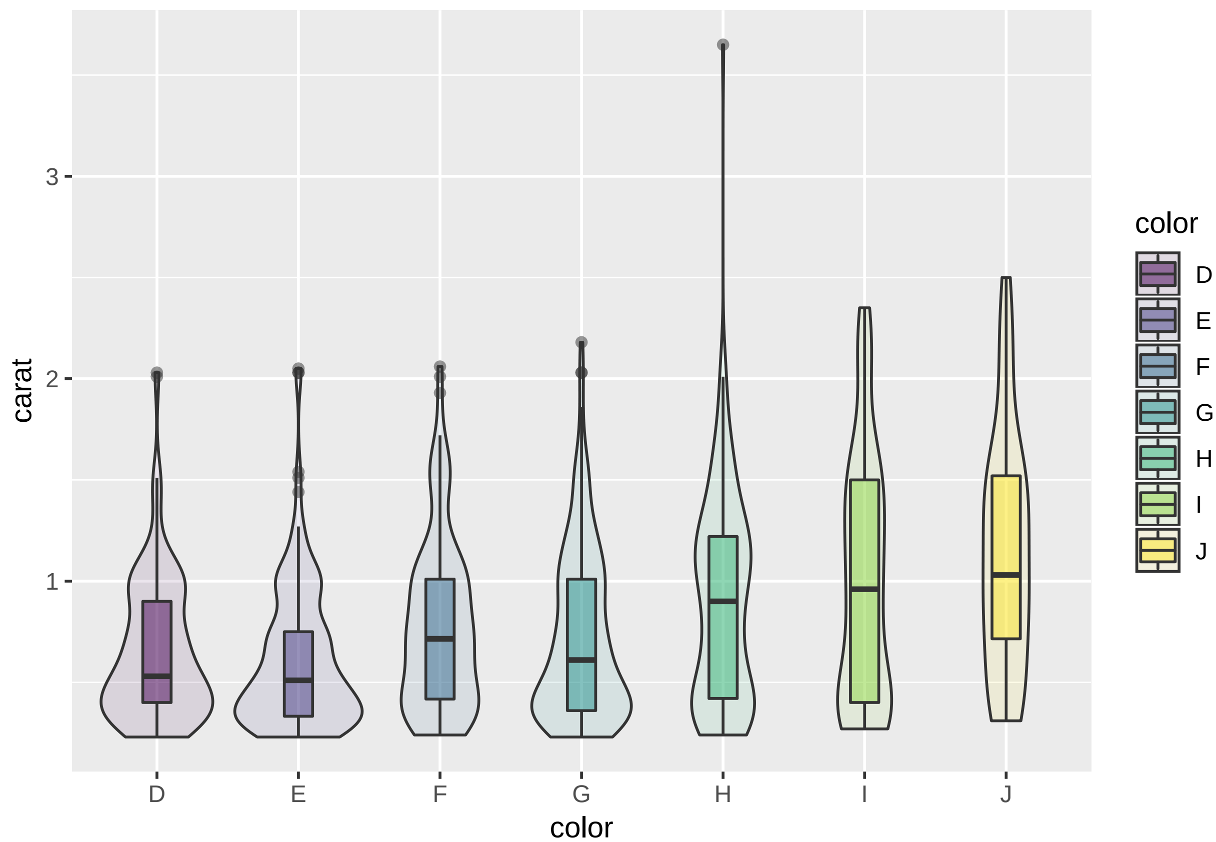
```
ggplot(dsmall, aes(x=color, y=carat, fill=color)) + geom_boxplot()
```




**Adding violins to the boxplot**

A violin plot is like a density plot, turned on it's side, and reflected around the axis for symmetry purposes. Overlaying a boxplot and a violin plot serves a similar purpose to Histograms + Density plots. It shows outliers, the location of most the data, and better shows the shape/skew of the distribution

```
ggplot(dsmall, aes(x=color, y=carat, fill=color)) +
        geom_violin(alpha=.1) +
        geom_boxplot(alpha=.5, width=.2)
```

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## Additional Resources

For a **full** , and comprehensive reference guide on how to do nearly anything in ggplot – this is by far my favorite reference http://www.cookbook-r.com/Graphs/ I reference things in there (like how to remove or change the title of a legend) constantly.

- R Graphics: https://www.stat.auckland.ac.nz/~paul/RGraphics/rgraphics.html The best book about using base graphics
- STHDA: Statisical tools for high-throughput data analysis. http://www.sthda.com/english/
- Quick-R: Basic Graphs
- Quick-R: ggplot2
- Books
  - ggplot2 http://ggplot2.org/book/ or http://amzn.com/0387981403
  - qplot http://ggplot2.org/book/qplot.pdf
- Help lists
  - ggplot2 mailing list http://groups.google.com/group/ggplot2
  - stackoverflow http://stackoverflow.com/tags/ggplot2
  - Chico R users group

For any other Google Search be sure to limit searches to within the past year or so. R packages get updated very frequently, and many functions change or become obsolete.