EDA

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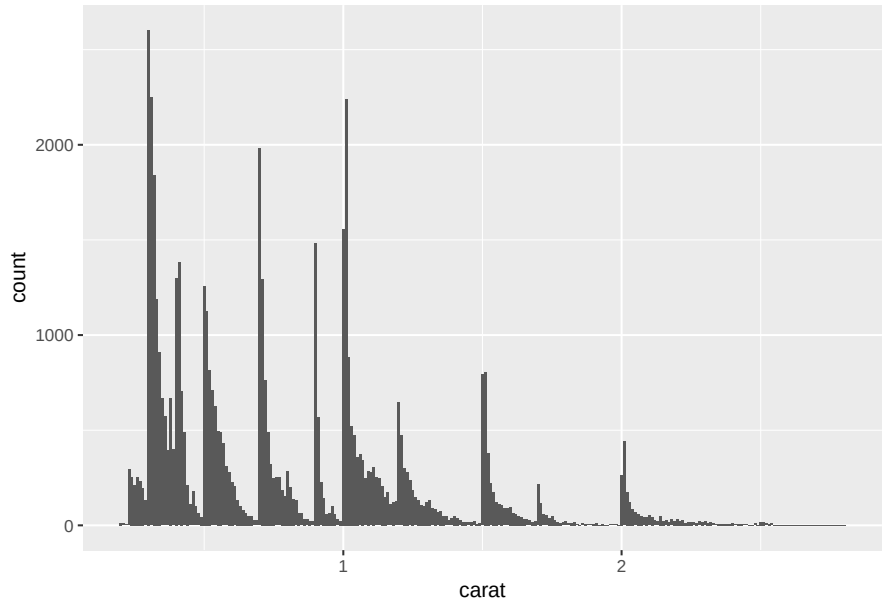
5/16/2019

Visualizing distributions with `geom_freqpoly()` (7.3.1) - Lorne

Histograms display the distribution of a continuous variable, preferably with a user-selected bin width:

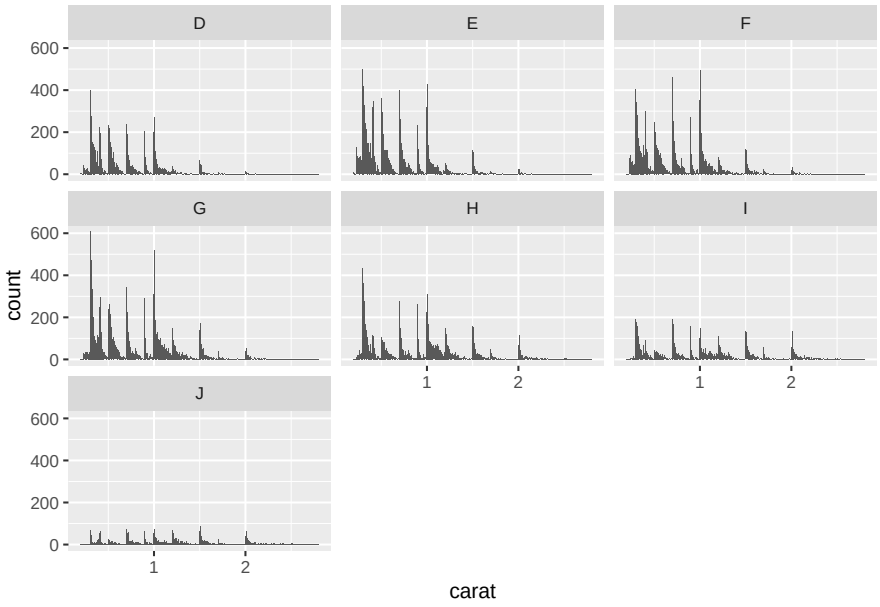
```
smaller <- diamonds %>%
  filter(carat < 3)

smaller %>% ggplot(mapping = aes(x = carat)) +
  geom_histogram(binwidth = 0.01)
```



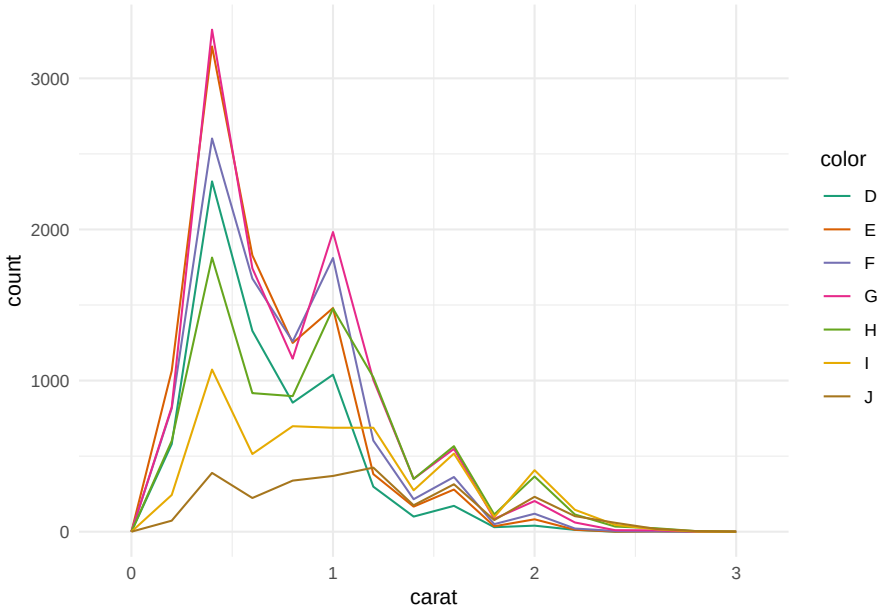
To look at `carat`'s distribution within groups of a categorical co-variable, we might use `facet_wrap`:

```
smaller %>% ggplot(mapping = aes(x = carat)) +
  geom_histogram(binwidth =  0.01) +
  facet_wrap(~ color)
```



Or we can employ `geom_freq_poly` to display the distribution of `carat` for each level of `color` as lines on the same plot:

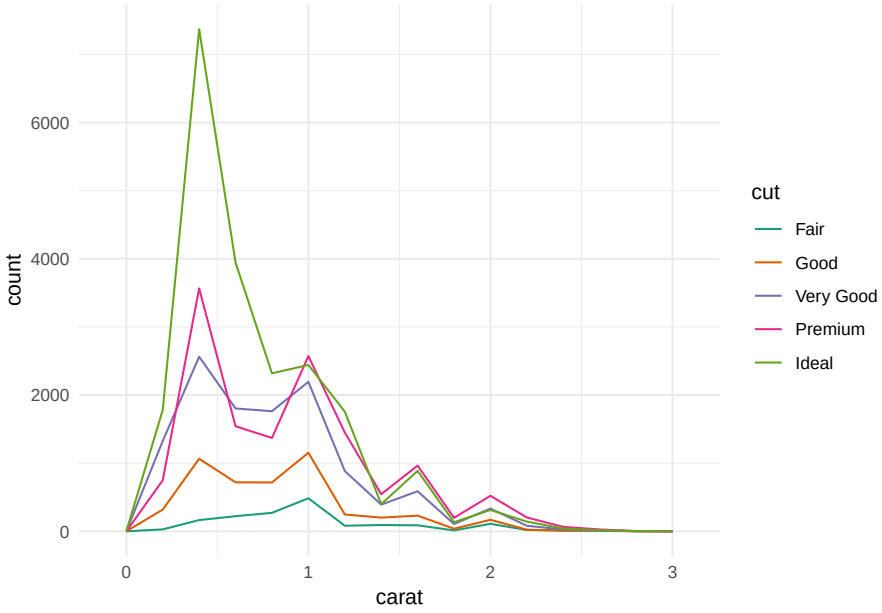
```
smaller %>% ggplot(mapping = aes(x = carat, color = color)) +
  geom_freqpoly(binwidth = 0.2) + # upping binwidth
  scale_color_brewer(palette = "Dark2") +
  theme_minimal()
```



There's 2 problems with this. The number of levels displayed is at the limit of what we may want to present in a single graph. And, despite the increase in bin width, it's hard to distinguish the distribution of a given group when its values are much smaller than others. To avoid the first, we could go back to the `carat` and

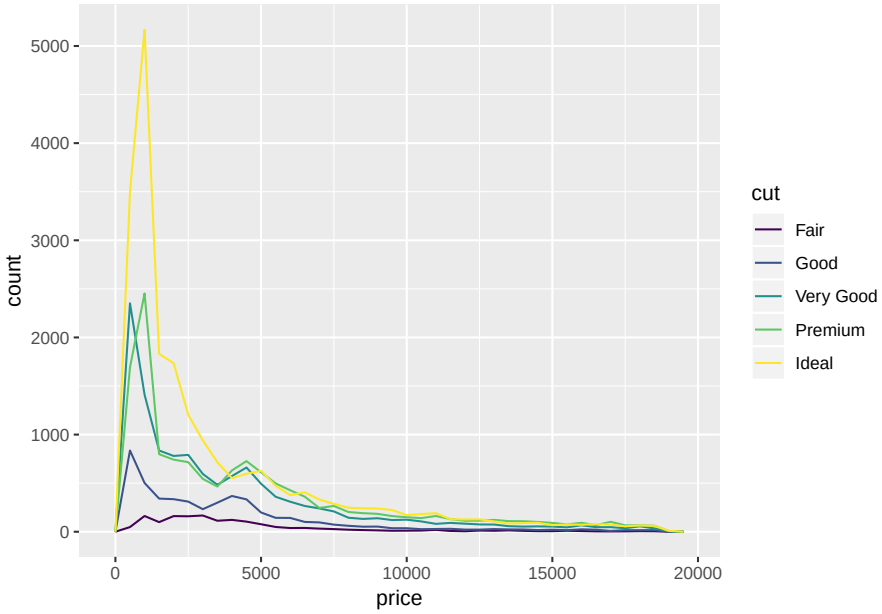
`cut` comparison (below). To solve the 2nd, we'd go on to R4DS **7.5.1 A categorical and continuous variable**.

```
smaller %>% ggplot(mapping = aes(x = carat, color = cut)) +
  geom_freqpoly(binwidth = 0.2) +
  scale_color_brewer(palette = "Dark2") +
  theme_minimal()
```



If we are interested to see how a continuous variable varies by the levels of a categorical variable, we have a few options. The first option is to use a frequency polygon:

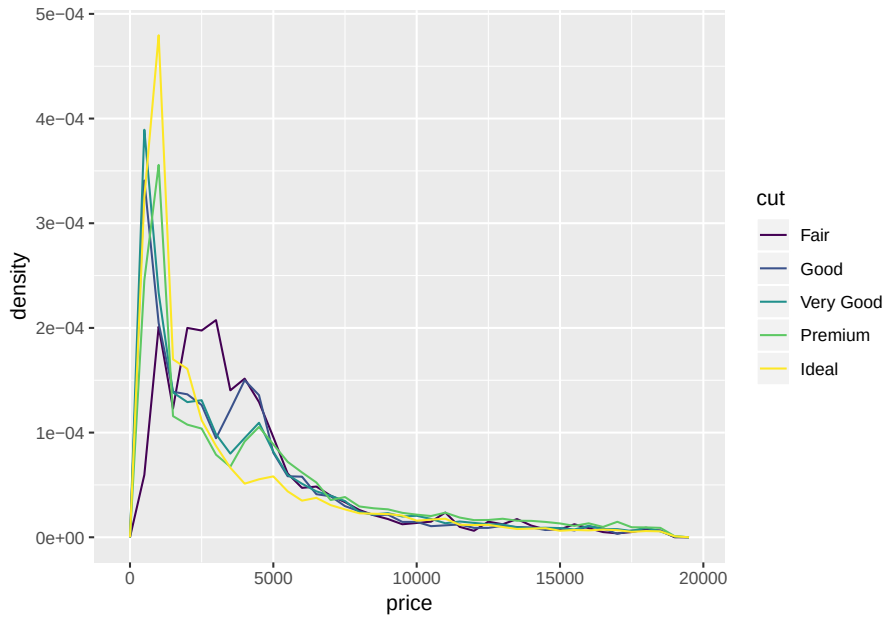
```
ggplot(data = diamonds, mapping = aes(x = price)) +
  geom_freqpoly(mapping = aes(colour = cut), binwidth = 500)
```



One issue with this display is that group sizes vary between diamond cuts, so a plot based on counts is not very useful. Instead, inside of the mapping argument above, we can specify `y=..density..` which

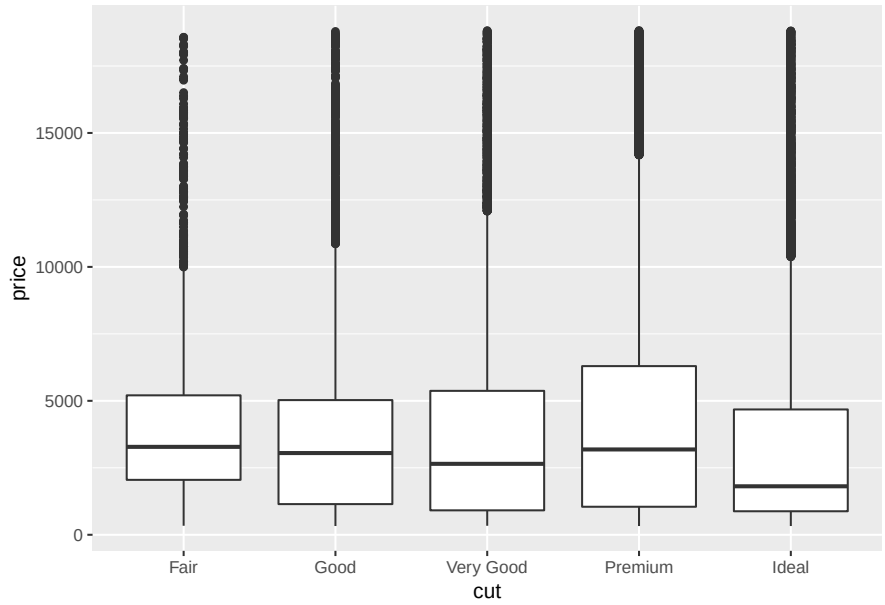
standardizes each distribution:

```
ggplot(data = diamonds, mapping = aes(x = price, y = ..density..)) +
  geom_freqpoly(mapping = aes(colour = cut), binwidth = 500)
```



Even with this it might be difficult to compare the variability between groups. For example, it seems that fair diamonds have the highest average price even though they are the lowest quality cut. However, since the plot is so cluttered the comparisons are not easy to make. An alternative plot to explore the variation between groups is a boxplot. With a boxplot some of the geometric information about the distribution is lost, but boxplots are much more compact and allow for easy comparisons. With this boxplot, it easier to see that fair diamonds on average have a higher price than higher quality diamonds. s

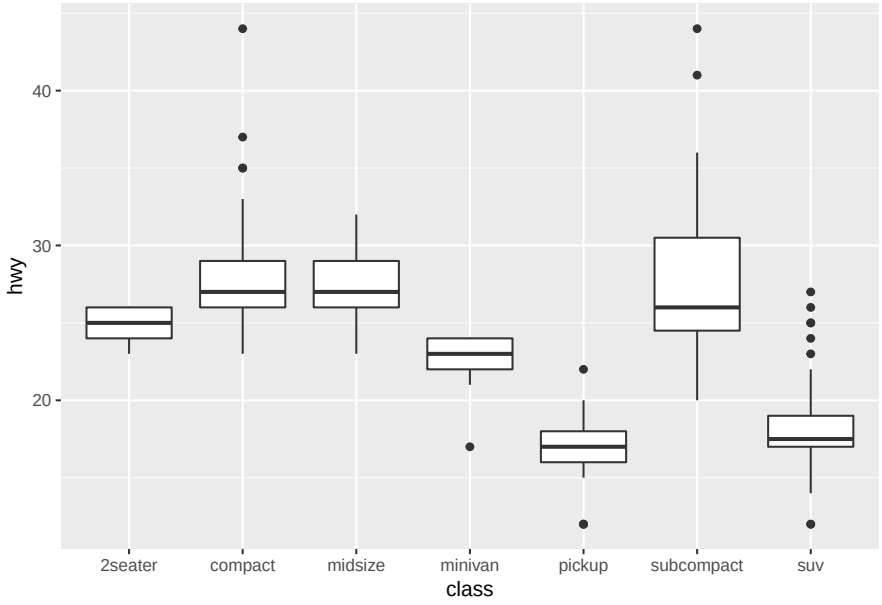
```
ggplot(data = diamonds, mapping = aes(x = cut, y = price)) +
  geom_boxplot()
```



Finally we can make use of the `reorder` function to change the order of the categorical variable in a boxplot.

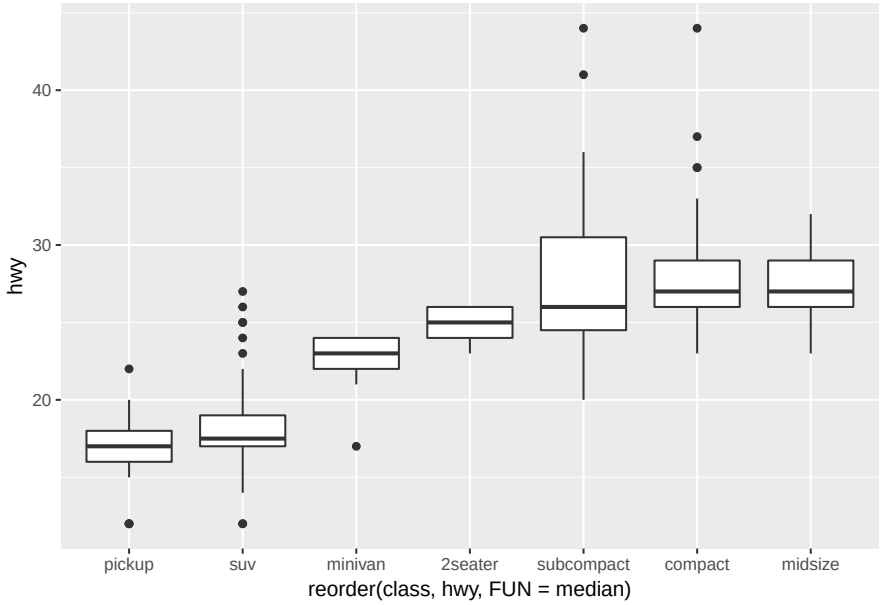
As an example, we can look at the `class` variable and the `hwy` variable in the `mpg` dataset. Notice how there is no intrinsic ordering of the `class` variable.

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



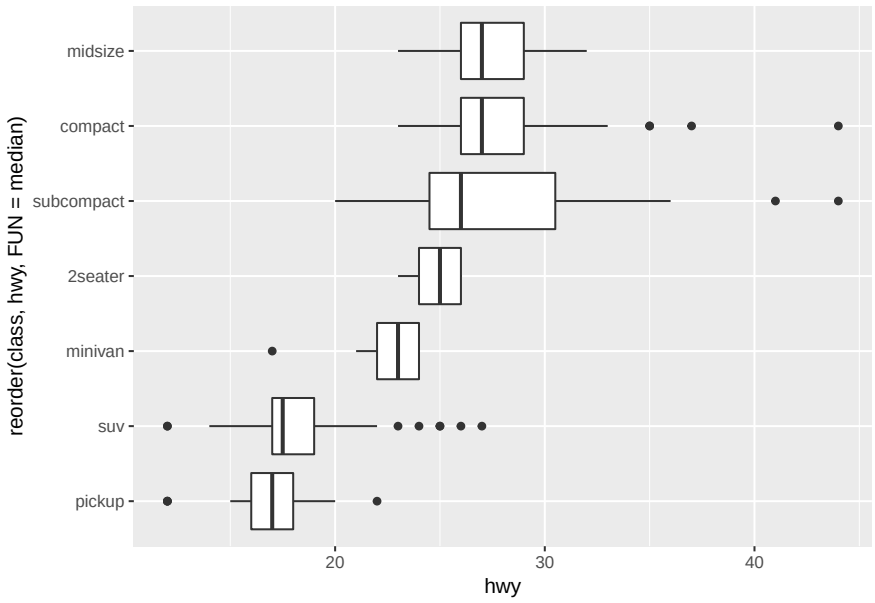
We could use the `reorder` function to order `class` by the median value of `hwy` which makes comparisons easier to make.

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



Finally if there are long variable names, then using `coord_flip` can make the plot easier to read.

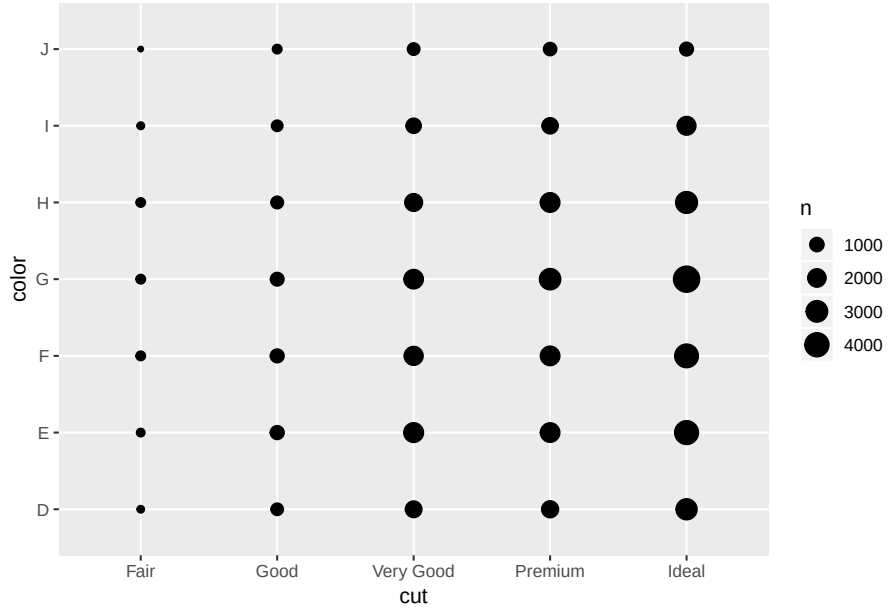
```
ggplot(data = mpg) +
  geom_boxplot(mapping = aes(x = reorder(class, hwy, FUN = median), y = hwy)) +
  coord_flip()
```


midsize
compact
subcompact
2seater
minivan
suv
pickup
reorder(class, hwy, FUN = median)
20
30
40
hwy

Covariation between two categorical variables (7.5.2) - Martin

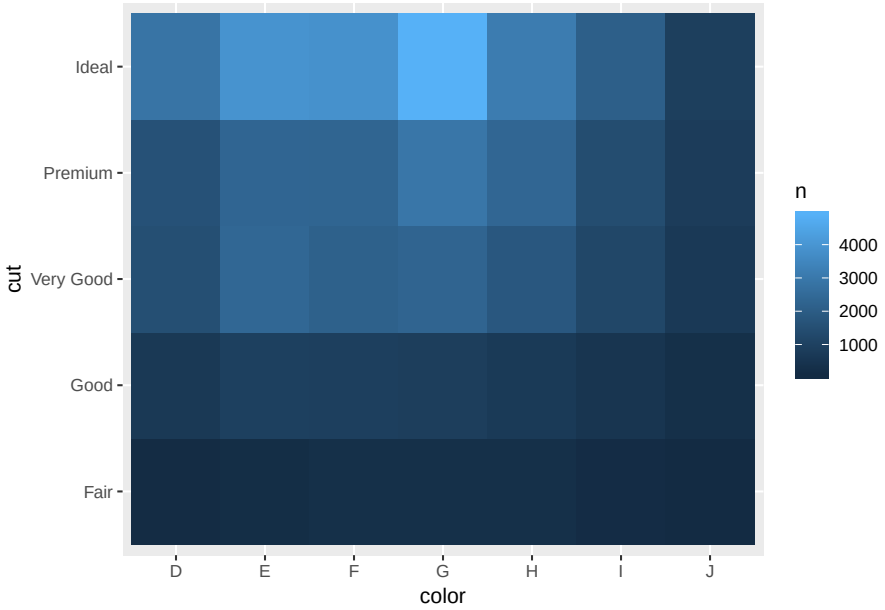
To see how to categorical variables are related we can count the number of observations for each level combination of both variables. We can do this using *geom*$_c$*ount* like in the following example:

```
ggplot(data = diamonds) +
  geom_count(mapping = aes(x = cut, y = color))
```



This graph has the disadvantage that we have to interpret the size of the dots which unless the difference between to neighbors is huge it can be difficult to assess the magnitude. One option, it to use *coun* of ddply and then use the function *geom*$_t$*ile* which make the visualization easier to interpret since use colors to display the covariation between both variables.

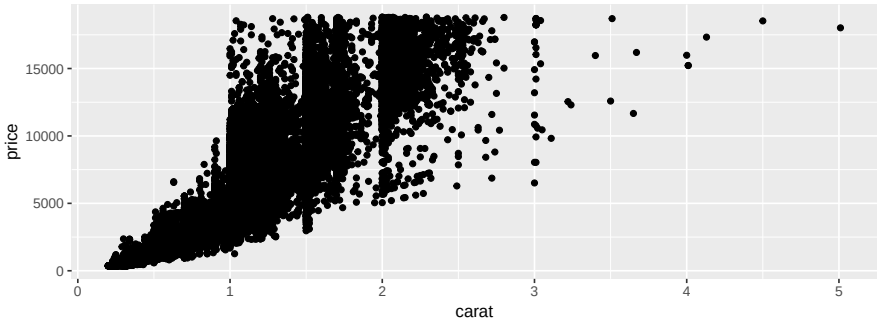
```
diamonds %>%
  count(color, cut) %>%
  ggplot(mapping = aes(x = color, y = cut)) +
    geom_tile(mapping = aes(fill = n))
```



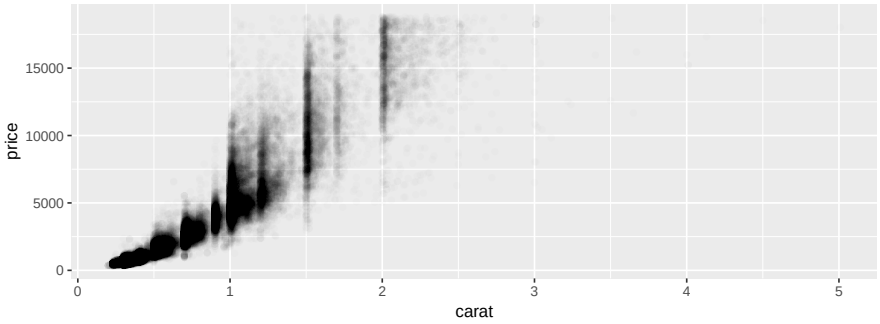
Covariation between two continuous variables (7.5.2) (7.6) - Finn

We've already used scatterplots to examine the coveriance between to continuous variables which tend to get cluttered with a lot of data. In the past we've added transparency using `alpha` to combat this when examining scatterplots woth a lot of data:

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




```
ggplot(data = diamonds) +
  geom_point(mapping = aes(x = carat, y = price), alpha = 1 / 100)
```

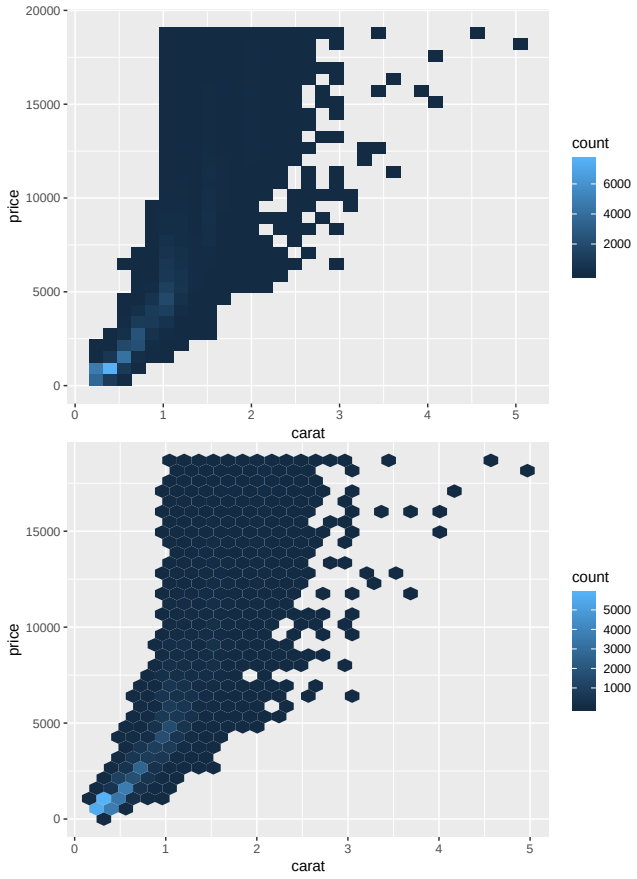


However, this technique of ajusting `alpha` can sometimes be difficult to use. If the data is too large and

transparency proved challenging then another possible way of exploring covariance between two continous vriables, which might be useful in this case, is to put them into bins and ajusting the color intead of transparency by using the `geom_bin2d()` and `geom_hex()` functions.

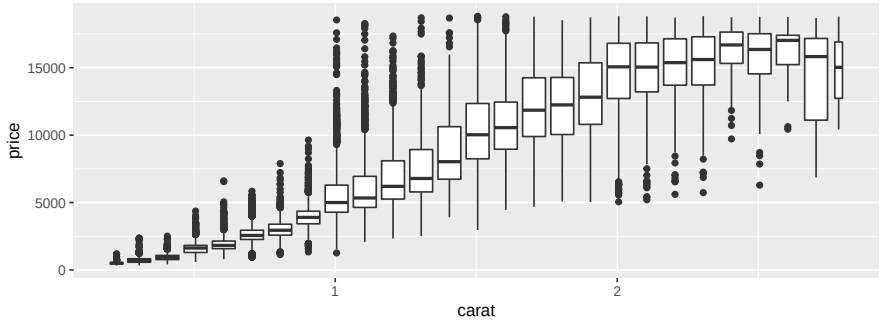
```
ggplot(data = diamonds) +
  geom_bin2d(mapping = aes(x = carat, y = price))

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



The binning strategy can also be selectivly abblied to just one of the variables then you can plot them as if one were continuous and the other categorical.

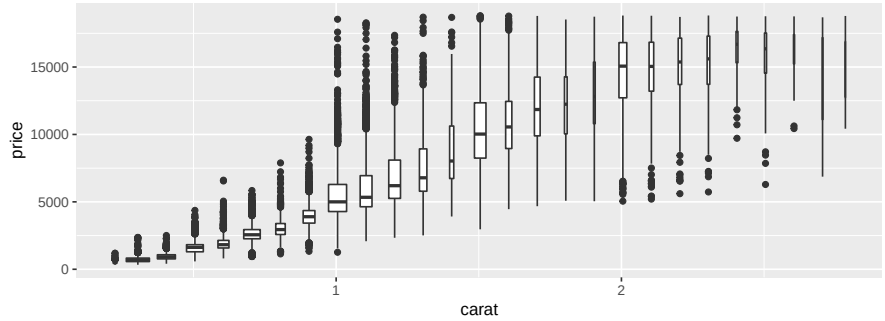
```
ggplot(data = smaller, mapping = aes(x = carat, y = price)) +
  geom_boxplot(mapping = aes(group = cut_width(carat, 0.1)))
```



If we want to also have an indicator as to how many ponts each plot is summerizing we can use `varwidth =`

TRUE.

```
ggplot(data = smaller, mapping = aes(x = carat, y = price)) +
  geom_boxplot(mapping = aes(group = cut_width(carat, 0.1)), varwidth = TRUE)
```



This way we can compair the boxes size to see which ones are summerizing smaller or larger sets of datapoints. Since in this case some of the boxes can be hard to see another way of dealing with this problem is to instead divide the variable into equaly sized partions for each bin with the size of the bins instead dictating the range over the axis (sine they now all have roughly the same number of data points) using `cut_number()`.

```
ggplot(data = smaller, mapping = aes(x = carat, y = price)) +
  geom_boxplot(mapping = aes(group = cut_number(carat, 20)))
```