30535 Skills Problem Set 3

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Notes on submission (15 points)

Front matter

Due: Saturday, April 23, 2020 at 9:00am Central

Submit to https://classroom.github.com/a/yOcbNjw- (https://classroom.github.com/a/yOcbNjw-)

The problem set is worth 100 points total.

This submission is my work alone and complies with the 30535 integrity policy.

Add your initials to indicate your agreement: **KEZG**

Add names of anyone you discussed this problem set with: **__**

Late coins used this pset: 0. Late coins left after submission: X.

We use (*) to indicate a problem that we think might be time consuming.

Notes on submission (15 points):

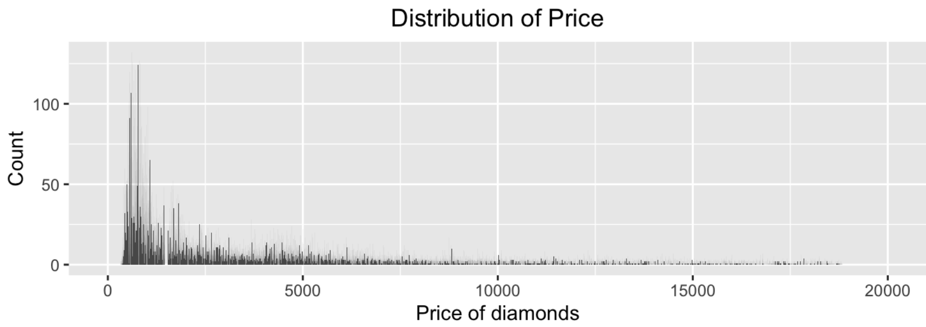
- Name your submission files skills_ps_3.Rmd and skills_ps_3.pdf.
- Your code should adhere to the style guide. (styler is your friend.)
- Knit your RmD to PDF and submit via Gradescope.
- Assign the correct page number to the question number on gradescope to help the grading process.
- The PDF should not be more than 25 pages, use head() and re-size figures when appropriate.

Exploratory Data Analysis (25 points)

EDA: Exploring variation

1. Using the diamonds dataset, explore the distribution of price.

```
ggplot(diamonds) +
  geom_bar(aes(x = price)) +
  labs(x = "Price of diamonds", y = "Count") +
  xlim(0, 20000) +
  ggtitle("Distribution of Price") +
  theme(plot.title = element_text(hjust = 0.5))
```

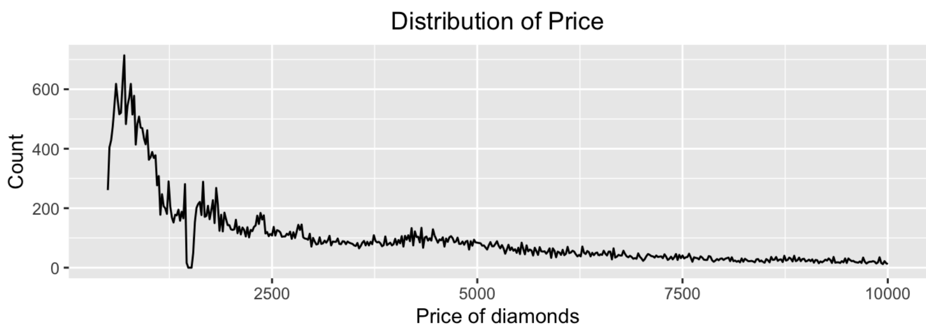


a. Describe the overall pattern. Does it fit your expectations?

From the previus chart, we can see that there are many spikes in prices. The distribution is right skewed, that is, there is a greater number of diamond prices with a value less than 5,000. The distribution is not what I expected, since I expected that the price of diamonds would be clustered in the highest values of the histogram.

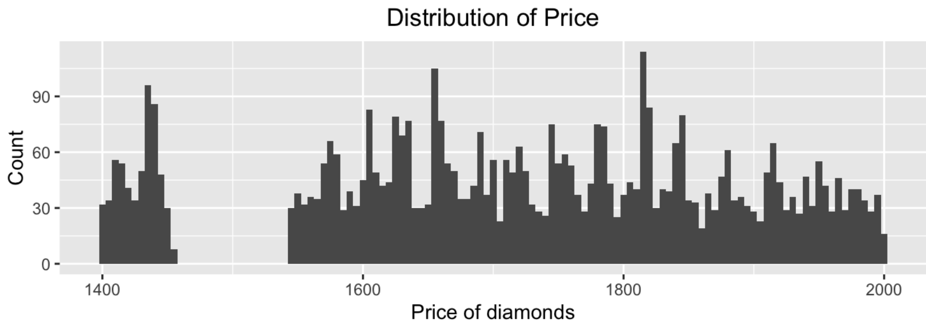
Likewise, we can see from the following graph that the prices are conglomerated in values less than $1400.

```
ggplot(diamonds) +
  geom_freqpoly(aes(x = price), binwidth = 20) +
  labs(x = "Price of diamonds", y = "Count") +
  xlim(500, 10000) +
  ggtitle("Distribution of Price") +
  theme(plot.title = element_text(hjust = 0.5))
```



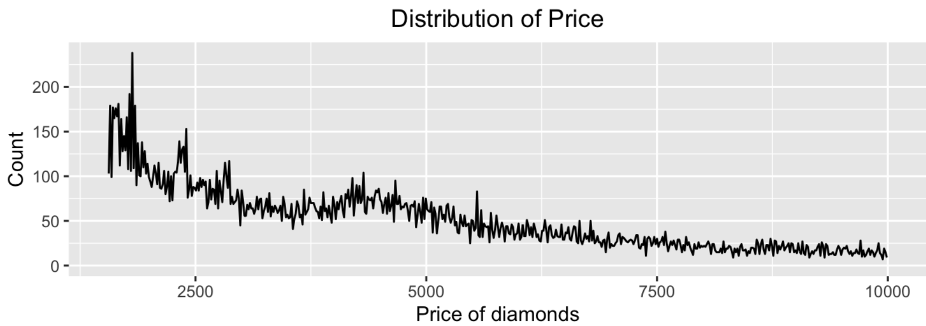
b. Do you discover anything unusual or surprising? (Hint: Carefully think about the binwidth and make sure you try a wide range of values.)

```
ggplot(filter(diamonds, price < 2000 & price > 1400)) +
  geom_histogram(aes(x = price), binwidth = 5) +
  labs(x = "Price of diamonds", y = "Count") +
  ggtitle("Distribution of Price") +
  theme(plot.title = element_text(hjust = 0.5))
```



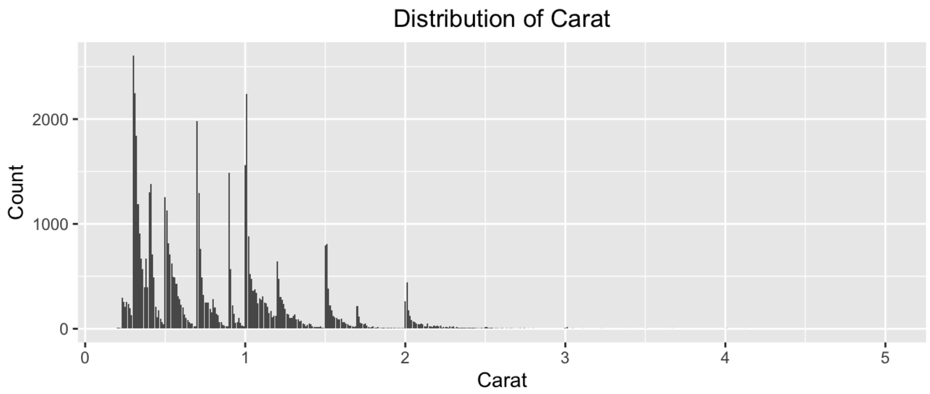
The unusual fact of this data set is that there are no values between 1454 and 1546. After the price cluster reaches zero, the next highest cluster is in the range of 1,550 to 2,500.

```
ggplot(diamonds) +
  geom_freqpoly(aes(x = price), binwidth = 15) +
  labs(x = "Price of diamonds", y = "Count") +
  xlim(1550, 10000) +
  ggtitle("Distribution of Price") +
  theme(plot.title = element_text(hjust = 0.5))
```



2. Explore the distribution of carat.

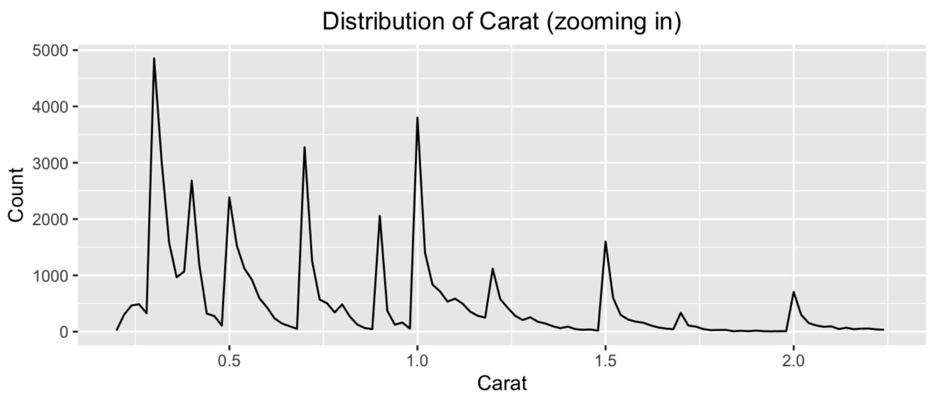
```
ggplot(diamonds) +
  geom_bar(aes(x = carat)) +
  labs(x = "Carat", y = "Count") +
  ggtitle("Distribution of Carat") +
  theme(plot.title = element_text(hjust = 0.5))
```



a. Describe the overall pattern. Does it fit your expectation given what you saw in prices?

I would expect the carat distribution to have the same pattern as the price distribution. However, this is not quite so. Given that there are more diamonds sold at a lower price (right skewed), one would expect there to be a larger demand or supply at the lower carat, but this is true as we see that the graph has different peaks along the board. We are facing a multimodal distribution, since it presents several peaks followed by a significant decrease in the data.

```
ggplot(diamonds) +
  geom_freqpoly(aes(x = carat), binwidth = 0.02) +
  labs(x = "Carat", y = "Count") +
  ggtitle("Distribution of Carat (zooming in)") +
  theme(plot.title = element_text(hjust = 0.5)) +
  xlim(0.2,2.25)
```



Also, in addition to seeing prominent peaks on the chart, outliers can be seen.

```
ggplot(diamonds) +
  geom_bar(aes(x = carat)) +
  labs(x = "Carat", y = "Count") +
  ggtitle("Outliers of Carat") +
  theme(plot.title = element_text(hjust = 0.5)) +
  xlim(3.25,5.1)
```

b. How many diamonds are 0.99 carat? How many are 1 carat? What do you think is the cause of the difference (feel free to make a plot to support your argument)?

- Number of Diamonds of 0.99 carat and 1 carat:

```
diamonds %>%
  filter(carat == 0.99 | carat == 1) %>%
  count(carat)
```

carat <dbl>	n <int>
0.99	23
1.00	1558

2 rows

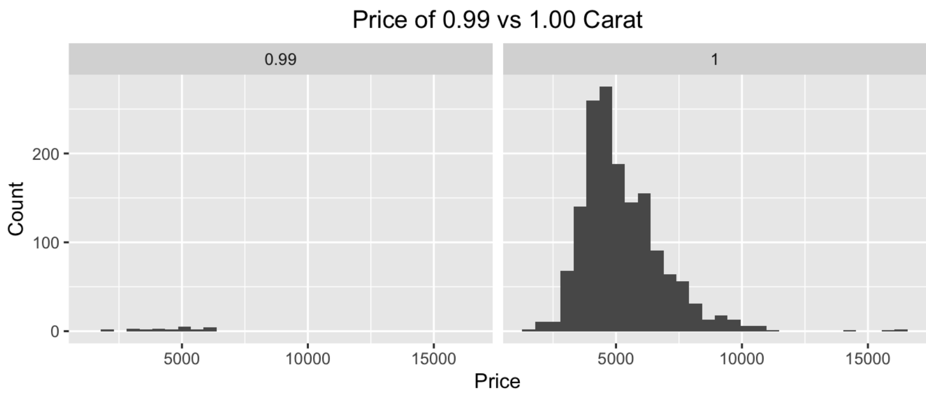
There are 23 diamonds of 0.99 carats and 1558 diamonds of 1.00 carats.

- Plots:

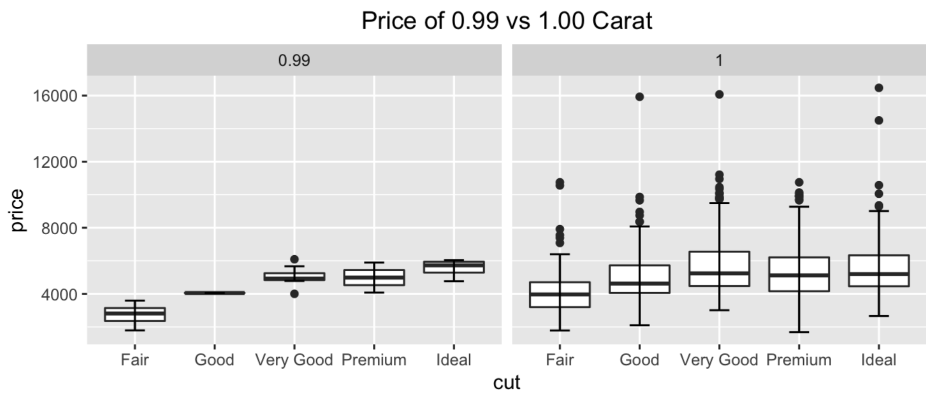
From the following graphs we can see that manufacturing or selling 1.00 carat diamonds brings much more economic benefits in any cut compared to selling 0.99 carat. Therefore, there are more 1 carat diamonds manufactured than 0.99 carat diamonds.

```
diamonds_filter <- diamonds %>%
  filter(carat == 0.99 | carat == 1)
```

```
ggplot(diamonds_filter) +
  geom_histogram(aes(x = price)) +
  labs(x = "Price", y = "Count") +
  ggtitle("Price of 0.99 vs 1.00 Carat") +
  theme(plot.title = element_text(hjust = 0.5)) +
  facet_wrap(~ carat)
```




```
ggplot(diamonds_filter, aes(x = cut, y = price)) +
  geom_boxplot() +
  stat_boxplot(
    geom = "errorbar", # Error bars
    width = 0.25
  ) +
  ggtitle("Price of 0.99 vs 1.00 Carat") +
  theme(plot.title = element_text(hjust = 0.5)) +
  facet_wrap(~ carat)
```



3. Compare and contrast + coord_cartesian() vs + xlim() or + ylim() when zooming in on a histogram for carat. What happens if you leave binwidth at its default value and zoom in further and further?

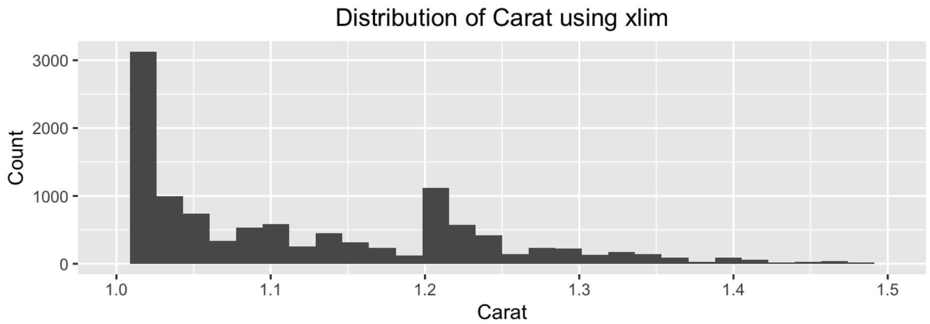
- Leaving binwidth at its default value and zoom in further using xlim()

```
ggplot(diamonds) +
  geom_histogram(aes(x = carat)) +
  labs(x = "Carat", y = "Count") +
  ggtitle("Distribution of Carat using xlim") +
  theme(plot.title = element_text(hjust = 0.5)) +
  xlim(1,1.5)
```

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

```
## Warning: Removed 40322 rows containing non-finite values (stat_bin).
```

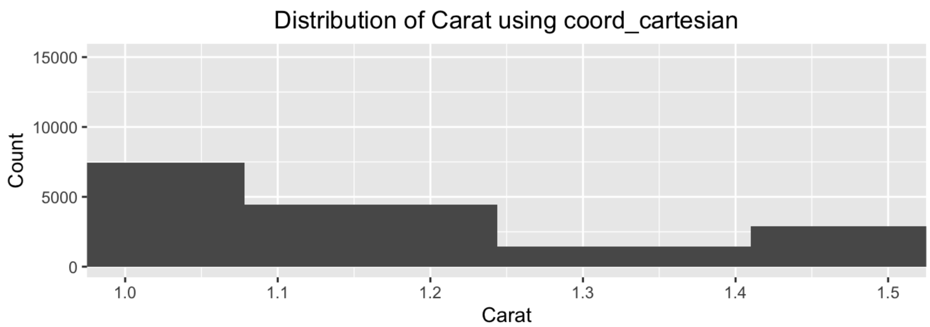
```
## Warning: Removed 2 rows containing missing values (geom_bar).
```



- Leaving binwidth at its default value and zoom in further using coord_cartesian

```
ggplot(diamonds) +
  geom_histogram(aes(x = carat)) +
  labs(x = "Carat", y = "Count") +
  ggtitle("Distribution of Carat using coord_cartesian") +
  theme(plot.title = element_text(hjust = 0.5)) +
  coord_cartesian( xlim = c(1,1.5))
```

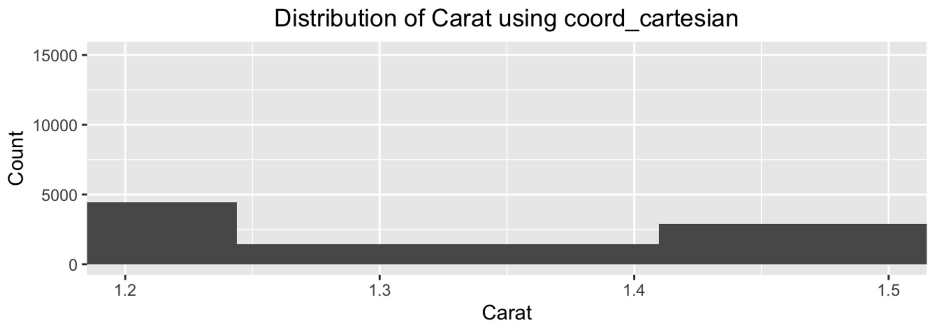
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



- Leaving binwidth at its default value and zoom in further and further using coord_cartesian

```
ggplot(diamonds) +
  geom_histogram(aes(x = carat)) +
  labs(x = "Carat", y = "Count") +
  ggtitle("Distribution of Carat using coord_cartesian") +
  theme(plot.title = element_text(hjust = 0.5)) +
  coord_cartesian( xlim = c(1.2,1.5))
```

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

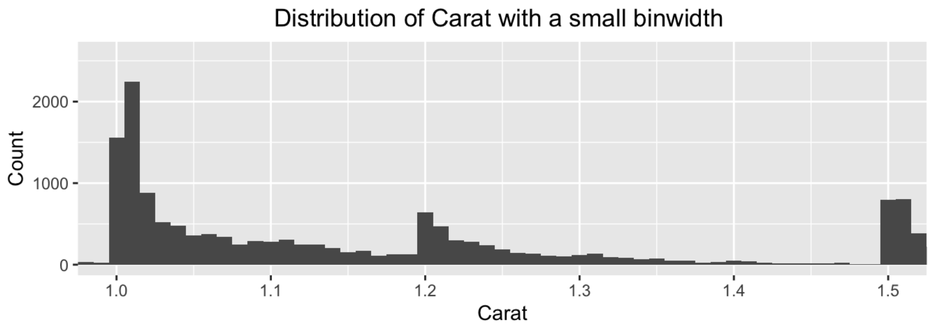


When using xlim, a message occurs stating that certain rows are being eliminated because they are not inside the axis limitations, i.e. some values are being lost. Also, is just after filtering the xlim, that the geom is calculated.

While no data is deleted when using coord_cartesian, the bins are calculated using the original geom because we are zooming in the data after calculating the geoms. As a result, the two graphs appear to be distinct.

- Changing the default binwidth

```
ggplot(data = diamonds, aes(x = carat)) +
  geom_histogram(binwidth = 0.01) +
  labs(x = "Carat", y = "Count") +
  ggtitle("Distribution of Carat with a small binwidth ") +
  theme(plot.title = element_text(hjust = 0.5)) +
  coord_cartesian(xlim = c(1.0,1.5))
```



Also, when we leave binwidth at its default value, the data is aggregated by bins, leading data to display in the histogram in an accumulating manner, regardless of whether we use coord cartesian or xlim. We're altering the binwidth default in the graph above, and data becomes less and less aggregated as the binwidth becomes smaller.

EDA: Navigating NAs

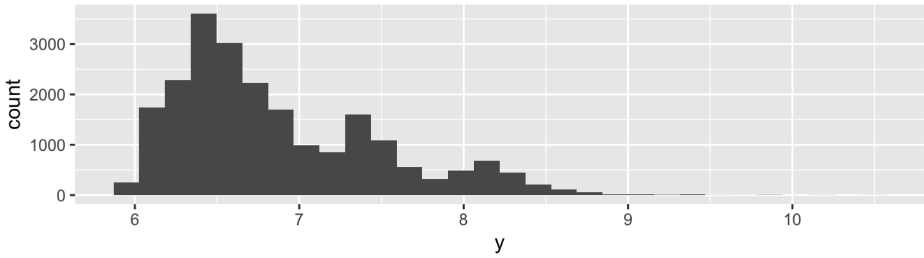
1. What happens to missing values in a histogram? What happens to missing values in a bar chart? Why is there a difference? Create plots supporting your response.

- We modify the diamonds dataframe to inserted NA's:

```
diamonds %>%
  mutate(y = ifelse(y < 6 | y > 20, NA, y)) %>%
  ggplot() +
  geom_histogram(aes(x = y))
```

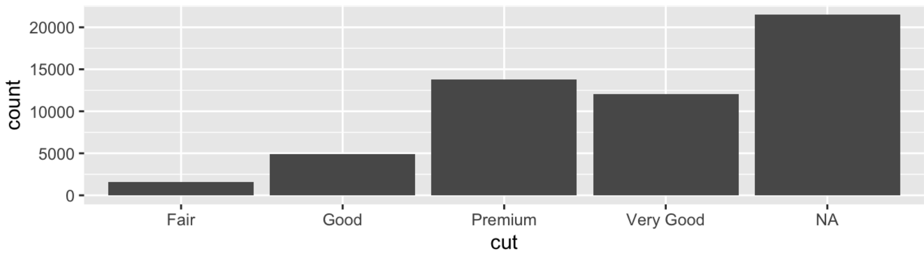
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 31632 rows containing non-finite values (stat_bin).
```



- We modify the diamonds dataframe to have characters:

```
diamonds$cut <- as.character(diamonds$cut)

diamonds %>%
  mutate(cut = ifelse(cut == "Ideal", NA, cut)) %>%
  ggplot() +
  geom_bar(aes(x = cut))
```



In a histogram NA values are removed, since they cannot be represented (they do not have a value).
On the other hand, in the bar chart, NA is a category that can be counted.

2. What does na.rm = TRUE do in mean() and sum()?

NA values cannot be included in calculations as they do not represent actual values, so if we try to average or sum a column that has NA values, the result will be NA. Therefore, the na.rm function acts as a logical parameter that removes (TRUE) or not (FALSE) the NA values, in other words, it excludes missing values when calculating descriptive statistics.

Exploratory Data Analysis: Covariation

Diamonds (40 points)

1.Looking at the table below it appears that fair is nearly the highest price cut of diamond and ideal the worst cut. But there is an omitted variable problem!

```
diamonds %>%
  group_by(cut)  %>%
  summarise(mean = mean(price)) %>%
  arrange(desc(mean))
```

cut <chr>	mean <dbl>
Premium	4584.258
Fair	4358.758
Very Good	3981.760
Good	3928.864
Ideal	3457.542

5 rows

For parts a. and b., please include plots along with your response.

a. What variable in the diamonds dataset is most important for predicting the price of a diamond?

- We are going to perform a regression to give us an idea of the correlation of variables:

```
summary(lm(price ~ ., data = diamonds))
```

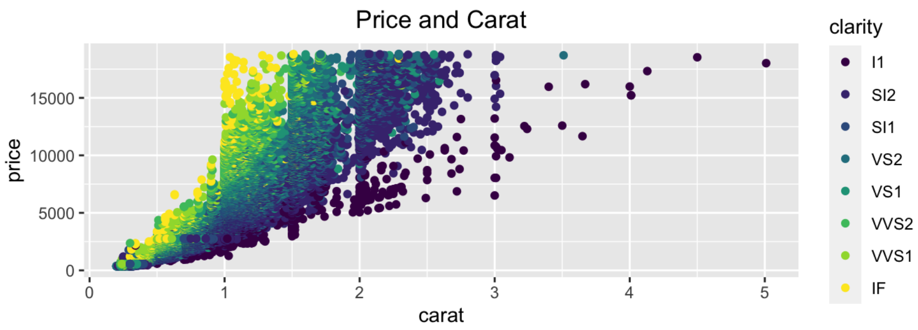
```
##
## Call:
## lm(formula = price ~ ., data = diamonds)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21376.0   -592.4   -183.5    376.4  10694.2
##
## Coefficients:
##               Estimate Std. Error  t value Pr(>|t|)
## (Intercept)   5173.444    405.136   12.770  < 2e-16 ***
## carat        11256.978     48.628  231.494  < 2e-16 ***
## cutGood        579.751     33.592   17.259  < 2e-16 ***
## cutIdeal       832.912     33.407   24.932  < 2e-16 ***
## cutPremium     762.144     32.228   23.649  < 2e-16 ***
## cutVery Good   726.783     32.241   22.542  < 2e-16 ***
## color.L      -1952.160     17.342 -112.570  < 2e-16 ***
## color.Q       -672.054     15.777  -42.597  < 2e-16 ***
## color.C       -165.283     14.725  -11.225  < 2e-16 ***
## color^4         38.195     13.527    2.824  0.00475 **
## color^5        -95.793     12.776   -7.498 6.59e-14 ***
## color^6        -48.466     11.614   -4.173 3.01e-05 ***
## clarity.L     4097.431     30.259  135.414  < 2e-16 ***
## clarity.Q    -1925.004     28.227  -68.197  < 2e-16 ***
## clarity.C      982.205     24.152   40.668  < 2e-16 ***
## clarity^4     -364.918     19.285  -18.922  < 2e-16 ***
## clarity^5      233.563     15.752   14.828  < 2e-16 ***
## clarity^6        6.883     13.715    0.502  0.61575
## clarity^7       90.640     12.103    7.489 7.06e-14 ***
## depth          -63.806      4.535  -14.071  < 2e-16 ***
## table          -26.474      2.912   -9.092  < 2e-16 ***
## x            -1008.261     32.898  -30.648  < 2e-16 ***
## y                9.609     19.333    0.497  0.61918
## z              -50.119     33.486   -1.497  0.13448
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1130 on 53916 degrees of freedom
## Multiple R-squared:  0.9198, Adjusted R-squared:  0.9198
## F-statistic: 2.688e+04 on 23 and 53916 DF,  p-value: < 2.2e-16
```

From the regression, we can see that the variable “carat” is the one that explains the variation in price to a greater extent. This statement will be verified in the following plots that I will make, when I explore the relationship with other variables of the data.

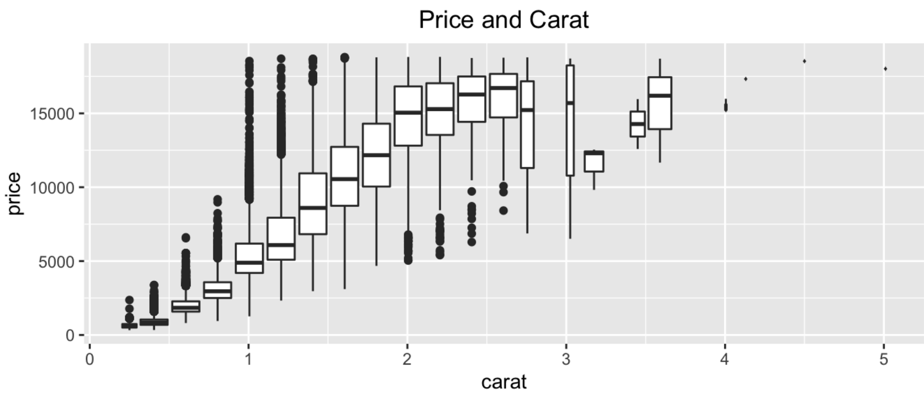
- Price and Carat

From the two graphs below we can see a positive relationship between carat and price. As the carat is higher, the price is higher.

```
ggplot(diamonds) +
  geom_point(aes(x = carat, y = price, color = clarity)) +
  ggtitle("Price and Carat") +
  theme(plot.title = element_text(hjust = 0.5))
```



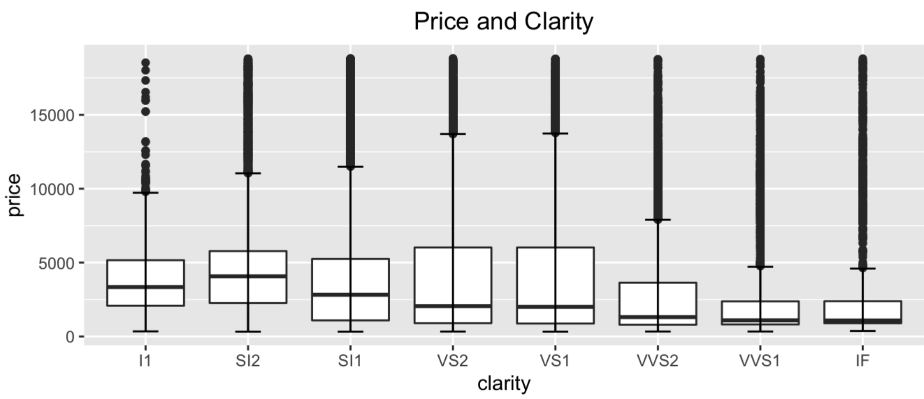

```
ggplot(diamonds, aes(x = carat, y = price)) +
  geom_boxplot(mapping = aes(group = cut_width(carat, 0.2))) +
  ggtitle("Price and Carat") +
  theme(plot.title = element_text(hjust = 0.5))
```



- Price and Clarity: From worst to best : I1, SI2, SI1, VS2, VS1, VVS2, VVS1, IF

Regarding price and clarity, we see a negative relationship: as the clarity is better, the price is lower

```
ggplot(diamonds, aes(x = clarity, y = price)) +
  geom_boxplot() +
  stat_boxplot(
    geom = "errorbar", # Error bars
    width = 0.25
  ) +
  ggtitle("Price and Clarity") +
  theme(plot.title = element_text(hjust = 0.5))
```

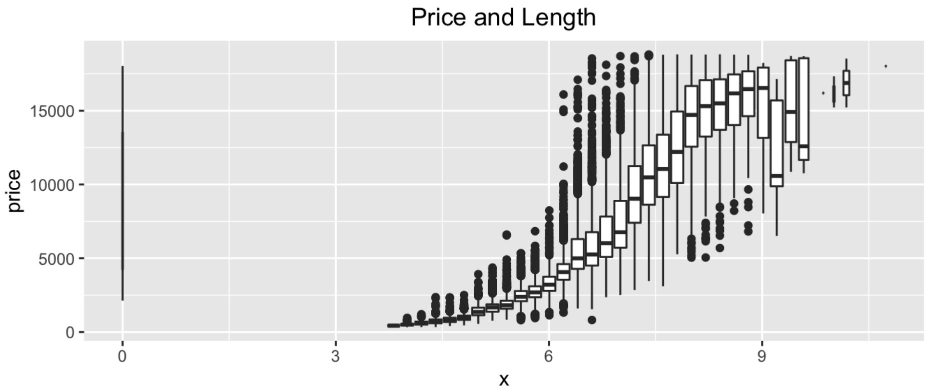


- Price and length (x variable)

With respect to the price and x (length) we appreciate a positive relationship. However, we can conclude that all the variables like length (x), width (y), depth (z), depth and table are contained in the variable “carat” which measures the weight of the diamond.

```
ggplot(diamonds) +
  geom_point(aes(x = x, y = price)) +
  ggtitle("Price and Length") +
  theme(plot.title = element_text(hjust = 0.5))
```

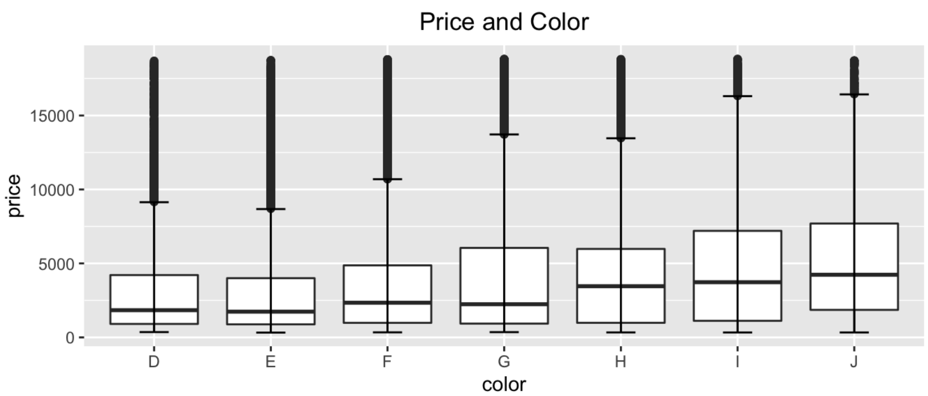

```
ggplot(diamonds, aes(x = x, y = price)) +
  geom_boxplot(mapping = aes(group = cut_width(x, 0.2)))  +
  ggtitle("Price and Length") +
  theme(plot.title = element_text(hjust = 0.5))
```



- Price and Color: from D (best) to J (worst)

As with the “clarity” variable, we can observe a negative relationship between price and color.

```
ggplot(diamonds, aes(x = color, y = price)) +
  geom_boxplot() +
  stat_boxplot(
    geom = "errorbar", # Error bars
    width = 0.25
  )  +
  ggtitle("Price and Color") +
  theme(plot.title = element_text(hjust = 0.5))
```

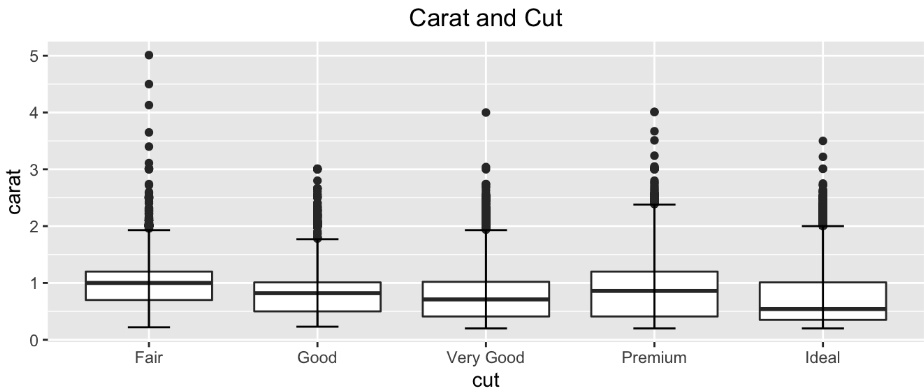


Of all the variables analyzed, we can see that the “carat” variable correlates more clearly with the “price” variable, that is, as the carat varies, there is a greater variation in the price. This conclusion is also supported by the regression performed.

b. How is that variable correlated with cut?

Between “carat” and “cut” there is a negative relationship, except for the “Premium” category of the cut variable. Leaving aside the mentioned category, the better the cut, the lower the carat.

```
diamonds$cut <- factor(diamonds$cut,
                          levels = c("Fair", "Good", "Very Good", "Premium", "Ideal"))

ggplot(diamonds, aes(x = cut, y = carat)) +
  geom_boxplot() +
  stat_boxplot(
    geom = "errorbar", # Error bars
    width = 0.25
  ) +
  ggtitle("Carat and Cut") +
  theme(plot.title = element_text(hjust = 0.5))
```



c. Explain why the table above is misleading.

```
diamonds %>%
  group_by(cut) %>%
  summarise(mean_price = mean(price), mean_carat = mean(carat)) %>%
  arrange(desc(mean_carat))
```

cut <fct>	mean_price <dbl>	mean_carat <dbl>
Fair	4358.758	1.0461366
Premium	4584.258	0.8919549
Good	3928.864	0.8491847
Very Good	3981.760	0.8063814
Ideal	3457.542	0.7028370

5 rows

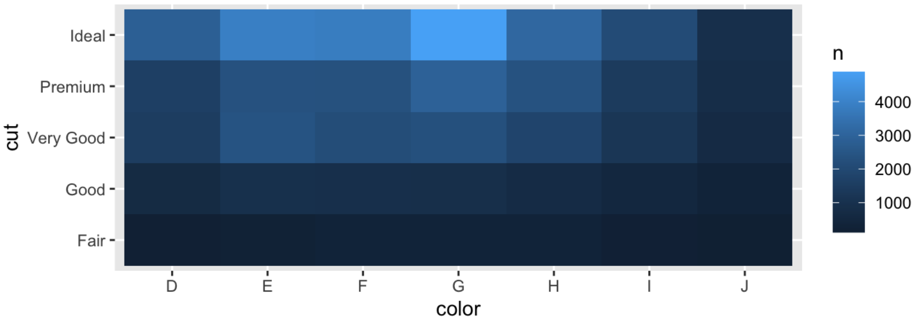
The table is deceptive since it does not include all of the attributes that must be considered when determining the diamond’s price. We’ve previously demonstrated that the carat accounts for a considerable portion of the range in diamond pricing. For example, the “ideal” diamond (the best cut) has a smaller average carat, which explains why it costs less (there are probably only small diamonds with ideal cut). In addition, the “Premium” cut has the greatest price as well as the largest average carat.

On the other hand, we discovered that other factors, such as color and clarity, are associated to pricing.

2. After recreating the two categorical variable dataframe in 7.5.2 from the textbook, adjust it to more clearly show the distribution of cut within colour.

- Graph from the text book:

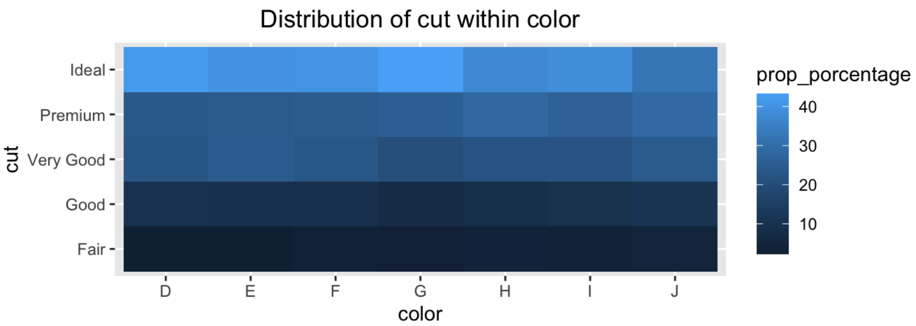
```
diamonds %>%
  count(color, cut) %>%
  ggplot(mapping = aes(x = color, y = cut)) +
    geom_tile(mapping = aes(fill = n))
```



- Adjusting to show more clearly the distribution of cut within color:

The number of repetitions of cuts in colors does not clearly show the distribution. Therefore, we are going to use the ratio of cuts for each color (total number of cuts per color divided by the total number of cuts in that color).

```
diamonds %>%
  count(color, cut) %>%
  group_by(color) %>%
  mutate(prop_porcentage = (n / sum(n))*100) %>% #we are multiplying by 100 to have porcentage
  ggplot(mapping = aes(x = color, y = cut)) +
  geom_tile(mapping = aes(fill = prop_porcentage)) +
  ggtitle("Distribution of cut within color") +
  theme(plot.title = element_text(hjust = 0.5))
```



a. Which cut is most common in every color category?

The “Ideal” color is more common in each category of the color variable. As we can see in the graph, the “Ideal” cut represents approximately 40% of the total cuts for all colors.

b. Repeat the exercise again to show distribution of colour within cut.

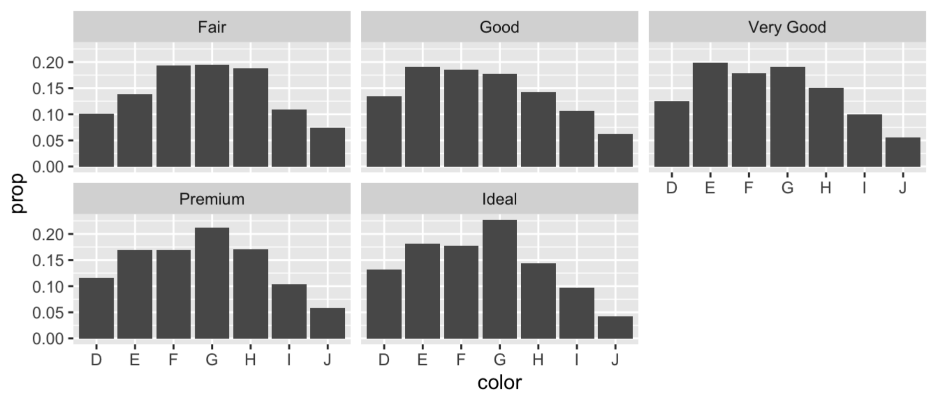
Now, let's group by cut:

```
diamonds %>%
  count(color, cut) %>%
  group_by(cut) %>%
  mutate(prop_porcentage = n / sum(n)*100) %>%
  ggplot(mapping = aes(x = color, y = cut)) +
  geom_tile(mapping = aes(fill = prop_porcentage)) +
  ggtitle("Distribution of colour within cut") +
  theme(plot.title = element_text(hjust = 0.5))
```

From the graph, we can see that color G is the one that is repeated the most within all the cut categories (it has the clearest grids).

c. Using the dataframe you just produced as input, reproduce the following graph.

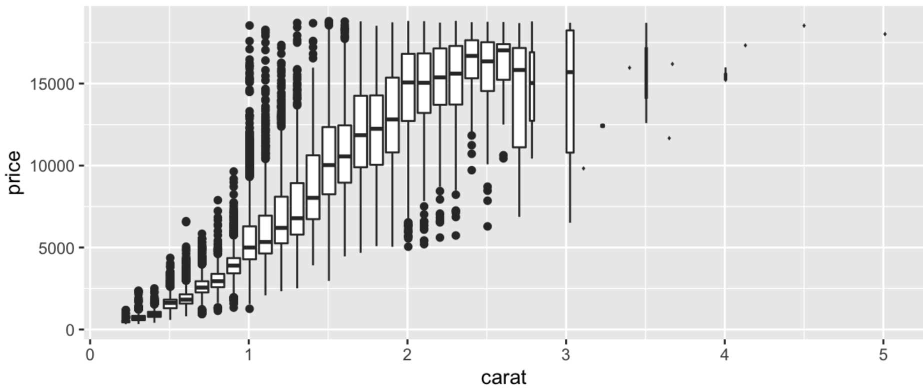
```
#Using the data frame from last plot
diamond2 <- diamonds %>%
  count(color, cut) %>%
  group_by(cut) %>%
  mutate(prop = n / sum(n))

ggplot(diamond2, aes(x = color, y = prop)) +
  geom_bar(stat = "identity") +
  facet_wrap(~cut)
```



3. Instead of summarising the conditional distribution of price by carat size with a boxplot (see 7.5.3), you could use a frequency polygon, where you map binned carat data to the color aesthetic.

- Graph from the book:

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

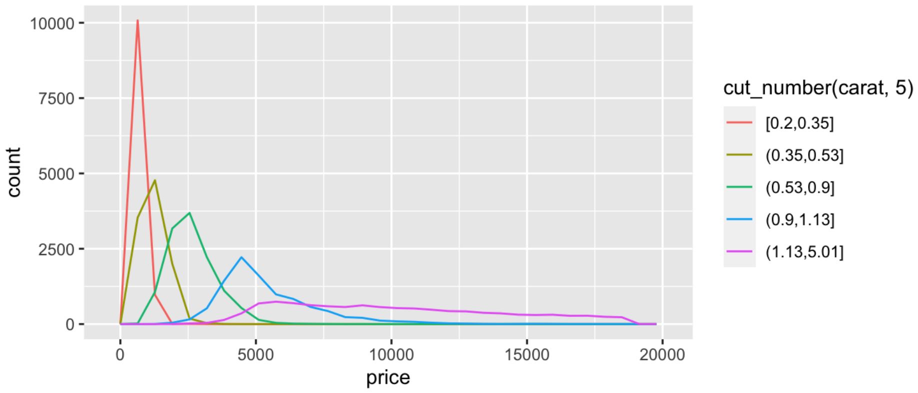


a. Make a frequency polygon using cut_width() and another using cut_number(). Adjust the parameters until you think both graphs are most useful.

By using cut_number we choose the number of bins that the graph should fetch. In this sense, in this case, five bins have been chosen since it is better perceived by sight, and contains the necessary information.

```
ggplot(diamonds, aes(x = price, color = cut_number(carat, 5))) +
    geom_freqpoly()
```

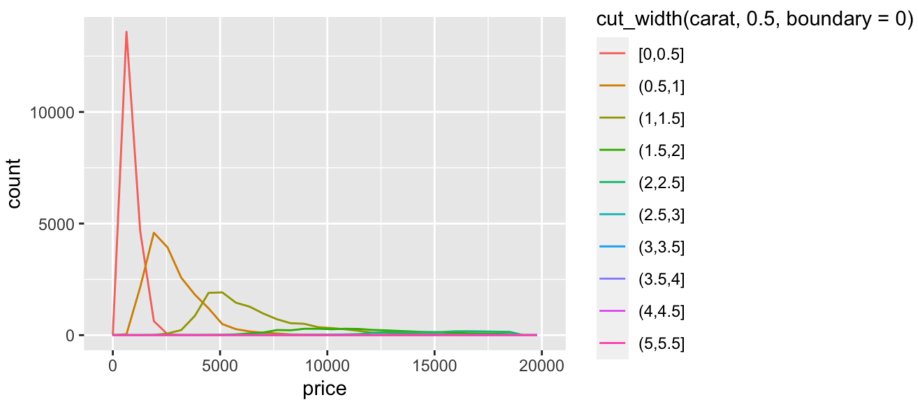
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



On the other hand, when we use cut_width, we determine the width and R performs the calculation of how many containers correspond. By choosing a larger width number, very little information is visible (only one frequency is visible); even though the width of 0.5 creates multiple clusters, only three are correctly perceived on the graph, so it is considered to present valuable information.

```
ggplot(diamonds, aes(x = price, color = cut_width(carat, 0.5, boundary = 0))) +
    geom_freqpoly()
```

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



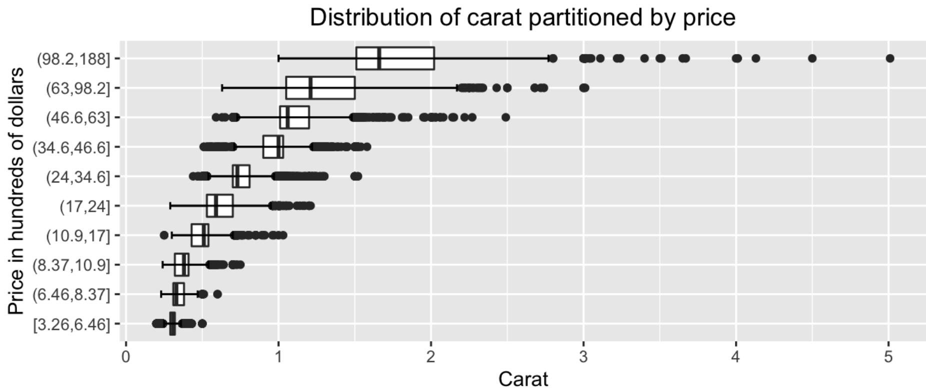

```
# we put boundary = 0 to ensure the first bin starts with 0
```

b. For this application (carat and price), what are the pros and cons of cut_width() relative to cut_number()?

Since the data is skewed to the right in this application, the downside of cut_width() is that it's hard to set a width that can display enough information in the rightmost bins. On the other hand, the advantage is that the intervals of each of the bits is the same, and can be quickly identified, unlike the cut_number function.

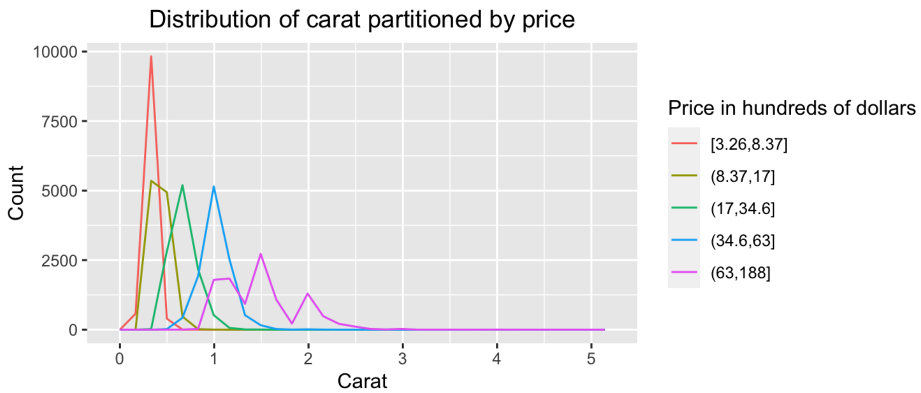
4. Visualize the distribution of carat, partitioned by price. The graph should have a clear story accentuated by a descriptive title.

```
ggplot(diamonds, aes(x = cut_number(price/100, 10), y = carat)) +
  geom_boxplot() +
  stat_boxplot(
    geom = "errorbar", # Error bars
    width = 0.25
  )  +
  ggtitle("Distribution of carat partitioned by price") +
  theme(plot.title = element_text(hjust = 0.5)) +
  labs(y = "Carat", x = "Price in hundreds of dollars") +
  coord_flip()
```




```
ggplot(diamonds, aes(x = carat, color = cut_number(price / 100, 5))) +
  geom_freqpoly() +
  ggtitle("Distribution of carat partitioned by price") +
  theme(plot.title = element_text(hjust = 0.5)) +
  labs(y = "Count", x = "Carat", color = "Price in hundreds of dollars")
```

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



5. How does the price distribution of very large diamonds (as measured by carat) compare to small diamonds? Is it as you expect, or does it surprise you? Why?

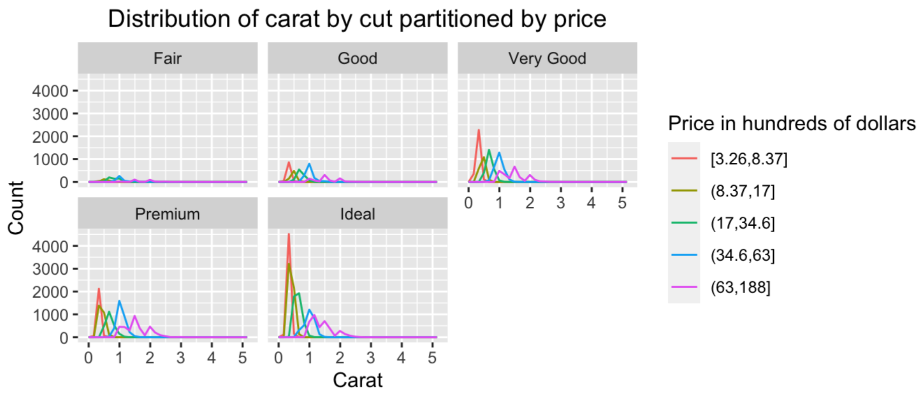
The variance in the distribution of bigger diamonds is significantly greater than the variation in the distribution of smaller diamonds, as can be seen in both graphs. In the first graph, for example, we can see that the box plot grows larger as the carat increases, and there are also more outliers. We can observe from graph 2 that smaller diamonds have a narrower bin. I'm not surprised, because I would anticipate people to seek out bigger diamonds. As a result, it's more likely that there will be a bigger supply (number) of big diamonds, and that their qualities will be more diverse in relation to them (affecting price).

We've seen in earlier questions that pricing is influenced by factors like clarity, cut, and color. As a result, having a larger number of huge diamonds increases the likelihood of a wider range of characteristics and, ultimately, a higher variation in price.

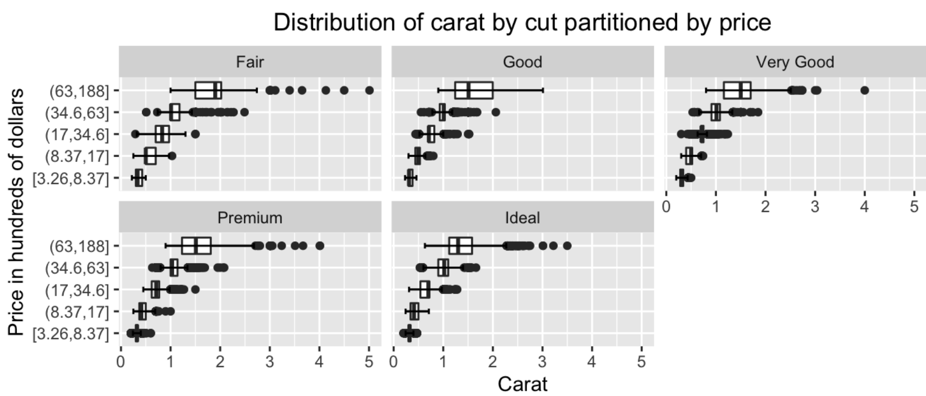
6. So far we've focused on visualizing covariation of two variables. We can add a third dimension in several ways. For example, we could map to a third aesthetic or add facets. Combine two of the techniques you've learned in this class to visualise the combined distribution of cut, carat, and price.

```
ggplot(diamonds, aes(x = carat, color = cut_number(price / 100, 5))) +
  geom_freqpoly() +
  ggtitle("Distribution of carat by cut partitioned by price") +
  theme(plot.title = element_text(hjust = 0.5)) +
  labs(y = "Count", x = "Carat", color = "Price in hundreds of dollars") +
  facet_wrap(~ cut)
```

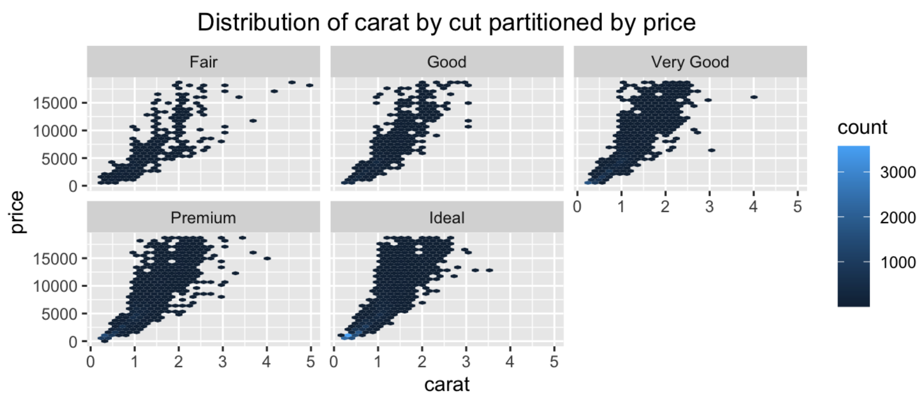
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ggplot(diamonds, aes(x = cut_number(price/100, 5), y = carat)) +
  geom_boxplot() +
  stat_boxplot(
    geom = "errorbar", # Error bars
    width = 0.25
  ) +
  ggtitle("Distribution of carat by cut partitioned by price") +
  theme(plot.title = element_text(hjust = 0.5)) +
  labs(y = "Carat", x = "Price in hundreds of dollars") +
  coord_flip() +
  facet_wrap(~ cut)
```

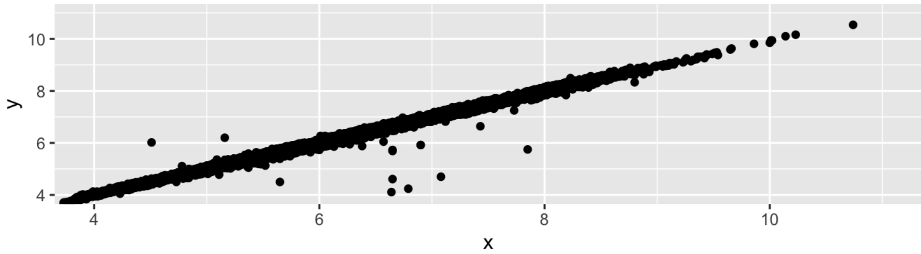



```
ggplot(diamonds) +
  geom_hex(aes(x = carat, y = price)) +
  facet_wrap(~ cut) +
  ggtitle("Distribution of carat by cut partitioned by price") +
  theme(plot.title = element_text(hjust = 0.5))
```

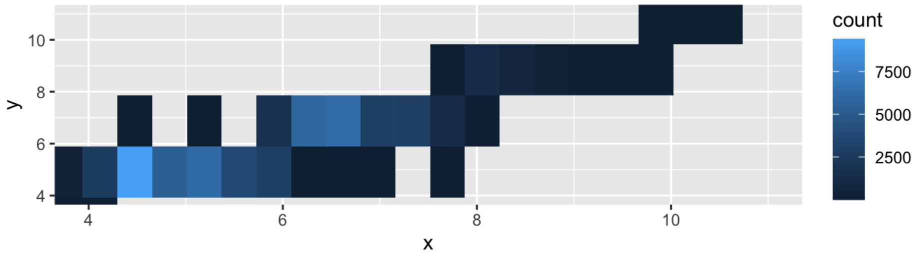


7. Two dimensional plots reveal outliers that are not visible in one dimensional plots. For example, some points in the plot below have an unusual combination of x and y values, which makes the points outliers even though their x and y values appear normal when examined separately. Consider the two plots below

```
ggplot(data = diamonds) +
geom_point(mapping = aes(x = x, y = y)) +
coord_cartesian(xlim = c(4, 11), ylim = c(4, 11))
```




```
ggplot(data = diamonds) +
geom_bin2d(mapping = aes(x = x, y = y)) +
coord_cartesian(xlim = c(4, 11), ylim = c(4, 11))
```



Which geom is better for identifying outliers? Why?

The geom_point plot.

The first plot, geom_point, more directly reveals the outliers of the x and y variables. The same cannot be said of the binned plot, because it has categorized data in bins, which does not allow the individual data to be identified at a glance. In this sense, the last graph does not allow to clearly establish an association between the variables and visualize the outliers.

Flights (10 points)

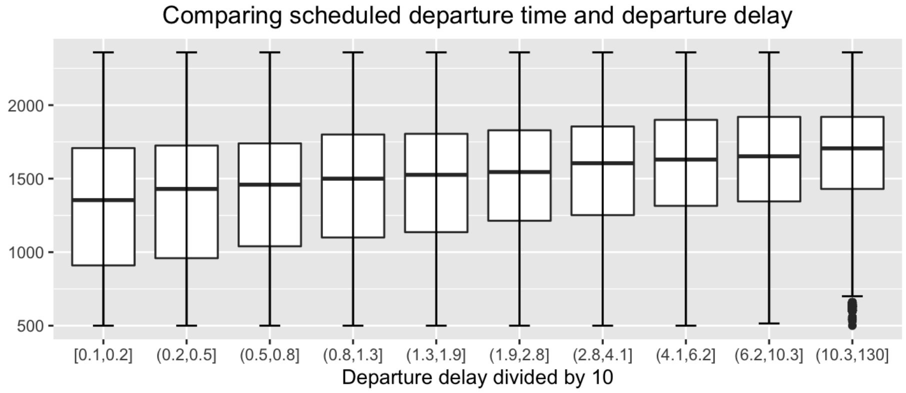
1. In class we saw three ways other than geom_point() to relate two continuous variables. Use these three ways to compare scheduled departure time and departure delay. (hint: you will need to construct groups for geom_boxplot() to get it to work.) What lessons stand out from each geom choice? Are any geoms dominated, meaning that you would never want to use them?

```
library(nycflights13)
view(flights)
```

- Using geom_boxplot

From the boxplot, we can conclude that as a flight is scheduled later, there is a higher average departure delay. Likewise, it can be seen that there is less variation in the variable “dep_delay” as the flight is scheduled for later.

```
flights %>%
  filter(dep_delay > 0) %>% # Using only delay flights (no flights that departed early)
  ggplot(aes(x = cut_number(dep_delay / 10, 10), y = sched_dep_time)) +
  geom_boxplot() +
  stat_boxplot(
    geom = "errorbar", # Error bars
    width = 0.25
  ) +
  ggtitle("Comparing scheduled departure time and departure delay") +
  theme(plot.title = element_text(hjust = 0.5)) +
  labs(y = "", x = "Departure delay divided by 10")
```

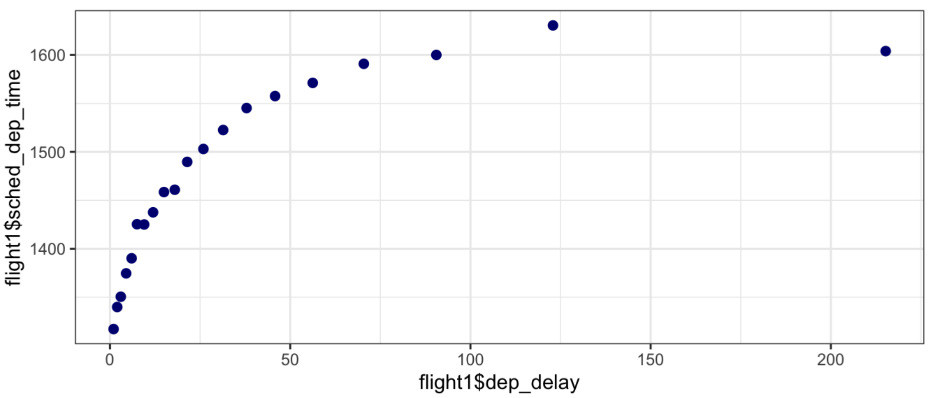



```
library(binsreg)
```

- Using binscatter

This graph shows us in a more direct way the relationship between the scheduled time of the flight and its delay. In this way, we can establish that both variables have a positive correlation, the latest the flight time is, the greater the probability of delay.

```
# Using only delay flights (no flights that departed early)
flight1 <- flights %>%
  filter(dep_delay > 0)

binsreg(flight1$sched_dep_time, flight1$dep_delay, nbins = 20)
```

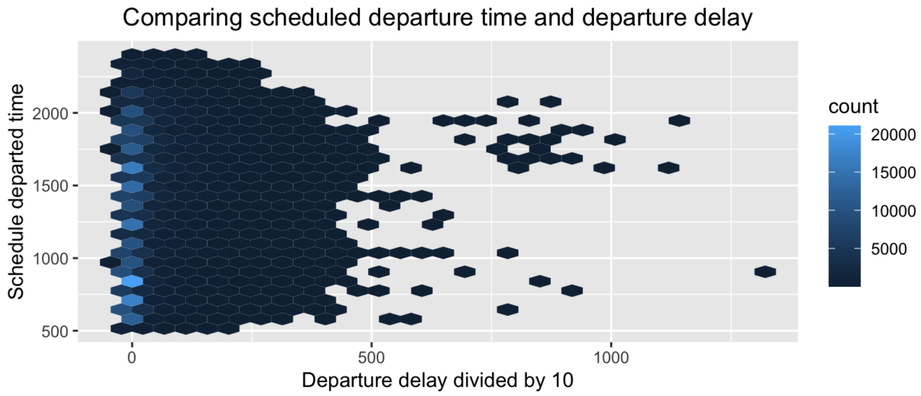


```
## Call: binsreg
##
## Binscatter Plot
## Bin selection method (binsmethod)  =  User-specified
## Placement (binspos)                =  Quantile-spaced
## Derivative (deriv)                 =  0
##
## Group (by)                         =  Full Sample
## Sample size (n)                    =  128432
## # of distinct values (Ndist)       =  495
## # of clusters (Nclust)             =  NA
## dots, degree (p)                   =  0
## dots, smooth (s)                   =  0
## # of bins (nbins)                  =  20
```

- Using geom_hex

We could say that this third plot is the one that is dominated by the two previous variables. This graph does not show the relationship of variables very clearly, since the data is divided into bins, i.e. that do not allow the data to be viewed well.

```
ggplot(flights) +
  geom_hex(aes(x = dep_delay, y = sched_dep_time))  +
  ggtitle("Comparing scheduled departure time and departure delay") +
  theme(plot.title = element_text(hjust = 0.5))  +
  labs(y = "Schedule departed time", x = "Departure delay divided by 10")
```



R4DS Chapter 10 and 11 (15 points)

1. Consider the code chunk below with three operations applied to the data.frame called d_f. Create a tibble with the same content and apply these same three operations to the tibble. How do the results differ? Why might the default data frame behaviours cause you frustration?

```
d_f <- data.frame(abc = 1, xyz = "a")
d_f$x
```

```
## [1] "a"
```

```
d_f[, "xyz"]
```

```
## [1] "a"
```

```
d_f[, c("abc", "xyz")]
```

abc	xyz
<dbl>	<chr>
1	a

1 row

-Create a tibble

```
tbl <- as_tibble(d_f)
tbl$x
```

```
## Warning: Unknown or uninitialised column: `x`.
```

```
## NULL
```

```
tbl[, "xyz"]
```

xyz
<chr>
a

1 row

```
tbl[, c("abc", "xyz")]
```

abc	xyz
<dbl>	<chr>
1	a

1 row

```
# This will be the same result than in the dataframe
```

The results differ in both the first and second application of the code. When using the d_f
xfunctiononthedataframe, theresultis " a ". However, withthetibblewenolongerhavethesameanswer. Thisdifferenceoccurs, sincewiththedatafram
function looks for any column that begins with the letter x. The frustrating thing is that this can cause complications in the treatment of the data. By chance, we can take a column that does not correspond to the one we want to work with.

To have the same result with the tibble, we would have to use tdf$xyz for the first application of the code.

Regarding the second application, the dataframe shows the result as a vector and not as a table. Instead, tibble returns the output as a table

2. Write code to import a file “file.xxx” where fields are separated with “|”?

we were told not to do this question

3. Identify what is wrong with each of the following inline CSV files.

- 1. read_csv(“a,b n 1,2,3 n 4,5,6”)

What is wrong with this table is that only two columns “a and b” have been created but we have data as if there were three columns. Therefore, the value of the third column is being merged with the value of the second column.

- 2. read_csv(“a,b,c n 1,2 n 1,2,3,4”)

Similar to the previous case, the error now occurs because the third row had four data, but only three columns “a,b and c” had been created. Likewise, the second row only had two data and was assigned the value of NA.

- 3. read_csv(“a,b n ”1")

We get data error that a value ("“) has been quoted, as there is an extra”". The problem is solved if you remove the quotes from the number 1.

- 4. read_csv(“a,b n 1,2 na,b”)

Since the second row is made up of “a” and “b” as strings, the numbers in the first row will also be considered as characters. Both columns are clasified as .

- 5. read_csv(“a;b;3”)

The function is treating the information poured as a single column. It does not recognize the semicolon (;), just commas. In this application, if we remove the semicolon and replace it with the comma, the tables will be fixed.

4. Review the textbook to understand locale(). What do the date_format and time_format options to locale() do? Figure out how to handle dates from Latin American countries. Provide a code line of code as an example of your understanding.

Date_format and time_format set a specific format to use for the date or time respectively. They help encapsulate the common characteristics by locality, in this case specifically referring to time and dates. For example, we would put the following:

- Using date_format:

```
parse_date("23/05/22", locale = locale(date_format = "%d/%m/%y"))
```

```
## [1] "2022-05-23"
```

- Using time_format:

```
parse_time("5:35 PM", locale = locale(time_format = "%H:%M %p"))
```

```
## 17:35:00
```

- Handling dates from Latin American countries

```
date_names_langs()
```

```
##   [1] "af"  "agq" "ak"  "am"  "ar"  "as"  "asa" "az"  "bas" "be"  "bem" "bez"
##  [13] "bg"  "bm"  "bn"  "bo"  "br"  "brx" "bs"  "ca"  "cgg" "chr" "cs"  "cy"
##  [25] "da"  "dav" "de"  "dje" "dsb" "dua" "dyo" "dz"  "ebu" "ee"  "el"  "en"
##  [37] "eo"  "es"  "et"  "eu"  "ewo" "fa"  "ff"  "fi"  "fil" "fo"  "fr"  "fur"
##  [49] "fy"  "ga"  "gd"  "gl"  "gsw" "gu"  "guz" "gv"  "ha"  "haw" "he"  "hi"
##  [61] "hr"  "hsb" "hu"  "hy"  "id"  "ig"  "ii"  "is"  "it"  "ja"  "jgo" "jmc"
##  [73] "ka"  "kab" "kam" "kde" "kea" "khq" "ki"  "kk"  "kkj" "kl"  "kln" "km"
##  [85] "kn"  "ko"  "kok" "ks"  "ksb" "ksf" "ksh" "kw"  "ky"  "lag" "lb"  "lg"
##  [97] "lkt" "ln"  "lo"  "lt"  "lu"  "luo" "luy" "lv"  "mas" "mer" "mfe" "mg"
## [109] "mgh" "mgo" "mk"  "ml"  "mn"  "mr"  "ms"  "mt"  "mua" "my"  "naq" "nb"
## [121] "nd"  "ne"  "nl"  "nmg" "nn"  "nnh" "nus" "nyn" "om"  "or"  "os"  "pa"
## [133] "pl"  "ps"  "pt"  "qu"  "rm"  "rn"  "ro"  "rof" "ru"  "rw"  "rwk" "sah"
## [145] "saq" "sbp" "se"  "seh" "ses" "sg"  "shi" "si"  "sk"  "sl"  "smn" "sn"
## [157] "so"  "sq"  "sr"  "sv"  "sw"  "ta"  "te"  "teo" "th"  "ti"  "to"  "tr"
## [169] "twq" "tzm" "ug"  "uk"  "ur"  "uz"  "vai" "vi"  "vun" "wae" "xog" "yav"
## [181] "yi"  "yo"  "zgh" "zh"  "zu"
```

```
parse_date("5 Marzo 2022", "%d %B %Y", locale = locale("es"))
```

```
## [1] "2022-03-05"
```

5. Generate the correct format string to parse each of the following dates and times:

```
d1 <- "January 1, 2010"
d2 <- "2015-Mar-07"
d3 <- "06-Jun-2016"
d4 <- c("August 19 (2015)", "July 1 (2015)")
d5 <- "12/30/14" # Dec 30, 2014
t1 <- "1805" # 6:05 pm
t2 <- "11:25:10.12 PM"
```

- Correct format d1:

```
parse_date(d1, "%B %d, %Y")
```

```
## [1] "2010-01-01"
```

- Correct format d2:

```
parse_date(d2, "%Y-%b-%d")
```

```
## [1] "2015-03-07"
```

- Correct format d3:

```
parse_date(d3, "%d-%b-%Y")
```

```
## [1] "2016-06-06"
```

- Correct format d4:

```
parse_date(d4, "%B %d (%Y)")
```

```
## [1] "2015-08-19" "2015-07-01"
```

- Correct format d5:

```
parse_date(d5, "%m/%d/%y")
```

```
## [1] "2014-12-30"
```

- Correct format t1:

```
parse_time(t1, "%H%M")
```

```
## 18:05:00
```

- Correct format t2:

```
parse_time(t2, "%I:%M:%OS %p")
```

```
## 23:25:10.12
```

6. Run fwf_empty() using readr_example("massey-rating.txt"). Describe the output.

```
readr_example("massey-rating.txt") %>%
  fwf_empty()
```

```
## $begin
##  [1]  0  4  8 12 17 22 26 30 34 38 42 47 63
##
## $end
##  [1]  3  7 11 15 19 25 29 33 37 41 46 59 NA
##
## $col_names
##  [1] "X1"  "X2"  "X3"  "X4"  "X5"  "X6"  "X7"  "X8"  "X9"  "X10" "X11" "X12"
## [13] "X13"
```

As an alternative to using parse, the fwf_empty function makes guesses based on the positions of empty columns. In that sense, we have an output that shows 13 column names (X1 to X13) and two additional columns: begin and end. The data of the last mentioned variables are ascending. We can also see that there is a missing value, which is set to "NA"