

Data Science

CS301

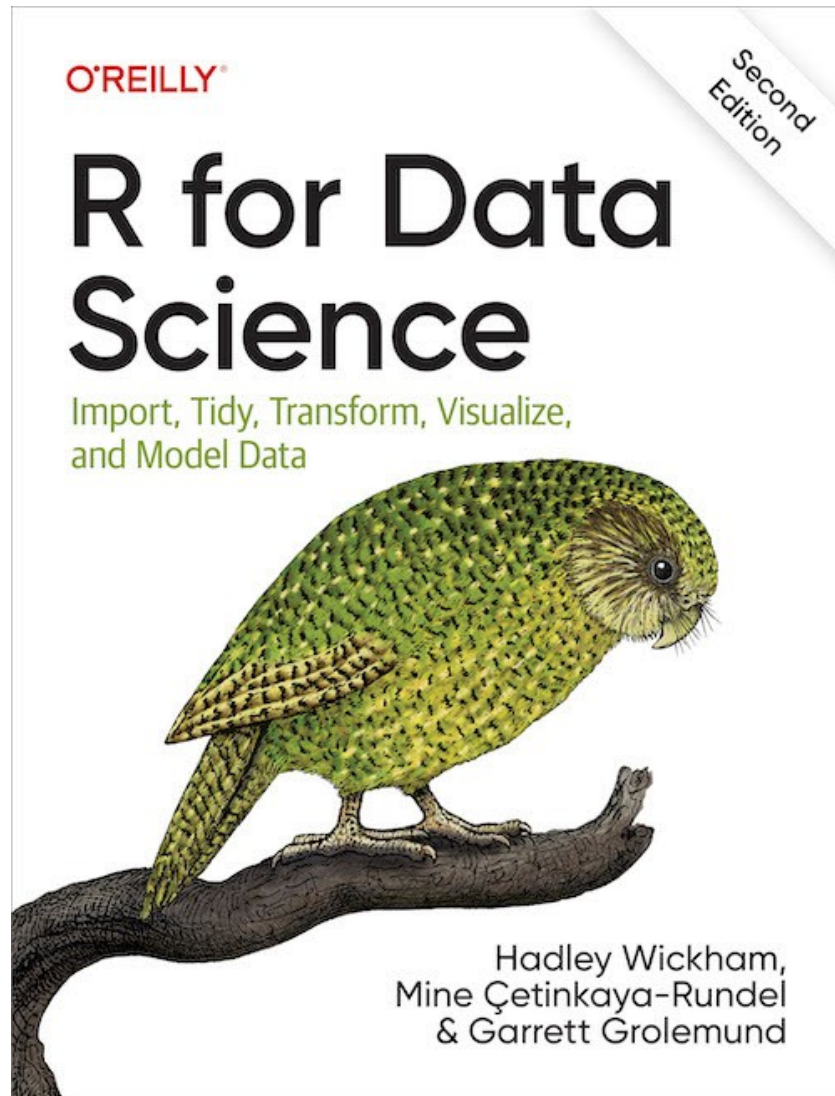
Exploratory First Steps, Continued

Week 4

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Where in the Web?



Web:

Chap 10: Exploratory
Data Analysis

– <https://r4ds.hadley.nz/eda>



Missing Data Points?

MISSING





Missing Data Entries

- Missing data in R appears as **NA**.
- **NA** is not a string or a numeric value, but an indicator of missing data.
- Let's create vectors with missing values to test

```
library(tidyverse)
library(tibble)
x1 <- c(1, 4, 3, NA, 7)
x2 <- c("a", "B", NA, "NA")
is.na(x1)
is.na(x2)
```

Spot
missing
data



Missing Data Entries

- What to do when elements of your data go missing?
- **Why not just DROP the ENTIRE ROW, as well as to drop all the value contained by its other variables as well??**

```
diamonds2 <- diamonds %>% filter(between(y, 3, 20))
```

This is a shortcut for $y \geq 3$ & $y \leq 20$

```
View(diamonds2)
```

```
# compare to the the size of original dataset
```

```
View(diamonds)
```

```
# Note: Good data may have been lost by dropping rows.
```



IfElse(): Condition Statement

```
y = ifelse(y < 3 | y > 20, NA, y)
```

- **Function**
- **Test Condition**
- **If True, then assign this**
- **If False, then assign this**



Data: *Diamond*

The book recommends to *mark* the data as bad or missing.

```
diamonds2 <- diamonds %>%
```

```
  mutate(y = ifelse(y < 3 | y > 20, NA, y))
```

syntax: `ifelse(test, yes, no)`

Inspect each value of *y*. If the *y* is not between 3 and 20, then *y* = NA, else *y* = *y*



We Plot All Non-NA Values

Missing, outliers values marked as NA

```
ggplot(data = diamonds2, mapping =  
aes(x = x, y = y)) + geom_point()
```

compared to, no removed missing or outlier
values

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

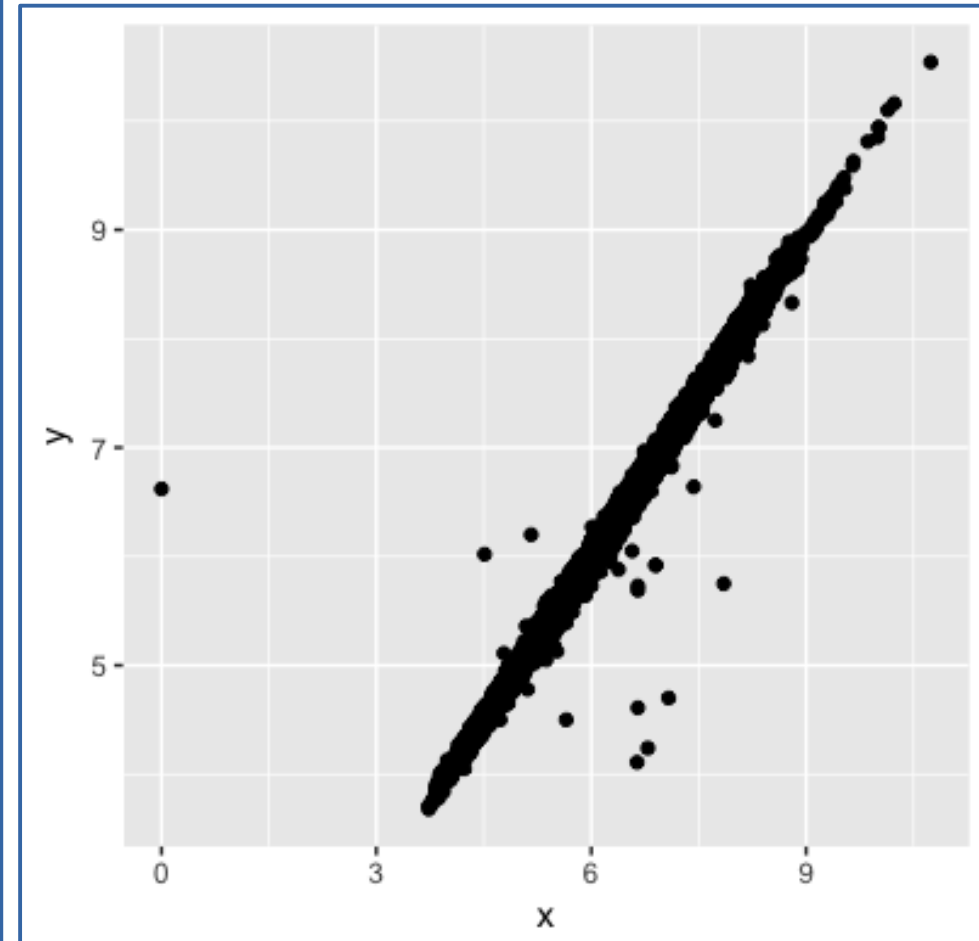
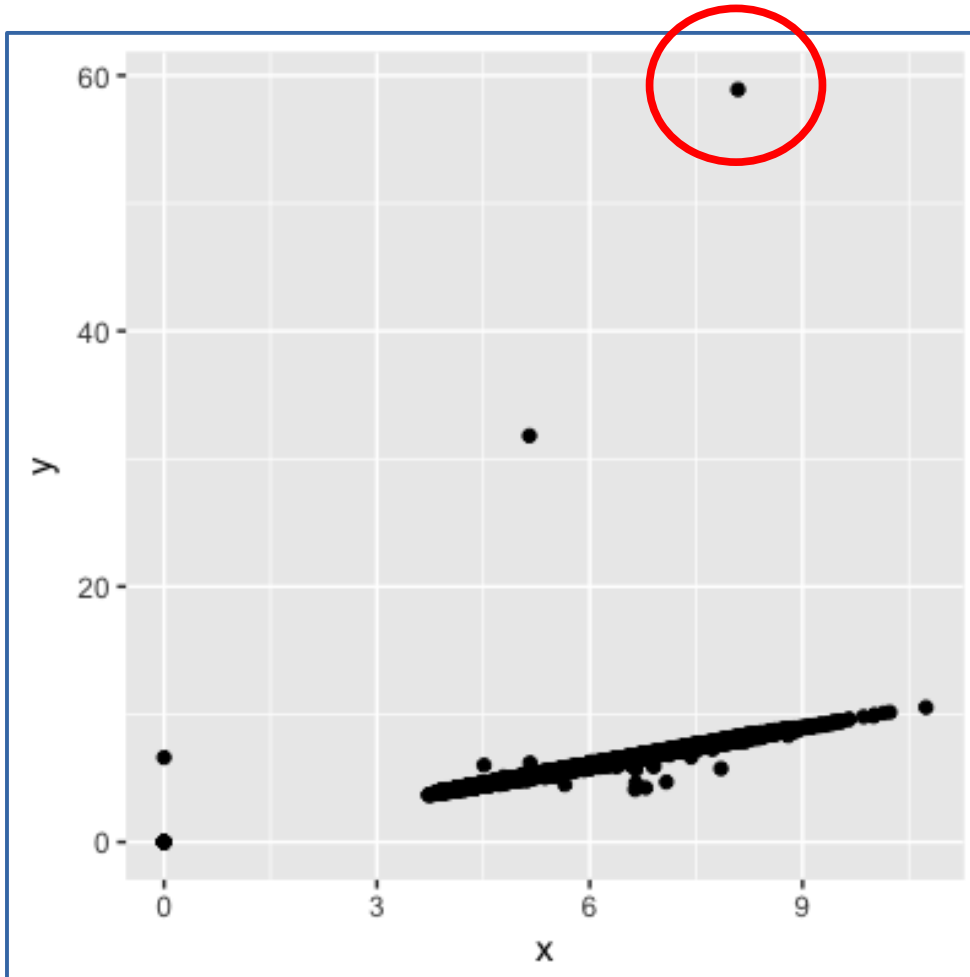



Missing Values, continued

```
# remove the outliers for y (i.e., y<3 and y >20)
library(tidyverse)
?ifelse # get online help
diamonds2 <- diamonds %>%
  mutate(y = ifelse(y < 3 | y > 20, NA, y))
ggplot(data = diamonds2,
  mapping = aes(x = x, y = y)) + geom_point()
```

**Add the ifelse() code
directly to your other code.**

Trimmed Data, Slightly Different Plot...



- Left: **WITH** outliers
- Above: **NO** outliers



Data: *Diamond*

Can you use the below code to further trim outliers or missing data?

Plot your new graphic after using *ifelse()*

```
diamonds3 <- diamonds %>%  
  mutate(y = ifelse(y < ## | y > ##, NA, y))
```

THINK

Missing Values May Have Their Own Meanings

- Q: Does missing flight arrival-time data indicate canceled flights?



A photograph of an airport flight information display board. The board has four columns: TIME, DESTINATION, GATE#, and STATUS. The text is displayed in green on a black background. All flights listed are marked as 'CANCELLED' in the STATUS column, and the GATE# column contains dashes ('---').

TIME	DESTINATION	GATE#	STATUS
12:00	COPENHAGEN	---	CANCELLED
12:15	PARIS	---	CANCELLED
12:25	LONDON	---	CANCELLED
13:20	FRANKFURT	---	CANCELLED
13:45	ZURICH	---	CANCELLED
14:35	BRUSSELS	---	CANCELLED
15:00	MILAN	---	CANCELLED
16:25	KYIV	---	CANCELLED
16:55	MOSKOW	---	CANCELLED

Missing Values May Have Their Own Meanings

```
# install the flights data, if necessary.  
#install.packages("nycflights13")  
library(tidyverse, nycflights13)  
flights <- nycflights13::flights  
View(flights)  
  
# Where are the missing values  
flights$dep_time
```



The Distribution of a **Continuous** Variable, Aggregated By a **Categorical** variable

```
# compare the scheduled departure times for cancelled and non-  
cancelled times
```

```
flights %>%
```

```
  mutate(
```

```
    cancelled = is.na(dep_time),
```

```
    #%%/% is a whole number division
```

```
    sched_hour = sched_dep_time %/% 100,
```

```
    sched_min = sched_dep_time %% 100,
```

```
    sched_dep_time = sched_hour + sched_min / 60
```

```
  ) %>%
```

```
  ggplot(mapping = aes(sched_dep_time)) +
```

```
  geom_freqpoly(mapping = aes(colour = cancelled),
```

```
  binwidth = 1/4)
```



Erm, What Did That Previous Code Do?

First, the data frame `flights` is being piped using the `%>%` operator to allow to transform for the next step.

1. `mutate()` creates new columns in the data frame

- `cancelled` is a logical column that gets a value of TRUE for cancelled flights (i.e., where `dep_time` is NA)
- `sched_hour` is the hour component of the scheduled departure time, obtained by using whole number division (`%/% 100`) on the `sched_dep_time` Note: `5 %/% 2 == 2` (quotient is 2)
- `sched_min` is the minute component of the scheduled departure time, obtained by using the *modulo* operator (`%% 100`) on `sched_dep_time` Note: `5 %% 2 == 0` (remainder is 0)
- `sched_dep_time` is a new column that combines the hour and minute components into one value, with the hour as an integer and minutes as a decimal

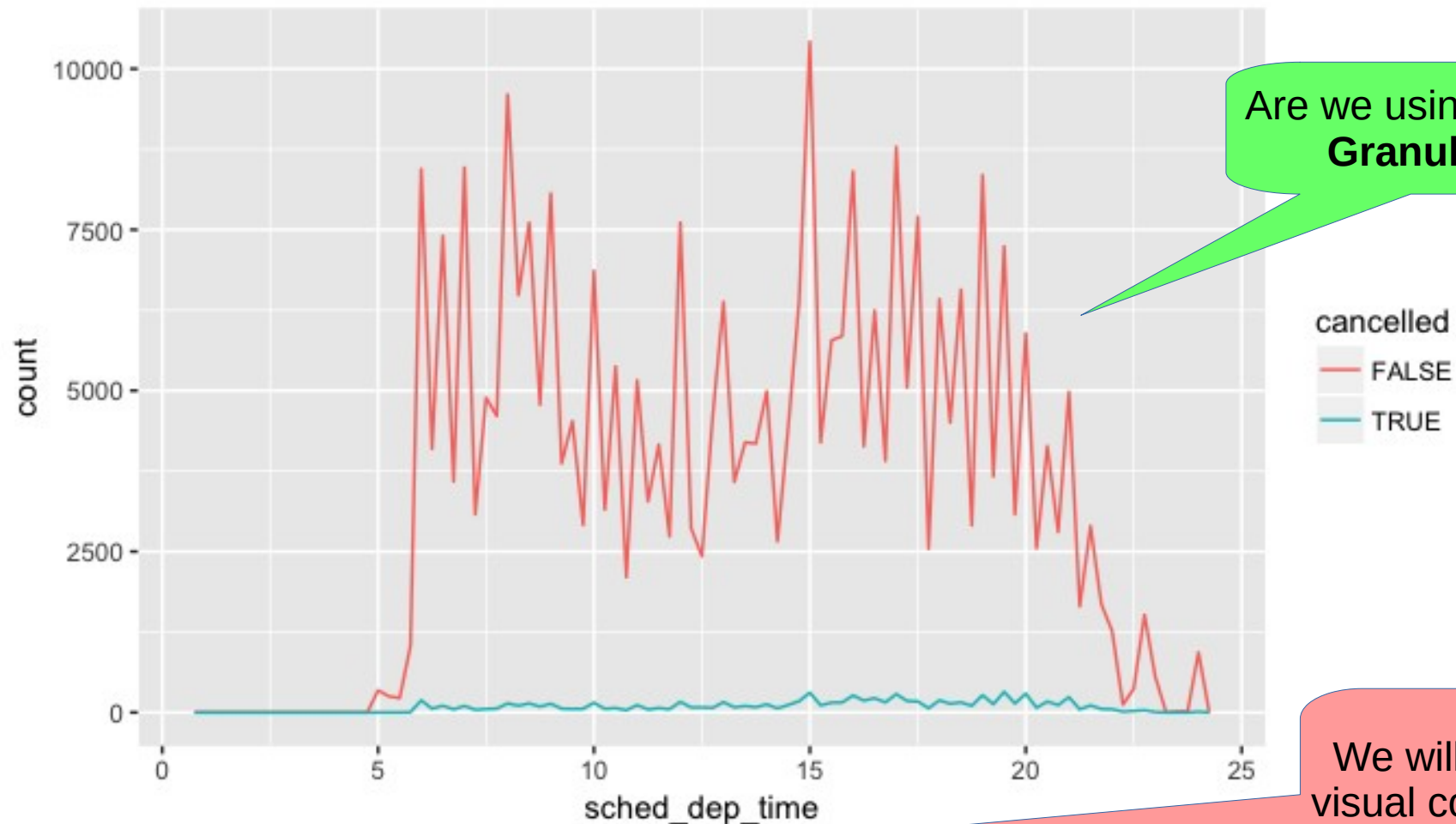
2. The resulting data frame is then being passed to `ggplot()` for visualization

3. In `ggplot()`, the data is being mapped to the *x-axis* using `sched_dep_time` and colored based on the `cancelled` column using the `aes()` function

4. The `geom_freqpoly()` layer is used for density estimation, which generates a histogram-like plot with polynomial lines connecting the bins. The `binwidth` argument sets the width of each bin to 1/4 hour



Potential Pitfalls in Theory



- We get an slight idea of when cancellations happen
- Many more non-cancelled flights than cancelled flights: *does the business side of flying introduce a bias for not-canceling flights?*



Covariation

covariance



co·var·i·ance

/ˌkōˈverēəns/

noun

1. MATHEMATICS

the property of a function of retaining its form when the variables are linearly transformed.

2. STATISTICS

the mean value of the product of the deviations of two variates from their respective means.

- **Covariation** is the tendency for the values of two or more variables to vary together in a related way.
- Study covariation by visualizing relationships between two or more variables.
- Pay attention to your variables to know how best to visualize these variables



Covariation

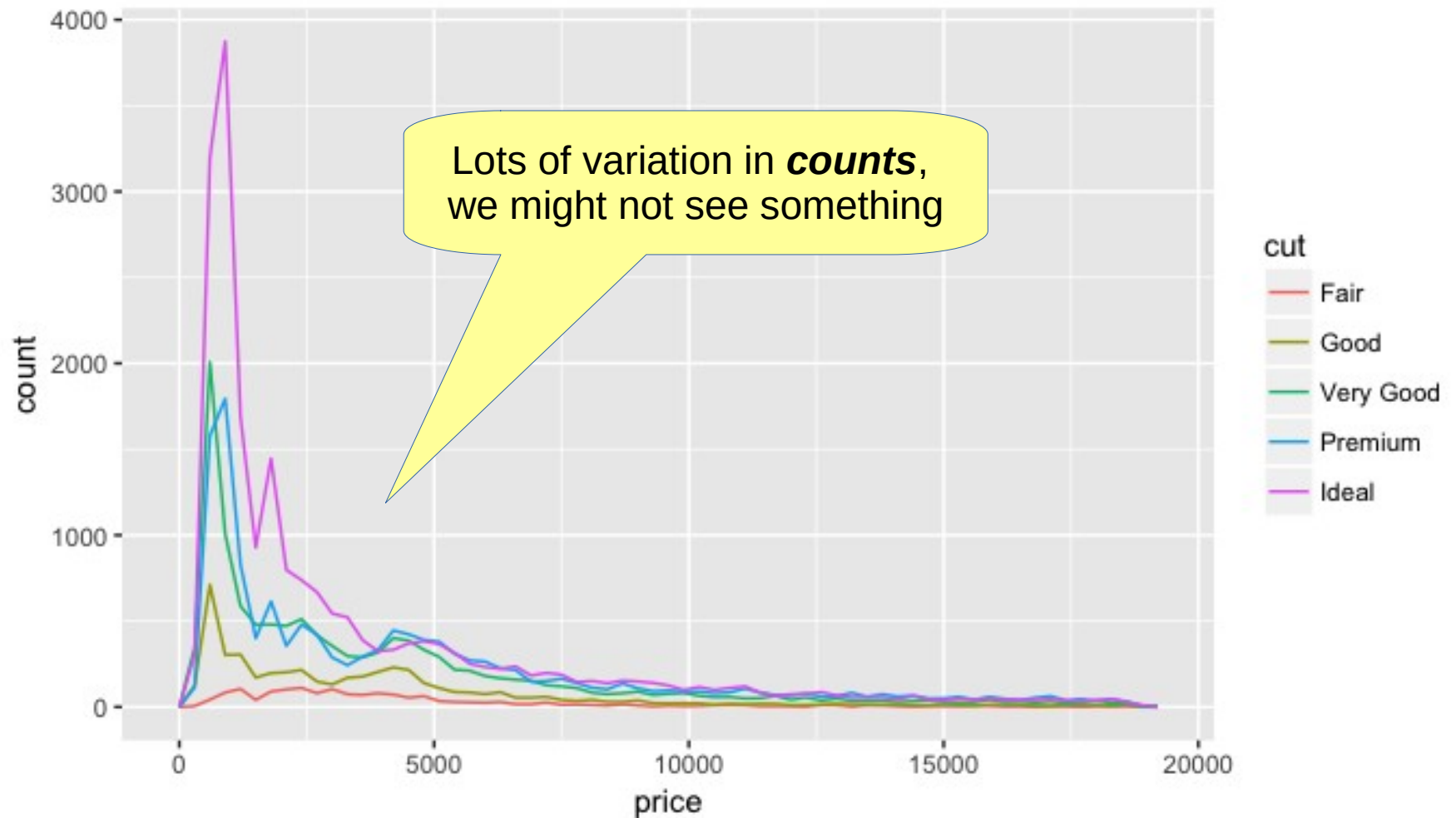
- Back to the **Diamonds** dataset
- How do the prices of diamonds vary with quality?

Plot the count of each cut quality according to price.

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



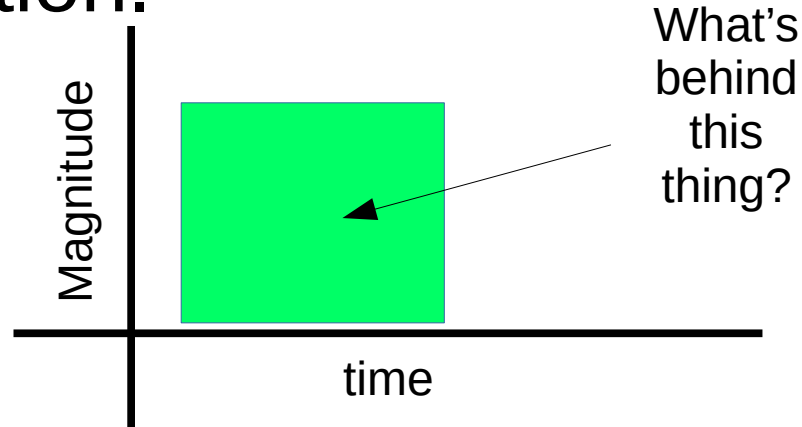
The Plot of the Diamond Counts





This Plot May Make It Hard To See The Phenomenon

- The counts variable seems to have values from all over the range.
- This is noise in our plot
- If one group is much smaller than the others, then it is hard to see the differences in its distribution.





Let's Change Our Plotting

Does a histogram help?

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

#Note: **Density**, the count is standardized so that the area under each frequency polygon is one unit

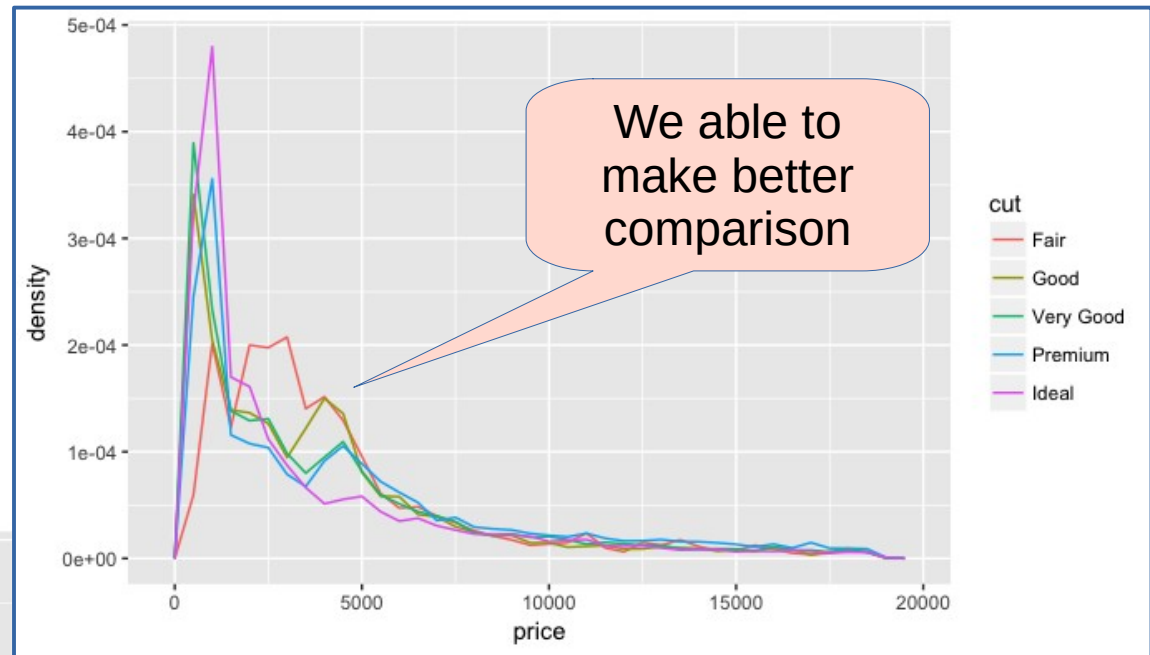
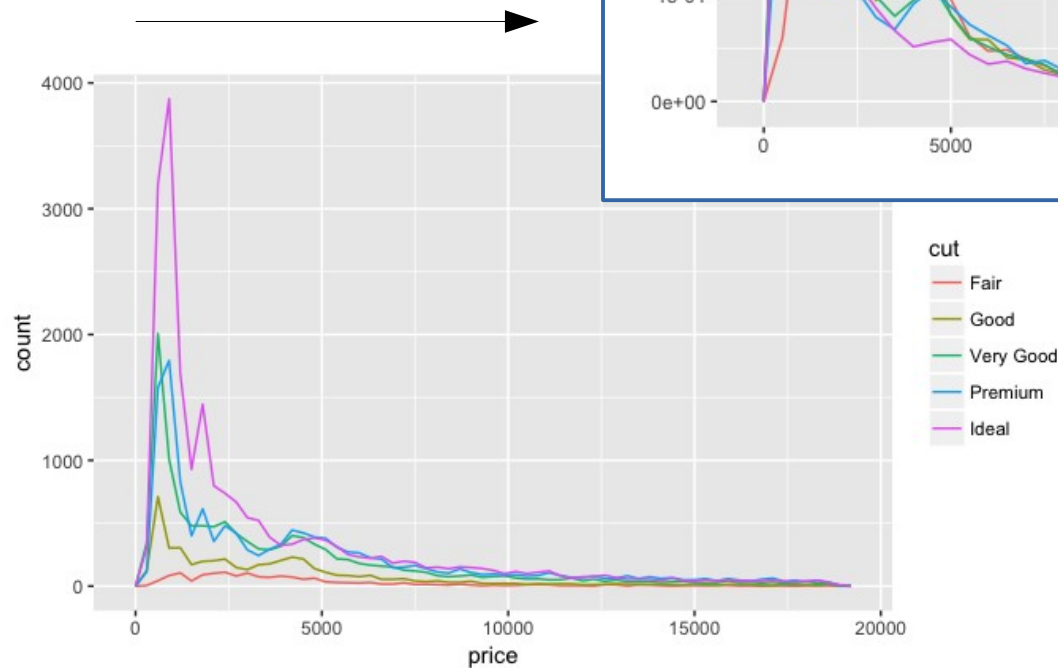
We change the axis “level” the view for all

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

Normalize Your View!

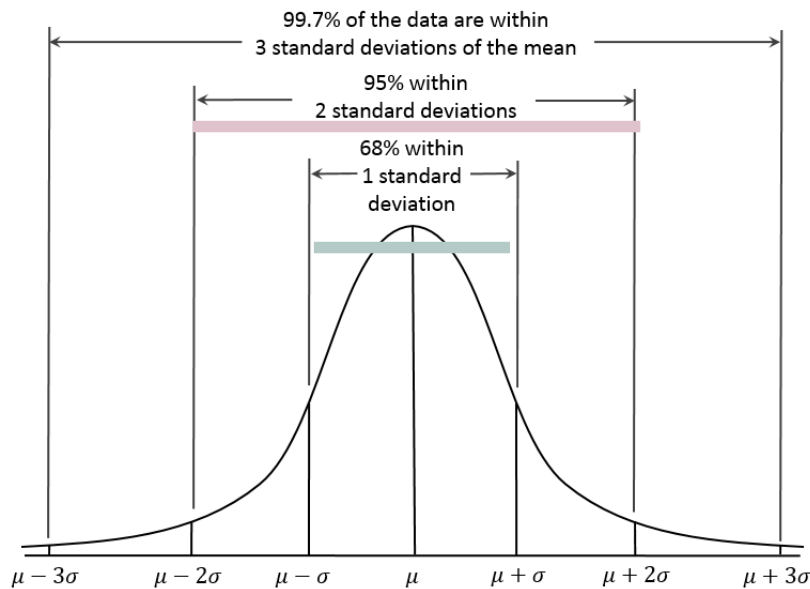
Different Plots

```
mapping = aes(
  x = price,
  y = ..density..
)
```

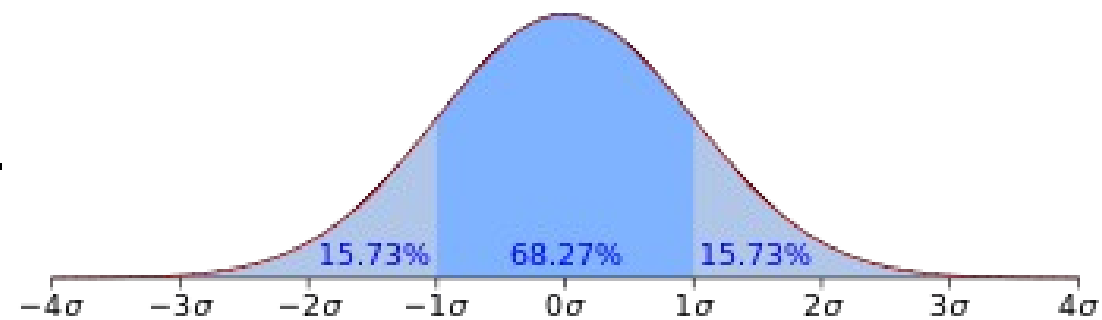
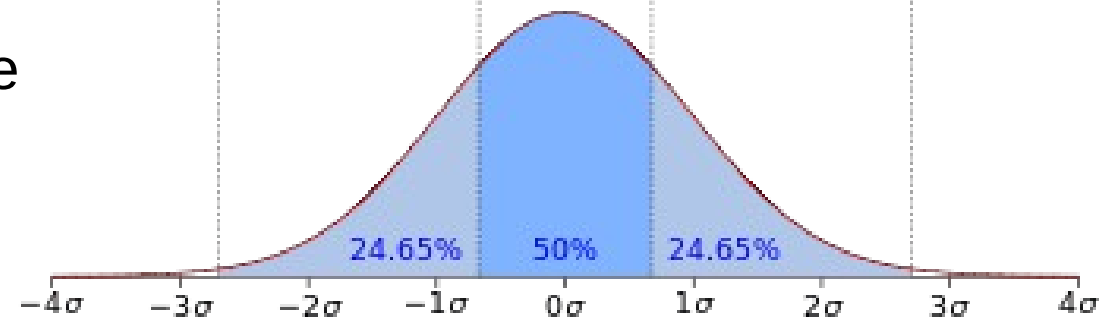
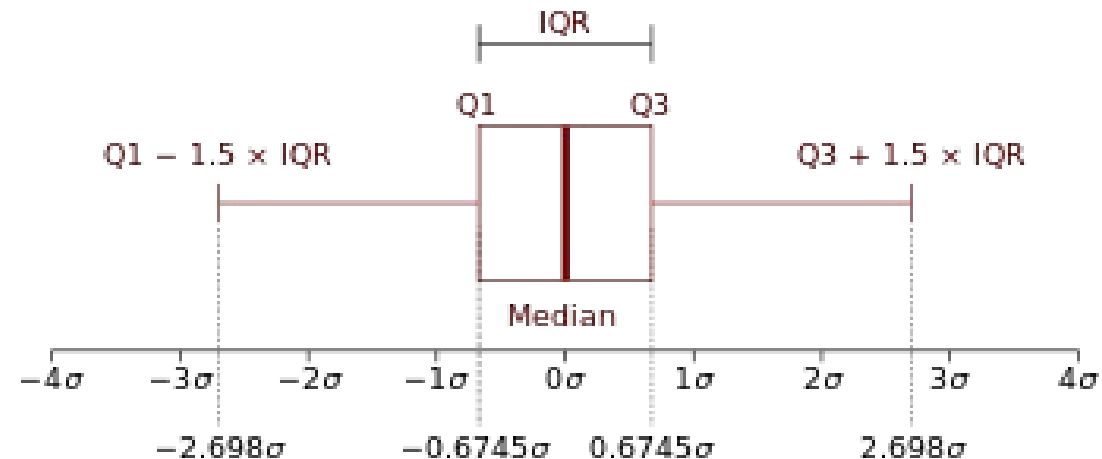


```
mapping = aes(
  x = price,
)
```

Box Plots



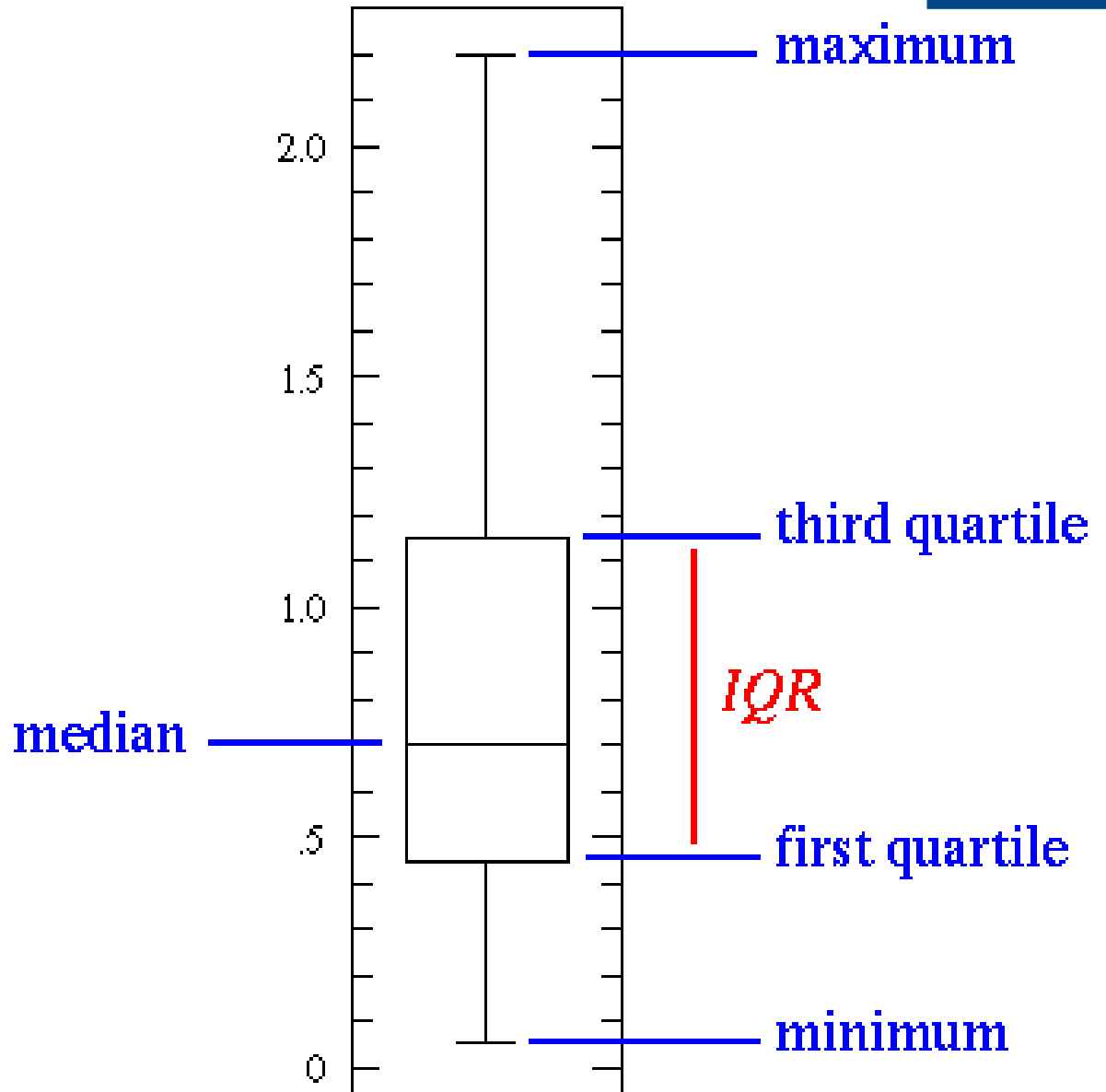
- For the Normal Distribution, the values less than one standard deviation away from the mean account for 68.27% of the set; while two standard deviations from the mean account for 95.45%; and three standard deviations account for 99.73%.





Explore Data Using Box Plots

Standardized way of displaying the distribution of data based on the five number summary: minimum, first quartile, median, third quartile, and maximum





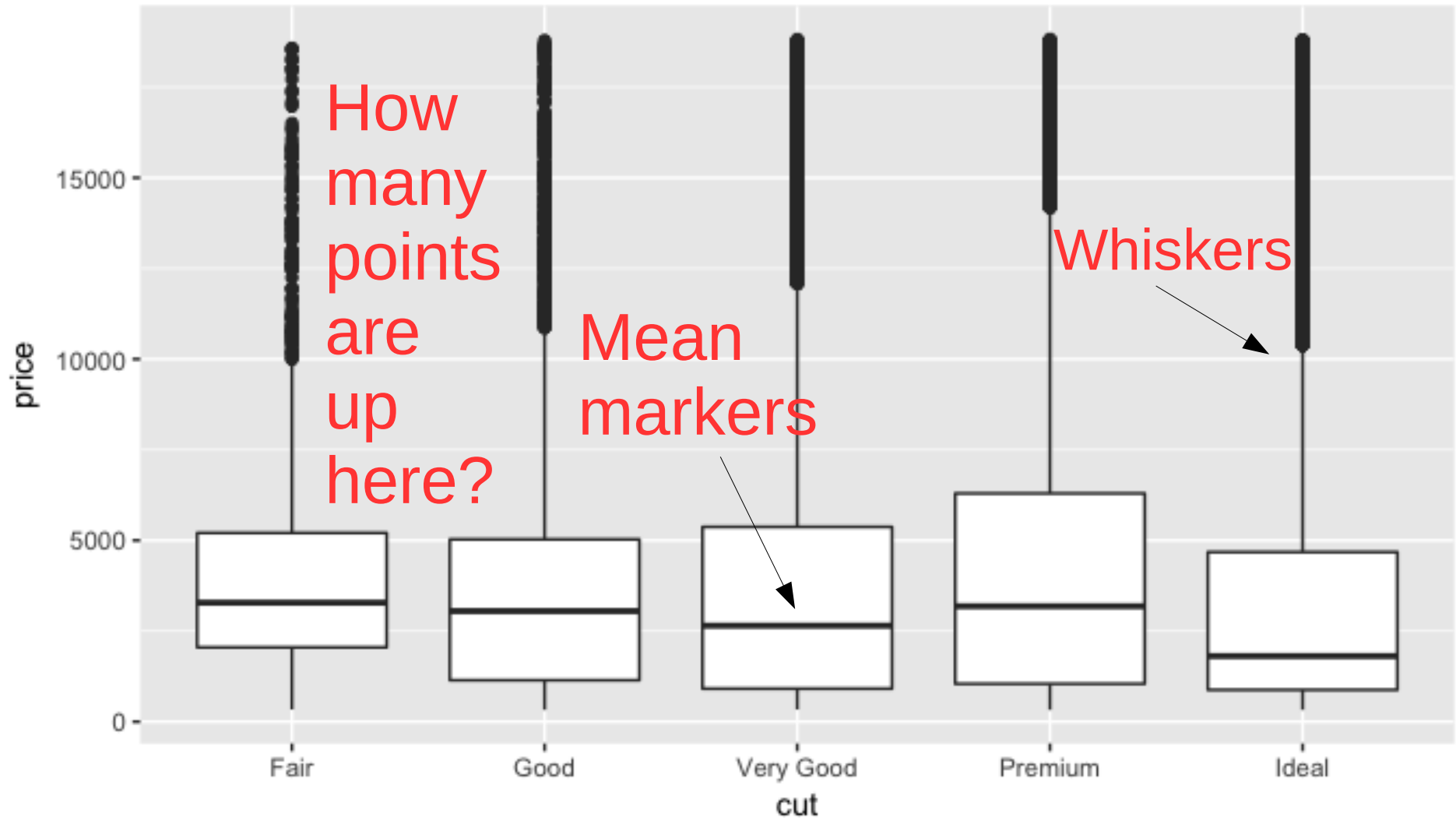
Explore Data Using Box Plots

Make a box plot to describe covariance between cut and price.

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



Explore Data Using Box Plots



Box Plots: Pros and Cons

- Pro
 - Box plots are more compact for convenient comparison
- Cons
 - Much less information about the *cut* distribution
 - Be careful, we could incorrectly conclude that better quality diamonds are cheaper on average!





Two Categorical Variables

Visualize the covariation between categorical variables with a “Plot of Dots” to determine observations.

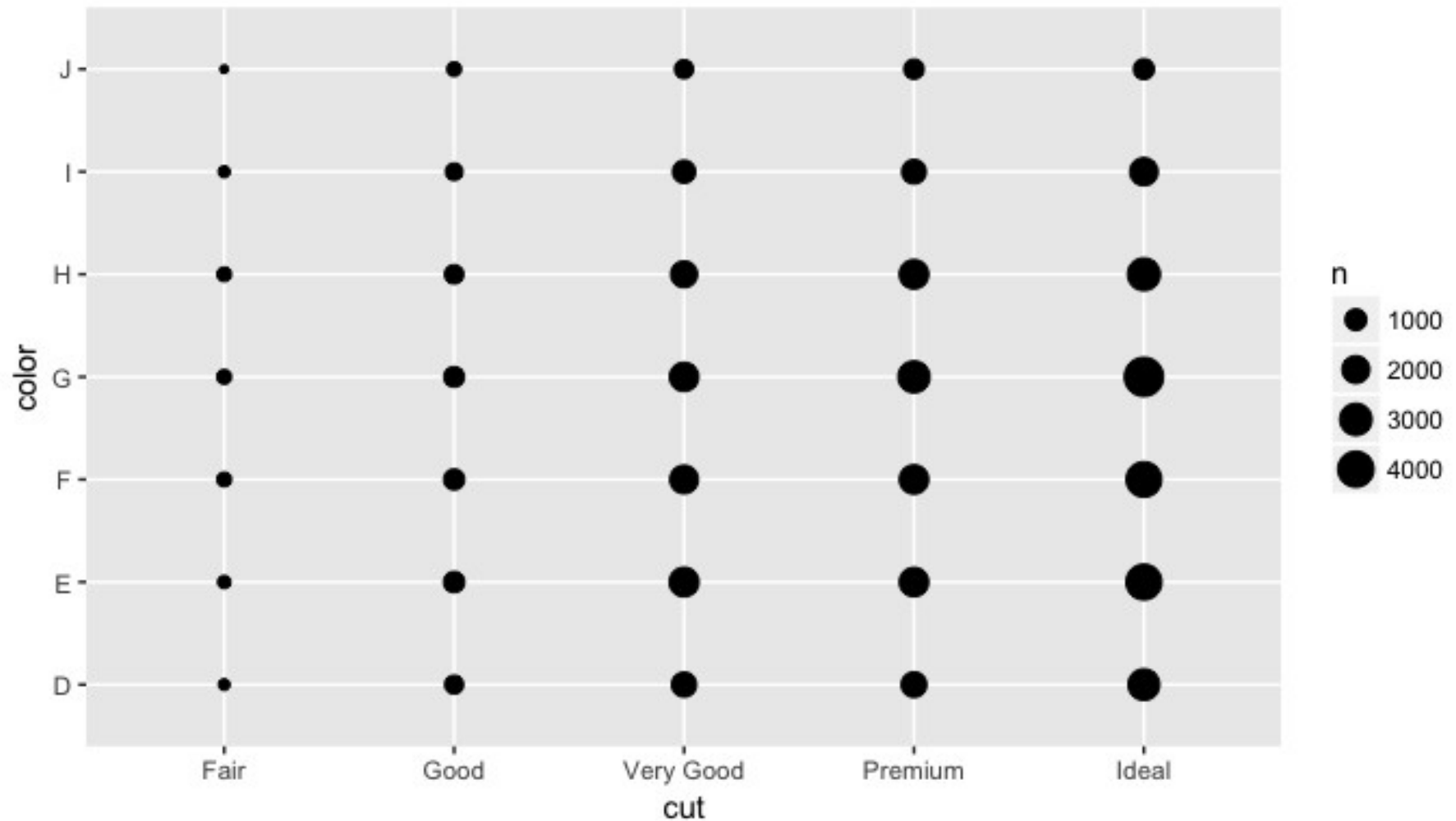
```
ggplot(data = diamonds) +  
geom_count(mapping = aes(x = cut, y = color))
```

Note: The size of each circle in the plot displays how many observations occurred at each combination of values

```
# Get exact text details of the plot  
diamonds %>% count(color, cut)
```



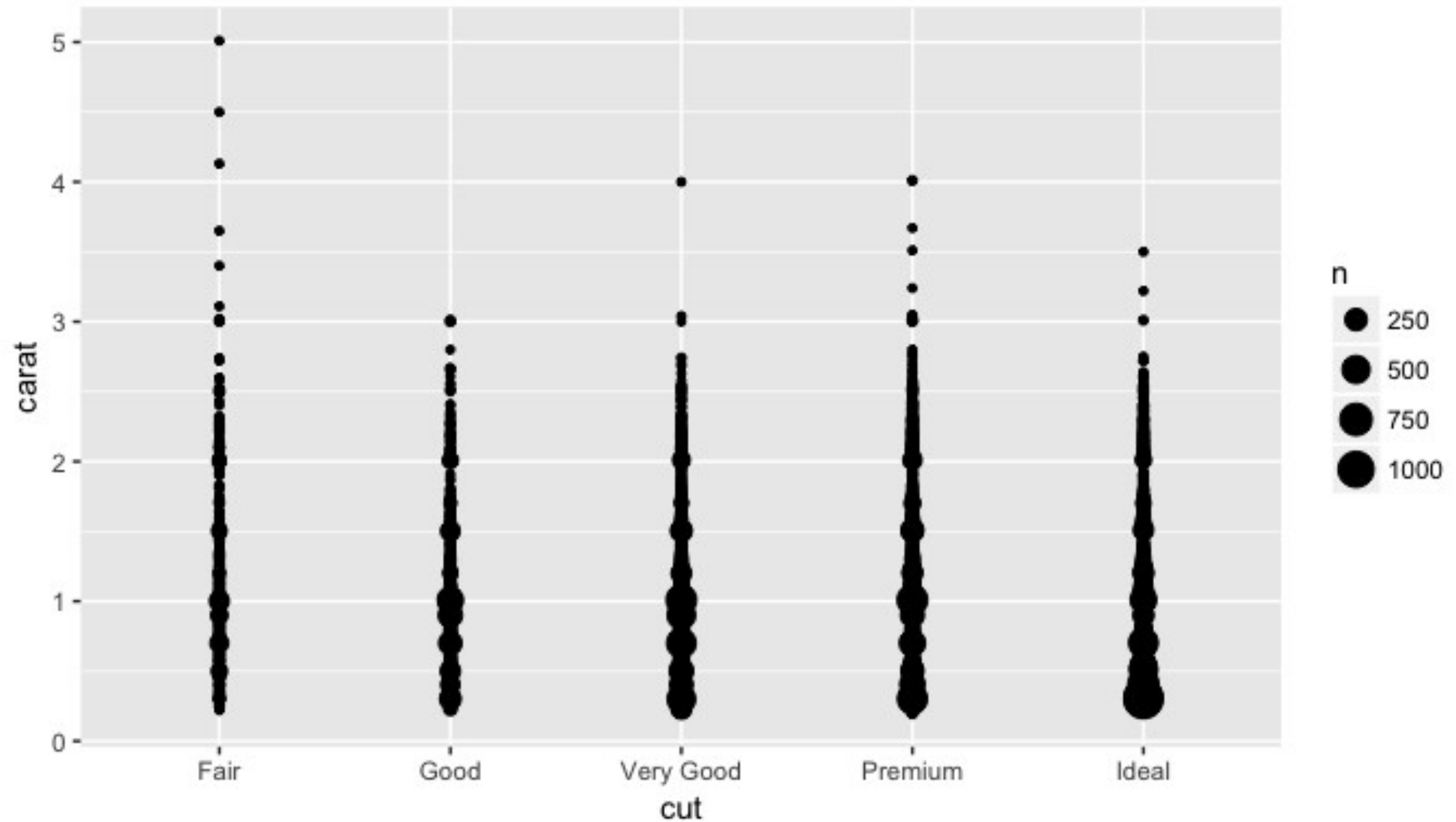
Mini Distributions: Cut vs Color



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



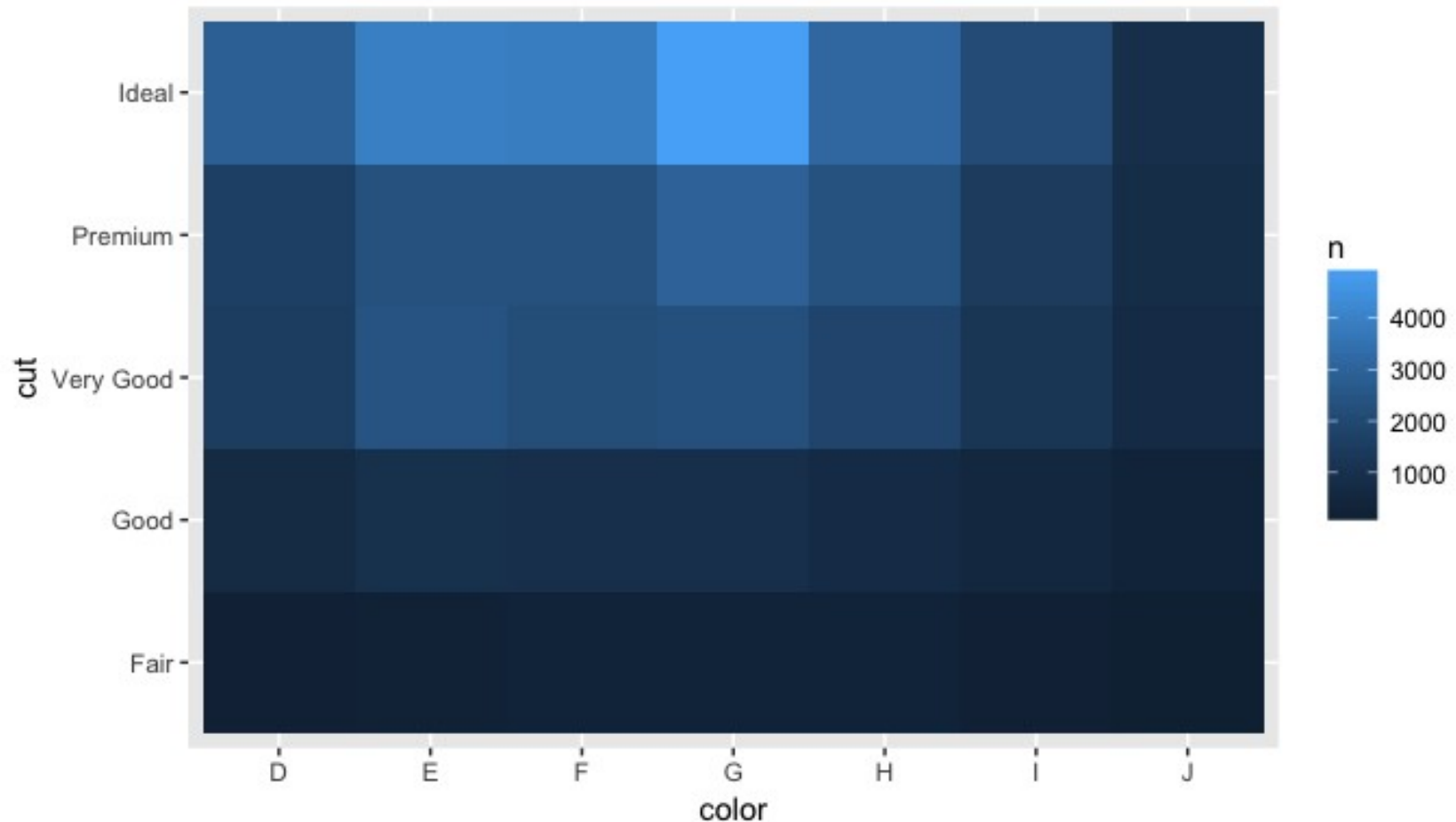
Mini Distributions: Cut vs Carat



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



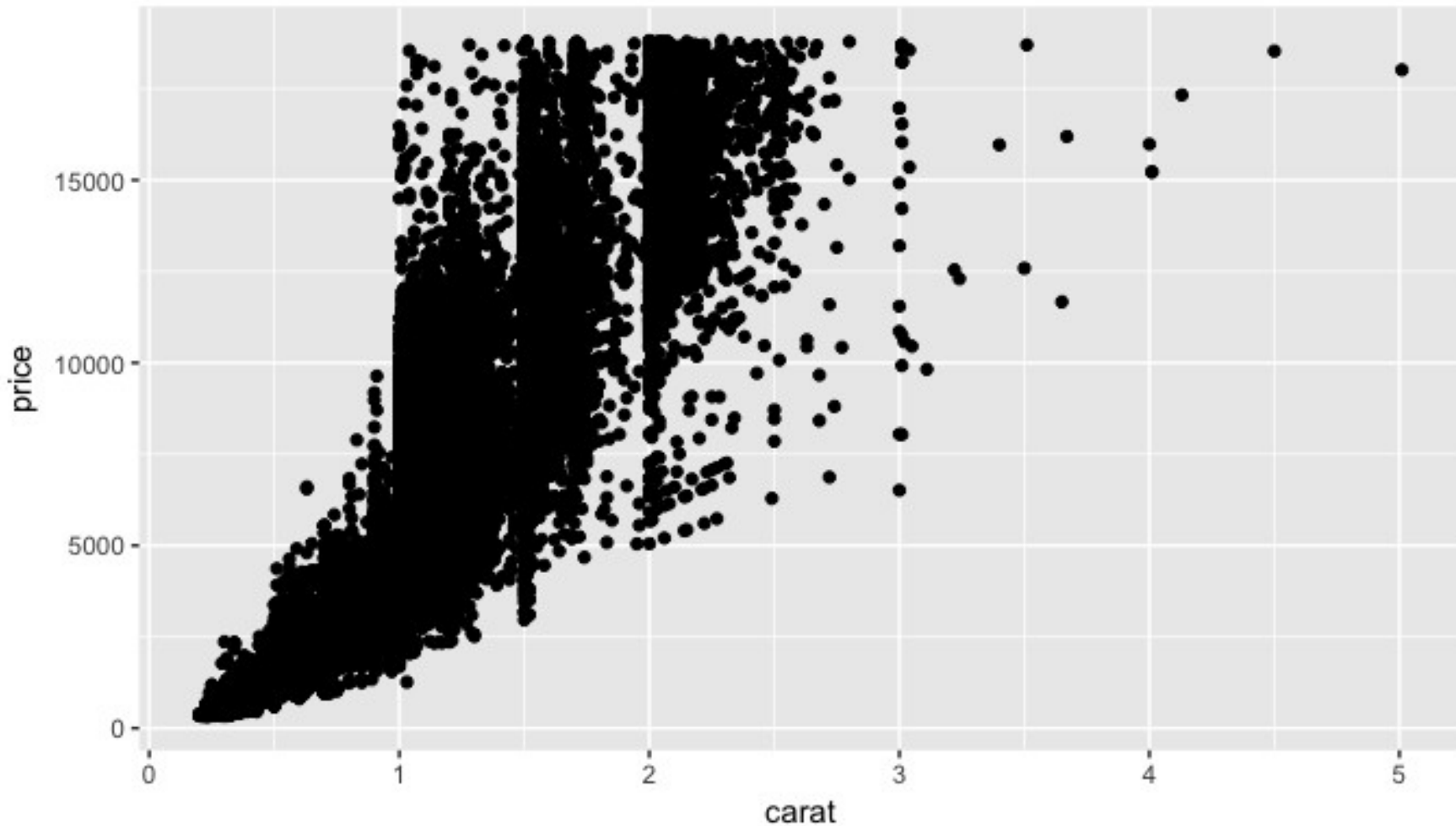
Mini Distributions: Cut vs Color



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



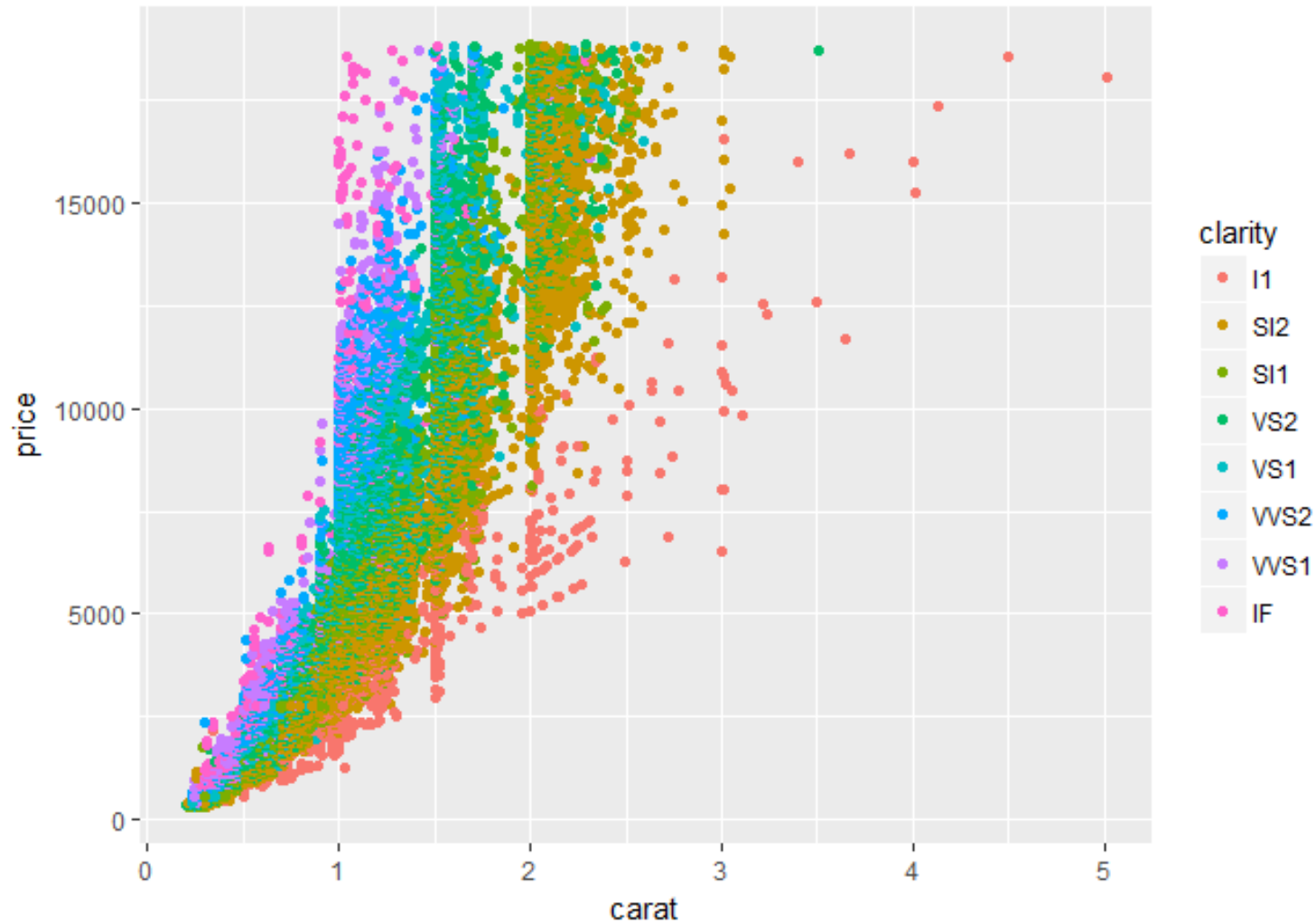
Mini Distributions: Carat vs Price



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



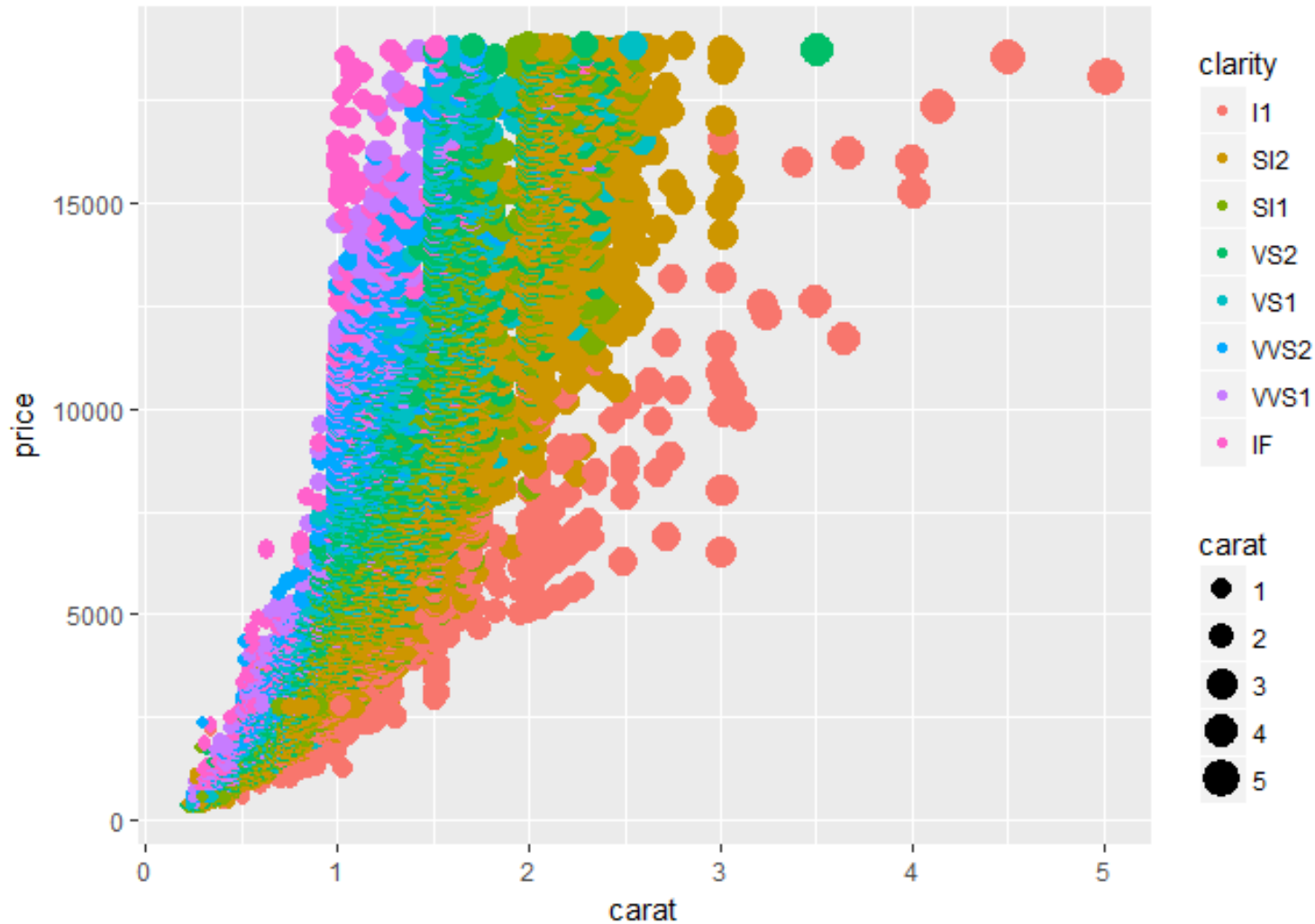

Mini Distributions: Carat vs Price



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



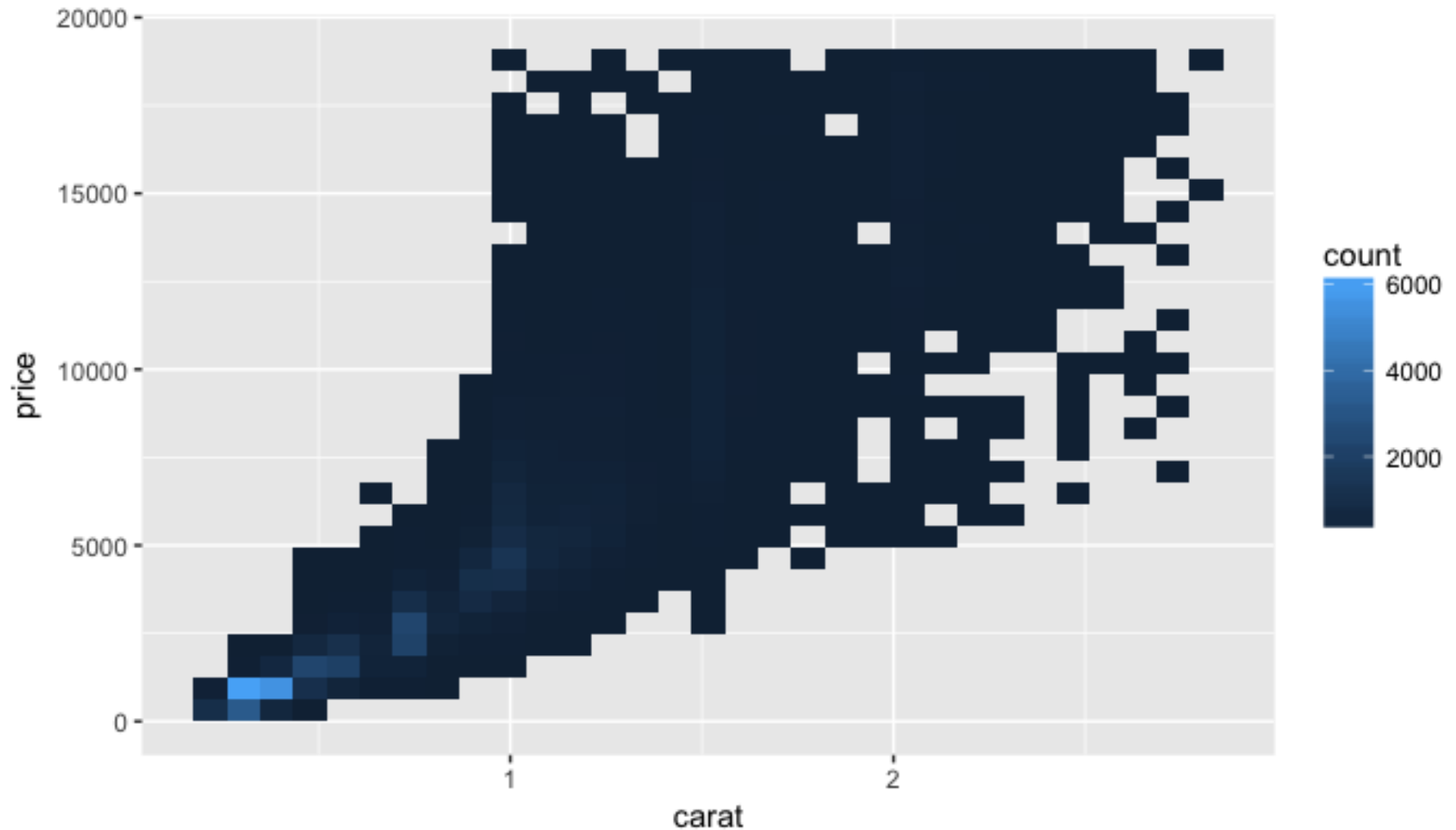
Mini Distributions: Carat vs Price



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



Mini Distributions: Carat vs Price



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



Consider This: *plots*

- Can you plot your diamond dataset with different subsets of data? Compare your plots!
- Play with the below code to see what you can isolate to plot
- Time permitting, can you find another dataset apply to plots?

```
diamonds3 <- diamonds %>%
```

```
mutate(y = ifelse(y < ## | y > ##, NA, y))
```

THINK