# STAT 6021: Project 1

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## Setup

## 6 1.00

```
## -- Attaching core tidyverse packages ----
                                              ----- tidyverse 2.0.0 --
## v dplyr
               1.1.2
                         v readr
                                      2.1.4
## v forcats
               1.0.0
                                      1.5.0
                         v stringr
## v ggplot2
               3.4.3
                         v tibble
                                      3.2.1
## v lubridate 1.9.2
                         v tidyr
                                      1.3.0
## v purrr
               1.0.2
                                            -----ctidyverse_conflicts() --
## -- Conflicts -----
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                     masks stats::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become error
##
## Attaching package: 'MASS'
##
##
## The following object is masked from 'package:dplyr':
##
##
       select
                                                       o casara
Poeta
##
     carat clarity color
                                cut price
## 1
               SI2
                       I Very Good
                                      774
     0.51
## 2
     0.93
                IF
                              Ideal
                                     6246
     0.50
              VVS2
## 3
                       D
                         Very Good
                                     1146
      0.30
               VS1
                       F
                              Ideal
                                      538
## 5
               SI1
                       F
                              Ideal
                                      502
     0.31
```

# Section 1: High Level Results of the Analysis

Ideal

7046

Our report studied the relationship between various factors associated with the grading of diamonds and the price of the diamonds. We found that the carat weight, roughly equal to 0.2 grams, is the most important factor in determining the price of the diamond. Thus, we analyzed the relationship between the carat weight of the diamond and its price. We found that, if the carat weight of a diamond increases by 1%, then the price of the diamond will increase by between 1.92% and 1.97%.

# Section 2: Data Description

VS1

The information in this section mostly comes from the following source: Blue Nile. "The 4Cs of Diamonds," n.d. https://www.bluenile.com/education/diamonds.

Formathing

### **Dataset Variables**

The quality, and consequently cost, of diamonds is measured with the "4Cs of Diamonds": the cut, color, clarity, and carat weight, which all appear in the dataset. as full as flur point

The cut of a diamond measures how "well-proportions a diamond's dimension are", as well as, once being processed, the "balance and brilliance of its facets". The facets of a diamond are the sides which are formed on the diamonds surface to give it its reflective, glittery appearance. The color of a diamond refers to the colorlessness of the diamond. Diamonds can often be yellowish, or off-white, depending on impurities in the source material. Therefore, the purest of diamonds are the ones which are completely colorless. The clarity of a diamond measures the cloudiness or impurities that can occur during diamond formation, due to impurities or foreign material. The carat weight refers to the physical weight of the diamond, and is often the most important indicator for showing how large, and subsequently how valuable, a diamond is. One carat is roughly equivalent to 0.2g, or 0.00705 oz. Finally, he price that the particular diamond sold for.

Created Variables Consider spacing During the analysis portion, we had to create a few new variables, namely xstar  $(x^*)$  and ystar  $(y^*)$ . The

variable xstar is the log of the carat variable, calculated as  $x^* = ln(carat)$ . The variable ystar is the log of

the price variable, similarly calculated as  $y^* = ln(price)$ 

Visualizations and Descriptions

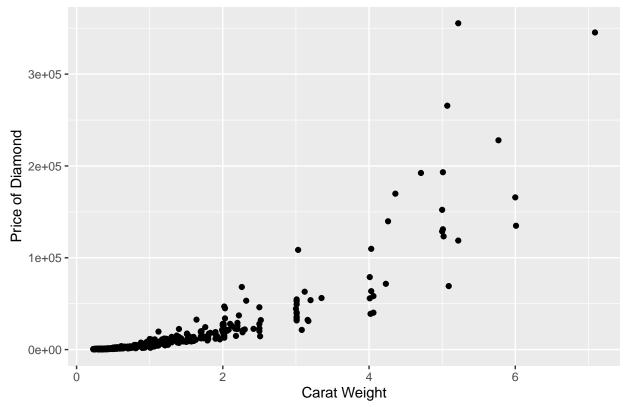
To better understand how price is related to the other variables in the dataset, and how the other variables are related to each other, we will create visualizations to see the appropriate scatterplots and boxplots of Why make there plots?

needed to

each variable against all of the others.

2

Price vs. Clarity
Price of Diamond vs. Carat Weight



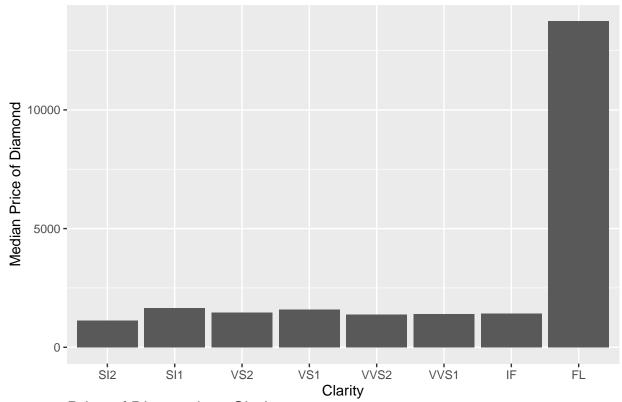
We can see from this scatterplot that the relationship between the price of a diamond and the carat weight appears exponential of some sort. As the carat weight increases, the price substantially increases.

need more

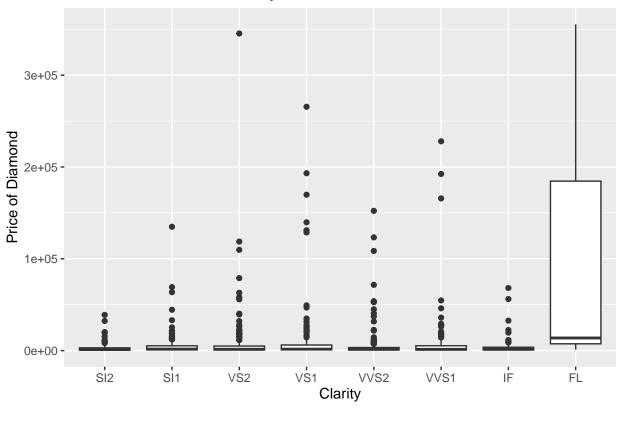
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Price vs. Clarity

Median Price of Diamond Based on Clarity





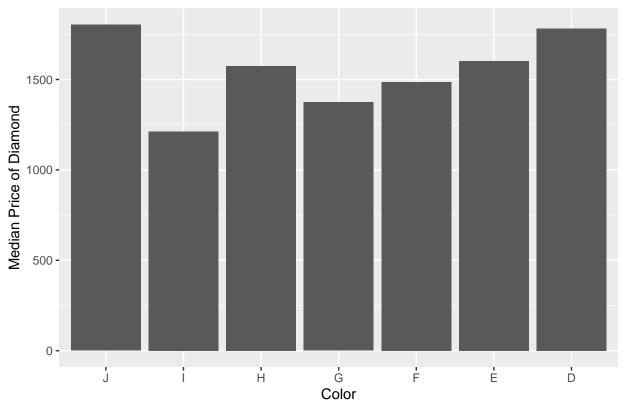


As we can see from the barplot above, the price increases dramatically when the clarity reaches the level of FL, which is flawless. Therefore, we can see that the median price of the diamond is not particularly affected by the clarity. However, based on the boxplot, the upper end of the prices for each quality do appear to have an upwards trend.

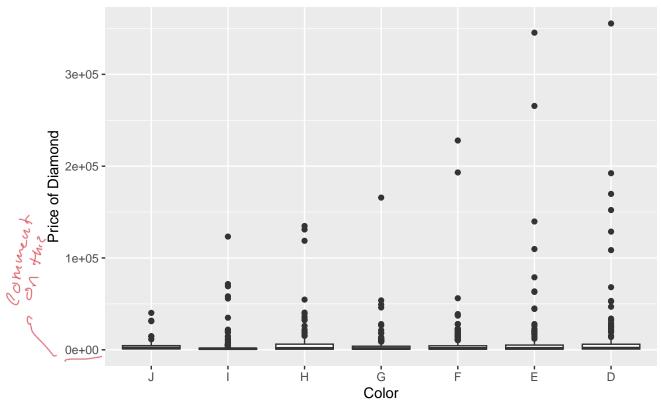
### Price vs. Color

```
## Warning: There was 1 warning in `mutate()`.
## i In argument: `color = color %>% fct_relevel(c("K", "J", "I", "H", "G", "F",
## "E", "D"))`.
## Caused by warning:
## ! 1 unknown level in `f`: K
```

# Median Price of Diamond Based on Color



# Price of Diamond vs. Color

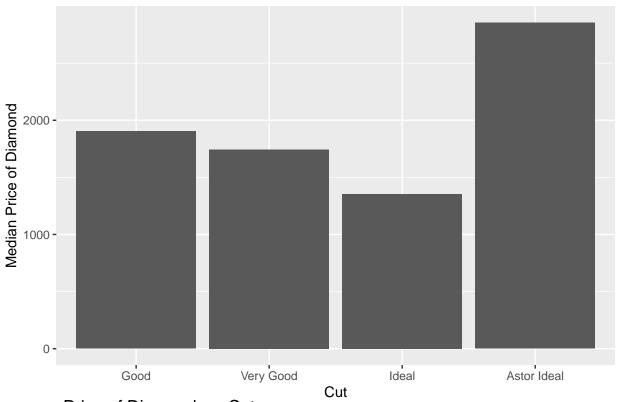


Based on the bar plot, we do not see much of a relationship between color and the price of the median diamond of each color. In fact, the highest median price for a diamond appears for the lowest color quality on the scale: J. However, when looking at the boxplots, the upper end of the diamonds sold at each color appear to have an upwards trajectory. That being said, the color does not appear to be a major factor in determining the price of a diamond.

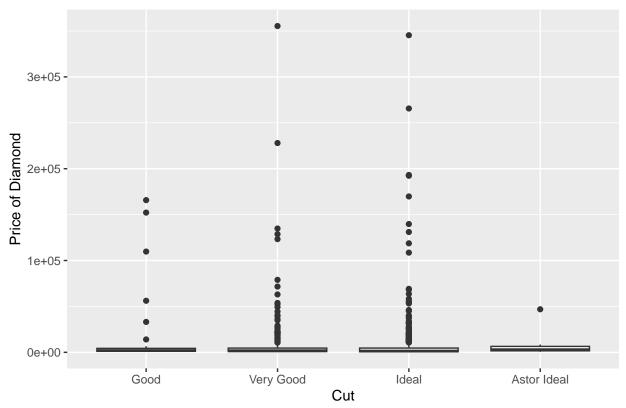


Price vs. Cut

Median Price of Diamond Based on Cut







In a pattern very similar to the last two variables, we see that the bar plot does not show much of an upwards trend in median prices based on the cut of the diamond. In fact, with the exception of the Astor Ideal cut, the median prices decline as the cut improves. This trend continues when looking at the boxplot. There is no considerable upwards trend in even the upper end of prices as the cut of the diamonds improve. Based on this information, it appears that the cut is not a significant variable when it comes to determining the price of a diamond

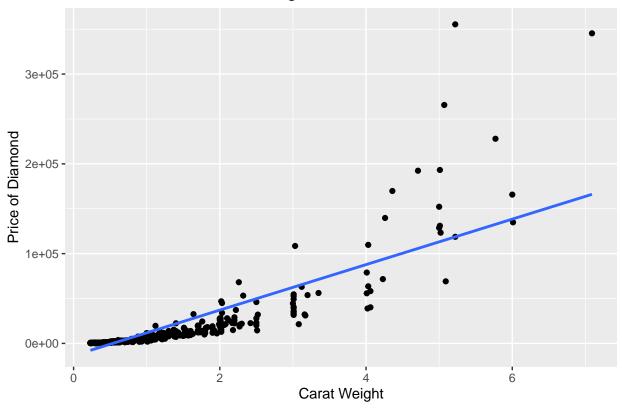
Based on the analysis above, the variable that best appears to predict the price of a diamond is its carat weight, which agrees with the claims made on the BlueNile diamond education page. We will use the carat weight variable as the predictor variable moving forward in our regressions. However, based on the exponential appearance of the graph, some data transformations may be needed.

# Section 4: Regression Description

First, we must take a look at the scatterplot of the response variable price against the designated predictor variable carat.

## `geom\_smooth()` using formula = 'y ~ x'

## Diamond Price vs. Carat Weight

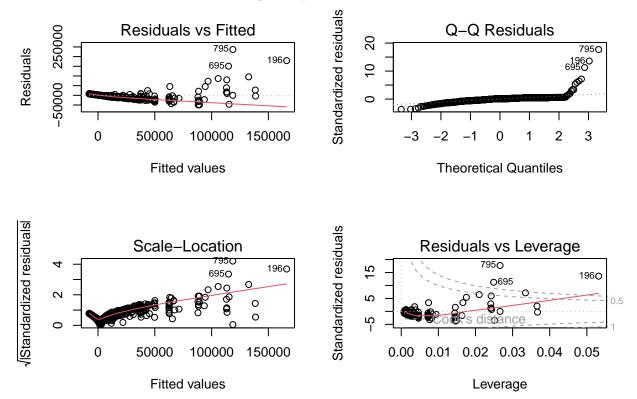


The scatterplot comparing carat and price looks exponential rather than linear. This would indicate that a transformation is needed, likely a log transformation.

As a reminder, the regression assumptions are as follows:

- The residuals have mean 0.
- The errors have constant variance.
- The errors are independent.
- The errors are normally distributed

To confirm, we will take a look at the diagnostic plots.

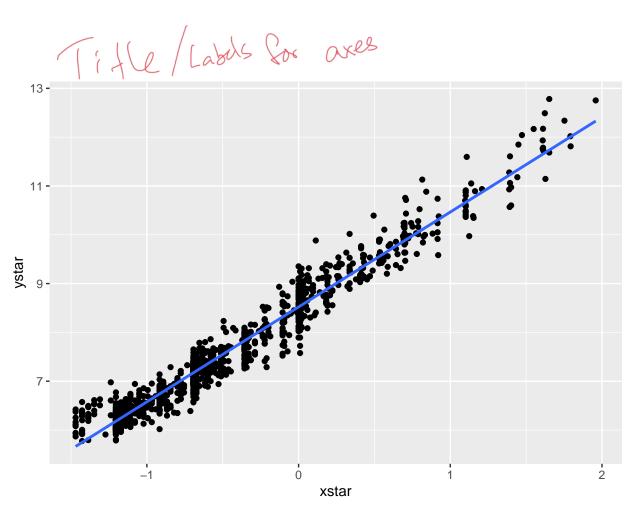


Based on the diagnostic plots as well as the Box-Cox plots, it seems that both regression assumptions 1 and 2 have been violated since the errors do not have mean 0 nor constant variance. The mean of the residuals appears to decrease, and the residuals appear to get more spread out. If both assumptions are violated, the best solution is to log transform both the x and y variables. The Box-Cox plot agrees with this since the confidence interval does not include 1, indicating the y variable must be transformed.

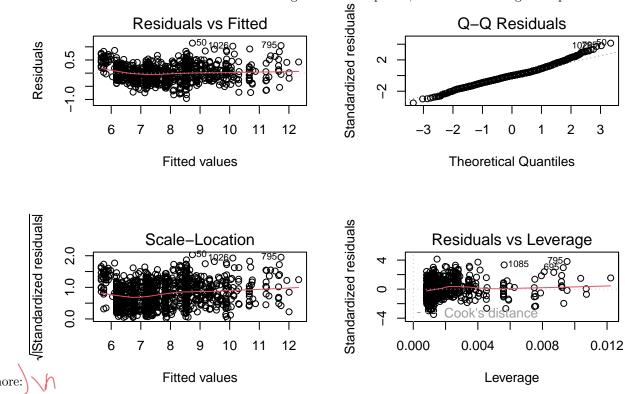
We will create the variable xstar, which is defined as  $x^* = ln(carat)$  and the variable ystar, defined as  $y^* = ln(price)$ :

## 'geom\_smooth()' using formula = 'y ~ x'

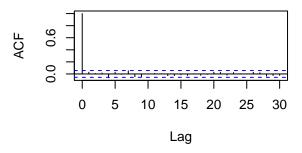
| Variation | Variatio



As we can see from this scatterplot, the relationship appears much more linear than the first scatterplot before. To be sure we have remediated the violations of the regression assumptions, we look at the diagnostic plots once



### ACF Plot of Residuals from Y\* ~ X\* Mod



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After log transforming both the x and y variables, the diagnostic plots also pass the assumption, with errors appearing to have both a mean of 0 and constant variance. Further, the Q-Q plot shows that the residuals have a fairly normal distribution. Based on the ACF plot we can also see that the errors are independent. Thus, all four regression assumptions are met.

So, our hypotheses are:

```
H_0: \beta_1 = 0<br/>H_0: \beta_1 \neq 0
```

When we run the regression, we see:

```
##
## Call:
  lm(formula = ystar ~ xstar, data = Data)
##
##
## Residuals:
##
        Min
                  1Q
                       Median
                                    3Q
                                            Max
##
  -0.96394 -0.17231 -0.00252 0.14742
                                        1.14095
##
##
  Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
##
  (Intercept) 8.521208
                          0.009734
                                     875.4
                                             <2e-16 ***
                                     159.8
                                             <2e-16 ***
## xstar
               1.944020
                          0.012166
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2761 on 1212 degrees of freedom
## Multiple R-squared: 0.9547, Adjusted R-squared: 0.9546
## F-statistic: 2.553e+04 on 1 and 1212 DF, p-value: < 2.2e-16
```

Based on the results of the model with both the response and the predictor being log transformed, xstar,  $x^* = \ln(carat)$ , is statistically significant with a p-value of  $2.2 \times 10^{-16}$  much lower than 0.05. This means that the log of carat is significant in predicting the log of the price of the diamond.

The regression equation is ln(price) = 8.521 + 1.944ln(carat). This means that for every 1% increase in the carat weight, the price of the diamond is expected to increase by around 1.944%.

The 95% confidence interval is:

```
## 2.5 % 97.5 %
## (Intercept) 8.502110 8.540306
## xstar 1.920152 1.967888
```

Which shows that we are 95% confident that for each 1% increase in the carat weight of a diamond, its price will increase between 1.92% and 1.97%.